

**FACTORS INFLUENCING THE ECONOMIC PERFORMANCE OF A PANEL OF  
COMMERCIAL MILK PRODUCERS FROM EAST GRIQUALAND, KWAZULU-  
NATAL, AND ALEXANDRIA, EASTERN CAPE, SOUTH AFRICA: 2007-2014**

BY

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## ABSTRACT

The South African dairy industry has been characterized, in recent years, by an observed movement towards fewer, larger producers, implying a more competitive milk market in which efficiency measures are likely to become increasingly important determinants of farm financial success and survival. Due to the imperfect nature of efficiency estimates, a more integrated approach is adopted in this study in which economic performance is defined as an unobservable variable for which there exist many imperfect indicators, including various measures of efficiency. This study presents a two-stage approach to analyse economic performance, and its key determinants, for a panel of commercial milk producers in East Griqualand (EG) and Alexandria, South Africa, over the period 2007-2014. Stochastic frontier analysis was used to estimate technical efficiency (TE) from a translogarithmic production function, selected ex-post from several specified models with different functional forms and distribution assumptions. Parametric scale efficiency (SE) was then estimated from the resulting scale elasticities and parameter estimates. Results indicate that sampled producers are, on average, highly technically efficient, generally operating close to the efficient frontier, and are relatively homogenous in production. The general decline of mean TE scores over the study period indicates that farms on the best practice frontier became more efficient over time, while the average farm has become less efficient in relation to the advancing frontier. High mean SE scores confirm that most farms do not experience a substantial loss in output due to scale efficiency problems, but rather to inefficiencies in production (TE). Analysis of SE scores reveals that most farms operated at suboptimal scale, with increasing returns to scale, and could improve output by expanding towards the optimal scale.

Latent economic performance was modelled in a Multiple-Indicators, Multiple-Causes (MIMIC) model framework, with estimated TE and SE serving as imperfect indicators. Three latent indices were constructed to represent managerial quality regarding the breeding, feeding and labour programme, and were included in the structural equation, in conjunction with traditional explanatory variables, as latent causes of economic performance. Evaluation of model fit for several specified models led to the selection of the most simplistic specification, in which the latent managerial constructs were not included. Results suggest efficiency, milk yield per cow, and level of specialization in dairying all have a significant effect on the economic performance of the

sampled farms. It should be noted that the sign of latent economic performance was not in line with expectations, and requires further research.

## DECLARATION

I, Jethro James Ross, declare that

- 1.1 The research reported in this dissertation, except where otherwise stated, is my own original research.
- 1.2 This dissertation has not been submitted for any degree or examination at any other tertiary institution.
- 1.3 This dissertation does not contain other persons' data, figures, graphs or other information, unless there is specific acknowledgement and appropriate reference to the source.
- 1.4 This dissertation does not contain any other authors' work, unless specifically acknowledged and appropriately referenced. Where other written works have been quoted:
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Signed:



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Jethro James Ross

16 March 2018

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Date

I, as the main supervisor, agree to the examination of this dissertation:



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Professor Gerald Ortmann

(Main Supervisor)

16 March 2018

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Date

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## LIST OF ABBREVIATIONS AND ACRONYMS

GDP	Gross Domestic Product
KZN	KwaZulu-Natal
TFP	Total Factor Productivity
GVA	Gross Value Added
ROI	Return on investment
ROE	Return on equity
SEM	Structural equation modelling
MIMIC	Multiple Indicators, Multiple Causes
LAC	Long run average cost
ISUR	Iterative Seemingly Unrelated Regression
FIML	Full information maximum likelihood
DEA	Data envelopment analysis
TPP	Total physical product
APP	Average physical product
MPP	Marginal physical product
TE	Technical efficiency
AE	Allocative efficiency
EE	Economic efficiency
SE	Scale efficiency
SFA	Stochastic Frontier Analysis
LCM	Latent class model
DMU	Decision making unit

FDH	Free Disposal Hull
CRS	Constant returns to scale
VRS	Variable returns to scale
NIRS	Non-increasing returns to scale
DGP	Data generating process
LML	Local maximum likelihood
RLb	Richardson-Lucy blind deconvolution algorithm
CNLS	Convex nonparametric least squares
stoNED	Stochastic non-smooth envelopment of data
MM	Method of moments
GAM	Generalized additive model
EFA	Exploratory factor analysis
CFA	Confirmatory factor analysis
ML	Maximum likelihood
TMR	Total mixed ration
KZNMPO	KwaZulu-Natal Milk Producers' Organisation
EG	East Griqualand
EC	Eastern Cape
BRG	Bioresource Group
MCAR	Missing completely at random
MAR	Missing at random
MNAR	Missing not at random
MCMC	Markov Chain Monte Carlo

TL	Translog
NQ	Normalized Quadratic
GL	Generalized Leontief
CD	Cobb-Douglas
STL	Simplified translog
TN	Truncated normal
HN	Half normal
MPSS	Most productive scale
OLS	Ordinary least squares
AI	Artificial insemination
TLI	Tucker Lewis Index
CFI	Comparative Fit Index
RMSEA	Root mean square error of approximation
SRMR	Standardized root mean square residual
AIC	Akaike information criterion
BIC	Bayesian information criterion
SSABIC	Sample-size adjusted BIC

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## CHAPTER 1: INTRODUCTION

### 1.1 General Introduction

Agricultural production is an integral part of the national economy contributing R72.2 billion to GDP in 2015. Despite a decrease in agriculture's share of GDP from 6% in the 1970's to 2% in 2015 it remains an important sector of the national economy (Department of Agriculture, Forestry and Fisheries (DAFF), 2016). The South African dairy industry is the fifth largest agricultural industry in the sector, providing 60 000 jobs at the farm level and a further 40 000 indirect jobs in associated value chains, such as processing and milking (DAFF, 2014b). South Africa is currently a net exporter of dairy products, importing 40 199 tons and exporting 71 099 tons during 2015 (DAFF, 2015). In global terms, South Africa is a relatively small milk producing country, contributing just 0.5% of world milk production in 2014 (DAFF, 2014b).

Dairy industries in many countries have undergone significant structural change in the past two decades, with a consolidation trend towards fewer, larger milk producers. Melhim *et al.* (2009) highlighted the magnitude of these structural changes in the United States (US) dairy industry, reporting that between 1974 and 2002 the number of farms with milking cows declined by 79%. Furthermore, from 1964 to 2005 the number of milking cows per farm in the US increased by 60%. Evidence of industry consolidation can be found in several other studies on US milk producers (El-Osta & Morehart, 2000; Gloy *et al.*, 2002; Tauer & Mishra, 2006; Gillespie *et al.*, 2009; Hanson *et al.*, 2013).

Evidence of significant structural change has also been found in other major milk producing countries such as New Zealand and Australia. Clark *et al.* (2007) found evidence of a consolidation trend in the New Zealand dairy industry, indicating that from 1994 to 2004 the number of cows on New Zealand dairy farms increased by 37%, while herd size increased by 63%. Kompas & Che (2003) reported a similar trend in the Australian dairy industry, reporting that between 1978-79 and 1999-2000 the number of dairy producers nearly halved. This large decrease in the number of dairy producers was, however, accompanied by almost a 70% increase in total milk production. This consolidation trend among Australian milk producers was further substantiated by Kompas & Che (2006). Furthermore, between 2001 and 2007, Hansson & Ferguson (2011) noted that the number of Swedish dairy farms decreased by 40%, while average herd size increased over the same period.

This observed movement towards fewer, larger producers is indicative of a more competitive milk market. In the face of increased competition, the economic efficiency of a milk producer's operation is likely to become an increasingly important determinant of farm financial success (Weersink *et al.*, 1990) and survival in the industry (Tauer & Belbase, 1987; Bravo-Ureta & Rieger, 1991).

There are several different measures of efficiency referenced in the literature, including technical, allocative, scale and economic efficiency. Technical efficiency may be defined as the ability of a firm to obtain maximum output from a given set of inputs (Farell, 1957). Scale efficiency measures the ray average productivity at the observed input scale relative to what is attainable at the most productive scale size (optimal scale) (Ray, 1998). In essence, this indicates how close the observed firm is to the optimal scale (Madau, 2011). Economic efficiency, which is the product of technical and allocative efficiency, refers to the ability of a firm to produce a predetermined quantity of output at minimum cost for a given level of technology (Farell, 1957). Economically efficient farmers utilize inputs to production effectively, producing output at lower cost for a given level of technology. This allows for improved profitability and a potential competitive advantage. In essence, commercial milk producers may be able to improve their competitive position in a highly competitive milk market through the exploitation of production advantages associated with improved levels of efficiency. In the long run, firms that are not technically efficiency will not survive, as the forces of competition will drive inefficient farms out of business (Tsionas, 2006).

Investigating firm performance through the analysis of various measures of efficiency is commonplace in the literature although most studies consider only technical efficiency in their analyses. Likewise, farm performance has commonly been defined in terms of technical efficiency (Sedik *et al.*, 1999; Diaz & Sanchez, 2008), although several studies have extended their scope to include allocative efficiency (Kalirajan & Shand, 2001) and economic efficiency (Hansson, 2007).

Despite the continued popularity of efficiency measures in productivity analysis, it is important to highlight several possible limitations associated with their use as indicators of farm performance. Firstly, many definitions of efficiency exist, including economic, allocative, scale and technical efficiency (Coelli, 1995; Hansson, 2007). Secondly, there are various empirical techniques for the measurement of any one type of efficiency, the choice of which may have a significant effect on the estimated parameters and hence the validity of the results (Kalaitzandonakes & Dunn, 1995;



Balcombe *et al.*, 2006; Bravo-Ureta *et al.*, 2007). Finally, farm performance may be investigated using alternative measurement approaches, such as Total Factor Productivity (TFP) (Fraser & Hone, 2001; Fogarasi & Latruffe, 2009a) and Gross Value Added (GVA) (Thomassen *et al.*, 2009; Giannakis & Bruggeman, 2015). TFP measures the overall efficiency of agricultural production and may be defined as the ratio of aggregate output to aggregate input (Pingali & Evenson, 2010; O'Donnell, 2010). Productivity growth therefore occurs when growth in output exceeds growth in inputs (Pingali & Evenson, 2010). GVA may be defined as the difference between the value of total production and non-factor costs, where non-factor costs may be defined as the total cost of all factors not directly attributable to the milk production process (Giannakis & Bruggeman, 2015).

Given the imperfect nature of efficiency based performance analysis, it may be desirable to investigate the determinants of farm performance on a more integrated level, considering factors other than efficiency estimates. Investigating the economic performance of a farm, for instance, provides a means of identifying the critical factors that determine the success or failure of a farm. However, before proceeding with an analysis of economic performance, an unambiguous definition of the concept must be established. Economic performance is a concept lacking a concise definition among the literature although there is a general consensus that the definition depends upon the nature of the study and the aspect of performance that is to be investigated. Paul & Siegel (2006) consider economic performance as being based on the analysis of marketed inputs and outputs and define the concept in terms of productivity, technical efficiency and cost effectiveness. Lanoski (2000) identifies profitability measures, such as return on investment (ROI) and return on equity (ROE); growth, in terms of sales and market share, and firm financial success as common measures of economic performance. Although definitions of economic performance differ per their application, measures of productivity, financial success and growth are common themes among the literature. For the purposes of this study it is proposed that economic performance be defined as a latent, unobservable variable for which there exist many imperfect indicators, including various measures of efficiency (Richards & Jeffrey, 2000).

Defining economic performance as a latent (unobservable) variable requires that an appropriate latent variable modelling framework be specified. For the purposes of this study, a structural equation modelling (SEM) framework is used to model latent economic performance. More specifically, the Multiple-Indicators, Multiple-Causes (MIMIC) model, a special case of SEM, is

selected for its ability simultaneously to model the effects of various “cause” and “indicator” variables on latent economic performance. Within the MIMIC framework, efficiency estimates, included as “indicator variables”, and traditional observable “cause” variables such as herd size can be modelled simultaneously. The result is a comprehensive analysis of dairy farm economic performance, and its key determinants, at a level of integration not typically considered among the literature.

The rapid rate of consolidation identified in several important milk producing nations raises several important research questions, such as: 1) Do larger milk producers possess an inherent advantage over smaller producers, indicating the presence of size economies in the dairy industry? 2) In a highly competitive milk market, what strategies or factors are most important in improving economic performance and, hence, financial success? 3) Is technological variation between producers a significant determinant of farm performance and, therefore, a possible contributing factor to the consolidation trend? The answers to these questions could give commercial milk producers insight into which strategies or factors are critical determinants of economic performance. This would enable farmers to target critical success factors, thereby focusing resources and managerial efforts on those factors most likely to improve farm performance. Through efficient allocation of resources, greater levels of production can be achieved, resulting in improved farm performance, market position, and hence, the likelihood of remaining in business despite industry consolidation.

Over the past 20 years the South African (SA) dairy industry has also undergone major structural change as the country has adopted the global trend of liberalizing the marketing of its agricultural products (Du Toit *et al.*, 2010). This change is characterized by concentration of production into fewer, larger dairy farms (Du Toit *et al.*, 2010; Mkhabela & Mndeme, 2010). From January 2007 to January 2015, the number of South African milk producers declined by 53%, from 3899 to 1834 (Coetzee & Maree, 2015). Despite the marked decrease in the number of national milk producers, total South African milk production has risen from 1939 million litres in 1980 to 2686 million litres in 2012, a 39% increase (DAFF, 2013). Greater aggregate milk production on a national level may be explained in part by an observed increase in the average herd size of South African milk producers. From 2009 to 2014, the average national herd size increased from 209 to 353 milk cows, a 69% increase (Coetzee & Maree, 2010; 2015). This evidence indicates a consolidation

trend within the South African dairy industry whereby fewer, larger producers are beginning to dominate the provincial and national industry.

The competitive nature of the domestic milk market, coupled with structural adjustment throughout the industry, has created the need for local milk producers to improve their economic performance in order to remain in the industry. Considering the consolidation trend, an important question is how performance varies across individual producers and what possible strategies or factors decision makers may consider to improve economic performance. Furthermore, variations in productivity at the farm level imply that some producers could improve their economic performance (Hansson, 2007).

The observed consolidation trend has been attributed, in part, to scale economies within dairy industries, enabling larger producers to remain in production through expansion of their operations (Melhim *et al.*, 2009). Kumbhakar (1993) highlighted the ability of large US dairy farms to achieve higher levels of economic efficiency and profit than smaller producers. Although US dairy producers may consider increasing herd size as a primary means of improving farm performance, this may not be the scenario in South Africa. To validate such a statement requires an investigation into the presence of scale economies on SA commercial dairy farms. Previous work on factors affecting various measures of performance and financial success on dairy farms has highlighted the positive effect of the following variables: herd size and milk yield (Gloy *et al.*, 2002), managerial ability (Ford & Shonkwiler, 1994), quality of breeding programmes, feeding strategies, labour quality (Richards & Jeffrey, 2000) and level of specialization in dairy (El-Osta & Morehart, 2000).

To date, there is a limited body of literature on the productivity of South African milk producers, with only a few studies employing empirical analysis to dairy industry data. Beyers & Hassan (2001a) investigated size economies in South African dairy production using a long run average cost (LAC) curve approach. Mkhabela & Mndeme (2010) adopted a two-step approach to cost analysis of milk producers in the KwaZulu-Natal (KZN) Midlands of South Africa. The first step involved the estimation of farmers planned output through the estimation of a production function. The second stage involved the estimation of the LAC curve by calculating the average cost as total cost divided by planned output.

Beyers & Hassan (2001b) considered an application of stochastic frontier analysis to a cross-section of South African milk producers in which the relative performance of translog and normalized quadratic profit function specifications were compared. Mkhabela *et al.* (2010) considered an application of stochastic frontier analysis to a panel of milk producers from the KZN Midlands, considering Cobb-Douglas and translog specifications of production technology. To the author's best knowledge, these are the only two applications of frontier analysis to the South African dairy industry. The lack of research into the efficiency and performance of South African dairy farmers highlights the potential importance of this study. Estimating technical and scale efficiency and identifying their key determinants, will provide valuable information to dairy farmers, policy makers and extension officers alike. Furthermore, a latent variable modelling framework, able to identify factors affecting farm economic performance, has not yet been considered in the South African context. The integrated approach proposed herein aims to extend the literature on dairy farm performance in South Africa through the use of structural equation modelling techniques and latent variable analysis. Section 1.3 contains a comprehensive breakdown of the importance of this study.

## **1.2 Objectives**

The primary objective of this study is to determine the factors contributing to the economic performance of a panel of commercial milk producers from East Griqualand, KwaZulu-Natal, and Alexandria, Eastern Cape, South Africa for the period 2007-2014. This objective will be achieved by meeting two other general objectives. The first of these objectives is to estimate technical and scale efficiencies for the sampled dairy farmers in the two study groups. This objective will be divided into a series of specific objectives for the purposes of clarity. The specific objectives are as follows:

- Identify the most appropriate functional form for stochastic frontier analysis.
- Identify the most suitable distributional assumption regarding the inefficiency component of the composed error term.
- Estimate technical efficiency for individual dairy farms using the most appropriate production technology for the data.
- Estimate scale efficiency from the estimated production function parameters and scale elasticities.

- Determine whether size economies are present in the two study areas.

The second general objective is to estimate the economic performance of the dairy farmers in the two samples. This will be achieved by meeting the following specific objectives:

- Model economic performance in a latent variable framework (MIMIC model).
- Identify the relative effects of the cause and indicator variables, including technical and scale efficiency, on economic performance.
- Identify how to improve economic performance in the study areas by estimating the factors contributing to economic performance and latent managerial input variables.

### **1.3 Importance of the study**

This study may be divided into two main sections, with the first section focusing on efficiency analysis and the second on economic performance. Pertaining to efficiency analysis, the estimation of technical and scale efficiency is important on several fronts.

Firstly, gaining insight into the technical efficiency of dairy farmers in the two study areas will help in understanding the financial position and sustainability of dairy farms in these areas. This will assist in understanding the potential drivers behind the continuing consolidation trend. Furthermore, this study aims to identify factors of production associated with higher levels of technical efficiency, providing valuable information to dairy farmers, researchers, policy makers and extension services.

Secondly, there has been a substantial amount of research regarding the effect of farm size on technical efficiency and farm survival in many countries. Very little of this research has been conducted on South African dairy farms. It is therefore important to determine whether smaller South African dairy farms are less technically efficient than their larger counterparts. Investigating returns to scale will reveal if economies of scale are present in the two study areas and subsequently allow for the determination of the optimal farm size for each region (if an optimal farm size does in fact exist). An important distinction between the concepts of scale and size economies must be made to avoid ambiguity and confusion. The concept of size economies encompasses economies of scale and represents a broader focus; the two concepts may be differentiated as follows: size economies evaluate variation in unit costs associated with changes in some or all inputs, whereas

scale economies evaluate the change in output due to proportionate changes in all inputs (Beyers & Hassan, 2001a).

Thirdly, this study attempts to extend the scope of previous dairy productivity literature by incorporating scale efficiency, in addition to technical efficiency. Scale efficiency is traditionally calculated using nonparametric techniques such as Data Envelopment Analysis (DEA), whereas this study adopts a parametric approach to the calculation of scale efficiency. By calculating scale efficiency, it is possible to determine whether farms are operating at or near optimal scale. This provides an indication as to whether further increases in productivity can be attained by moving towards optimal scale. To the author's knowledge, there are no examples in the South African literature in which parametric scale efficiency is incorporated into an analysis of dairy farm productivity. Furthermore, the inclusion of scale efficiency as an additional response variable is expected to reduce the chance of identification errors in the secondary analysis involving the MIMIC model.

Finally, this study acknowledges the sensitivity of stochastic frontier analysis to the choice of functional form and distributional assumptions regarding the error terms. As such, a wide range of possible model specifications are considered in an effort to minimize bias and ensure the most appropriate milk production technology is modelled. In total, five functional forms, each with two distributional assumptions, and the assumption of either time variant or invariant efficiency are specified, resulting in 20 possible models. Researchers often fail to select a production technology based on comparative tests, and instead base their choices on criteria such as preference, familiarity, or computational convenience. As a result, very few studies consider a wide range of possible model specifications, particularly in the South African dairy literature.

On the second front, the concept of economic performance will be defined in terms of the dairy industry and estimated using a latent variable (MIMIC) framework. The investigation of latent economic performance may be valuable on several fronts. Firstly, it allows for a more integrated approach to performance analysis than previous South African studies have allowed. Traditionally farm performance, or farm financial success, has been explained by simple measures of productivity such as total factor productivity or various measures of efficiency, as highlighted in the introduction. However, in reality these measures may be best considered imperfect estimates

of true farm performance. The decision to model economic performance as a latent variable is therefore justified on these grounds.

The MIMIC model framework adopted in the second stage allows technical efficiency and scale efficiency (estimated in the first stage) to be incorporated as indicators of economic performance, while traditional explanatory variables such as herd size and milk yield are incorporated as causal variables. Furthermore, three latent management variables are introduced in attempt to capture the effect of managerial quality of the breeding, feeding and labour programmes on farm economic performance. These three indices are included in the MIMIC model framework as latent causes of economic performance as managerial performance is not directly observable and is therefore best modelled in a latent variable framework. It is important to note that, although these managerial indices are included as latent variables, they remain explanatory in nature, with economic performance being the only endogenous (dependent) variable. To the author's knowledge, the inclusion of latent "quality" or "managerial quality" indices in performance analysis has not yet been considered in any South African studies regarding the dairy industry.

The analysis of economic performance, within the MIMIC framework, not only provides a more in-depth insight into the factors affecting farm financial success, but will also provide dairy farmers with information on which aspects of the dairy enterprise are the most critical drivers of economic performance. In the face of industry consolidation, this information is of particular importance to those farmers who wish to improve their overall economic performance, beyond the scope of simple efficiency measures, in an effort to remain in business. This study is therefore an effort to extend the South African literature on the performance of dairy farms, using methods which have not yet been applied in the SA context. This study is by no means exhaustive and the author acknowledges room for future studies to improve upon the methodologies employed herein. It does, however, provide an investigation into the factors affecting the performance of dairy farms from a new, more integrated, perspective and provides a solid statistical foundation for future analysis.

#### **1.4 Structure of the dissertation**

The structure of this study is presented as follows: Chapter 1 presents background information on the South African dairy industry, including characteristics, policy environment, production information, and consolidation trends. The remainder of the introductory chapter deals with

objectives, the importance of this study to South African dairy farmers and policy makers, and finally an introduction to the data employed herein.

Chapter 2 involves a comprehensive review of the literature on the analysis of productivity and efficiency measurement. This chapter begins with a review of fundamental production theory, followed by specification of a simple production function and definition of the associated parameters. Various measurement techniques, functional forms and one-sided error distributional assumptions are then discussed. Finally, the chapter gives a brief review of the techniques for measuring technical change before closing with previous literature on the measurement of efficiency on South African dairy farms.

Chapter 3 involves a review of the literature on latent variable analysis, SEM techniques and economic performance. The concept of latent variables is introduced and applications in various fields of study discussed. The concept of economic performance is discussed and an appropriate definition established. Estimation of economic performance, using SEM techniques, more specifically the Multiple-Indicators, Multiple-Causes (MIMIC) model, is then discussed before highlighting previous applications of this technique. The chapter ends with previous agricultural research involving applications of latent variable analysis.

Chapter 4 covers milk production in South Africa, including a discussion on the South African dairy industry as well as detailed descriptions of the dairy industries in KwaZulu-Natal and the Eastern Cape. Climatic, production, and marketing conditions of each production region are discussed in detail to provide insight into the factors and decisions faced by dairy farmers in these regions.

Chapter 5 covers the modelling of technical and scale efficiency of dairy farms, beginning with detailed descriptions of the two study areas and of the data collected. Variables used in the production function are then defined before a preliminary analysis of the data is conducted, including multiple imputation and missing data analysis. Various functional forms are then specified and the methodology for the calculation of technical efficiency introduced. Finally, the methodology behind the calculation of parametric scale efficiency is presented.

Chapter 6 presents the results of likelihood ratio testing, leading to the selection of the most appropriate functional form. Stochastic frontier results are then presented for the sampled dairy



farms and subsequently discussed. Resulting technical efficiency scores are benchmarked against previous studies and the temporal pattern of technical efficiency discussed. Parametric scale efficiency is then calculated from the resulting stochastic frontier parameter estimates. Finally, the relationship between farm size and technical efficiency is discussed, before closing with a general discussion at the end of the chapter.

Chapter 7 covers the modelling of the economic performance of dairy farms, beginning with an introduction into modelling techniques and a preliminary analysis of the data. The variables used in the analysis of economic performance are then defined and discussed before the MIMIC model is specified and estimated using maximum likelihood techniques. Finally, the results of the MIMIC model are presented followed by a comprehensive discussion and comparison. The dissertation ends with a conclusion and a summary.

## **CHAPTER 2: REVIEW OF PRODUCTIVITY AND EFFICIENCY ANALYSIS**

### **2.1 Introduction**

The concepts of productivity and efficiency are terms often used synonymously in the literature, despite important differences between the two concepts (Coelli *et al.*, 2005). Although they may differ in their definition, these two concepts are closely linked. Productivity, in essence, refers to relationship between outputs and inputs in a production process whereby an improvement in productivity is brought about by producing more output with the same inputs or producing the same output with fewer inputs (Rogers, 1998). The basic concept of efficiency refers to the relationship between a firm's realised output and its potential output (Fan, 1991), in other words, the firm's current production possibilities relative to the "best practice" production possibilities. A firm will achieve maximum productivity at the point where it is operating on the best practice frontier (is efficient) and is using the least possible combination of inputs to do so. The remainder of the chapter presents a review of the literature on the analysis of productivity and efficiency measurement, in which these concepts are developed and reviewed, with a number of different measurement techniques, functional forms and distributional assumptions being reviewed, compared and contrasted. The concept of technological change is then introduced before closing with a literature review of the measurement of efficiency on South African dairy farms.

### **2.2 Productivity and the production function**

The productivity of a firm may be defined as the ratio of aggregate output to aggregate input (O'Donnell, 2010). In the case of a multiple-input, multiple-output production process the term Total Factor Productivity (TFP), which is a productivity measure involving all factors of production, is often used (Coelli *et al.*, 2005).

Productivity change can be decomposed into three general elements: technological change, efficiency change (technical and/or allocative) and scale efficiency change (Fan, 1991; Lovell, 1996; Balk, 2001; Newman & Matthews, 2006). Technological change refers to the adoption of improved technologies that shift the frontier of potential production, while efficiency change refers to a reduction in the distance between a firm's realized output and its potential output (Fan, 1991; Newman & Matthews, 2006; Diaz & Sanchez, 2008). The discrepancy between a firm's realized and potential output may be attributed to a number of factors. These include: failure to account for

inherent quality differences (e.g. land quality), market failures, credit market constraints and different levels of technology (Helfand & Levine, 2004). Finally, scale efficiency change relates to economies in production that can be realized at certain scales of production (Stewart *et al.*, 2009), represented by movements along the production frontier (Balk, 2001; Newman & Matthews, 2006).

For simplicity, and to illustrate conceptual differences between productivity and efficiency, consider a simple production process in which a single input ( $x$ ) is used to produce a single output ( $y$ ) in a single time period. The curve  $OF$  in Figure 2.1 represents the production frontier that defines the relationship between the input and the output. The production frontier represents the maximum level of output that is attainable from each input level, given existing technology. The feasible production set is represented by the area between the production frontier and the X-axis (Coelli *et al.*, 2005).

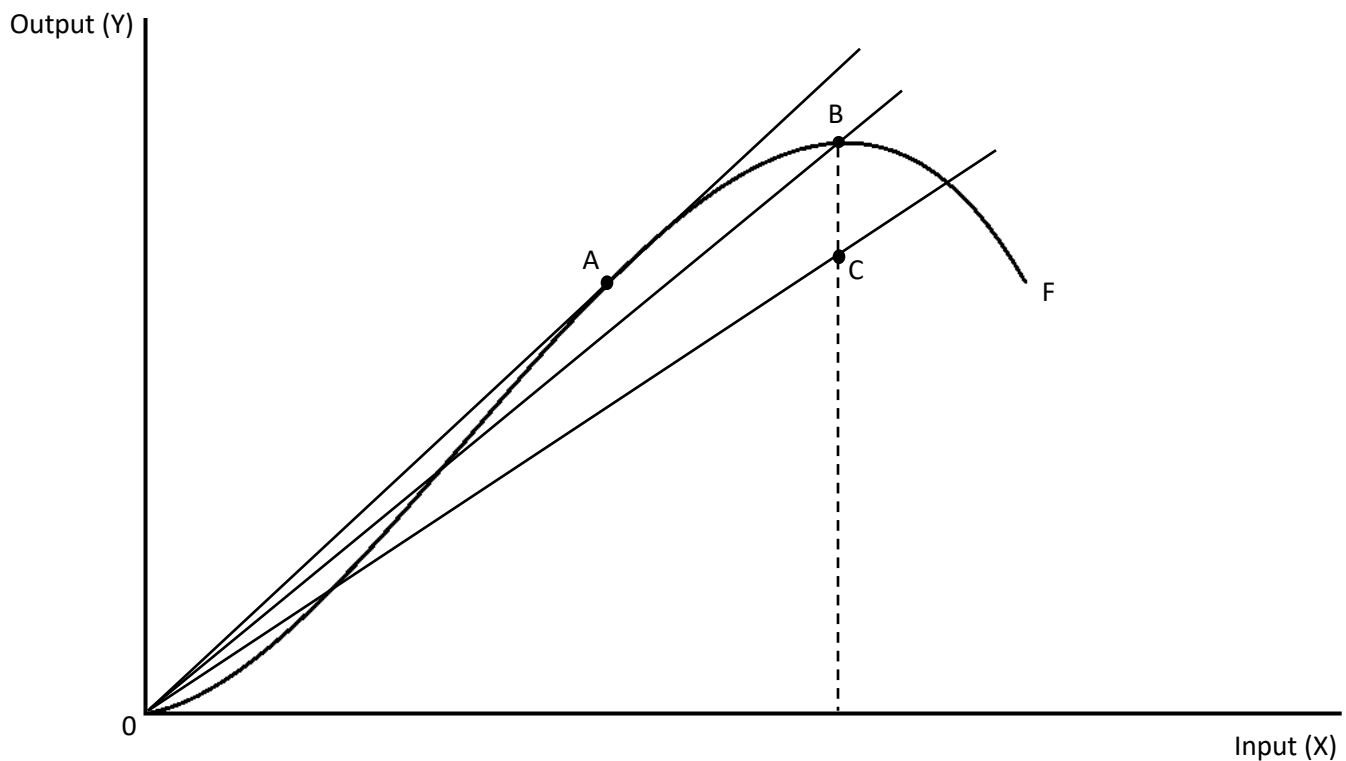


Figure 2.1: Single input-output production process

Source: Own illustration adapted from Coelli *et al.* (2005)

All points on the production frontier are considered technically efficient; however, not all these points are equally productive. The efficiency of each firm is represented by the distance of the firm from the production frontier. For example, point C is within the feasible production set but is below the frontier by the distance BC. This distance represents technical inefficiency. The productivity of any point may be measured by calculating the slope of a line emanating from the origin to that point. Consider point B, which represents a technically efficient firm, in comparison to point A, which is also a technically efficient firm. The line OA from the origin is tangent to the production function and has the greatest slope, therefore represents the point of maximum possible productivity. Firms operating at any other point on the production frontier, other than point A, will experience lower productivity. The improved productivity, found at point A, is achieved by exploiting scale economies (Coelli *et al.*, 2005).

Technical change becomes an additional source of productivity change when time is considered. Technical change involves improvements in both physical technologies and improvements in the knowledge base that creates a shift of the production frontier (Stewart *et al.*, 2009). This shift in the production frontier introduces a new set of production possibilities which allows the firm to produce greater quantities of output with the same quantity of inputs.

The production function describes the rate at which resources are transformed into products (Doll & Orazem, 1984) and may be defined as a mathematical representation of the various technical production possibilities faced by a firm (Beattie & Taylor, 1985). It is, however, more commonly defined as the maximum output that can be produced from a given set of inputs, for a specific level of technology (Rasmussen, 2010). The production function defining the technical possibilities of the firm may be given by:

$$y = f(x_1, x_2, x_3, \dots, x_{n-1} | x_n)$$

where  $y$  denotes output,  $x_1, \dots, x_{n-1}$  are variable inputs,  $x_n$  is a fixed input and  $f$  is a function. Since output ( $y$ ) is often measured in physical terms it may be referred to as total physical product (TPP). Average physical product (APP) is another important concept which may be defined as the ratio of output to input usage. Since the concept of efficiency is measured as output divided by input, APP provides a measure of the efficiency of the variable input ( $x_i$ ) used in the production process (Doll & Orazem, 1984). APP may be expressed by the following equation:

$$APP = \frac{y}{x}$$

The most important physical concept is that of marginal physical productivity (MPP), which is given by the slope of the production function at a particular point. MPP may be calculated by taking the first order derivative of the production function with respect to the variable input (Doll & Orazem, 1984). It therefore refers to the change in output associated with a one-unit increase in input. MPP may be expressed by the following equation:

$$MPP = \frac{dy}{dx} = f'(x)$$

The neoclassical production function has been used to describe agricultural production relationships for many years (Debertin, 1986). This classical production function may be divided into three distinct stages, each of which has important implications for the efficient use of resources (Doll & Orazem, 1984). Figure 2.2 illustrates the three-stage neoclassical production function and the associated marginal and average product curves.

It is evident that as input use increases, the production (TPP) function initially increases at an increasing rate, due to increasing MPP. When MPP reaches its maximum, a point of inflexion occurs on the TPP curve, which marks the end of increasing marginal returns and the start of decreasing marginal returns. It is important to note that before the point of inflexion, the function is convex to the horizontal axis while after this point it becomes concave to the horizontal axis. The concavity after the point of inflexion reflects diminishing marginal returns to production. Stage I and Stage II may be delineated by the point where APP reaches its maximum. This occurs at the point where MPP and APP intersect and become equal (Beattie & Taylor, 1985).

In Stage I, APP is increasing at an increasing rate, indicating that the average rate at which the (x) variable input is being transformed into product is increasing up until APP reaches its maximum at the end of Stage I. In Stage II, total output continues to increase at a decreasing rate until the function reaches a maximum. Stage II and III may be delineated by the point at which TPP reaches its maximum (Beattie & Taylor, 1985). In Stage III, once TPP has reached its maximum, the use of an additional unit of input results in a decrease in total output. This may occur, for example, if a farmer applies so much fertilizer that he negatively effects his crop yields (Debertin, 1986).

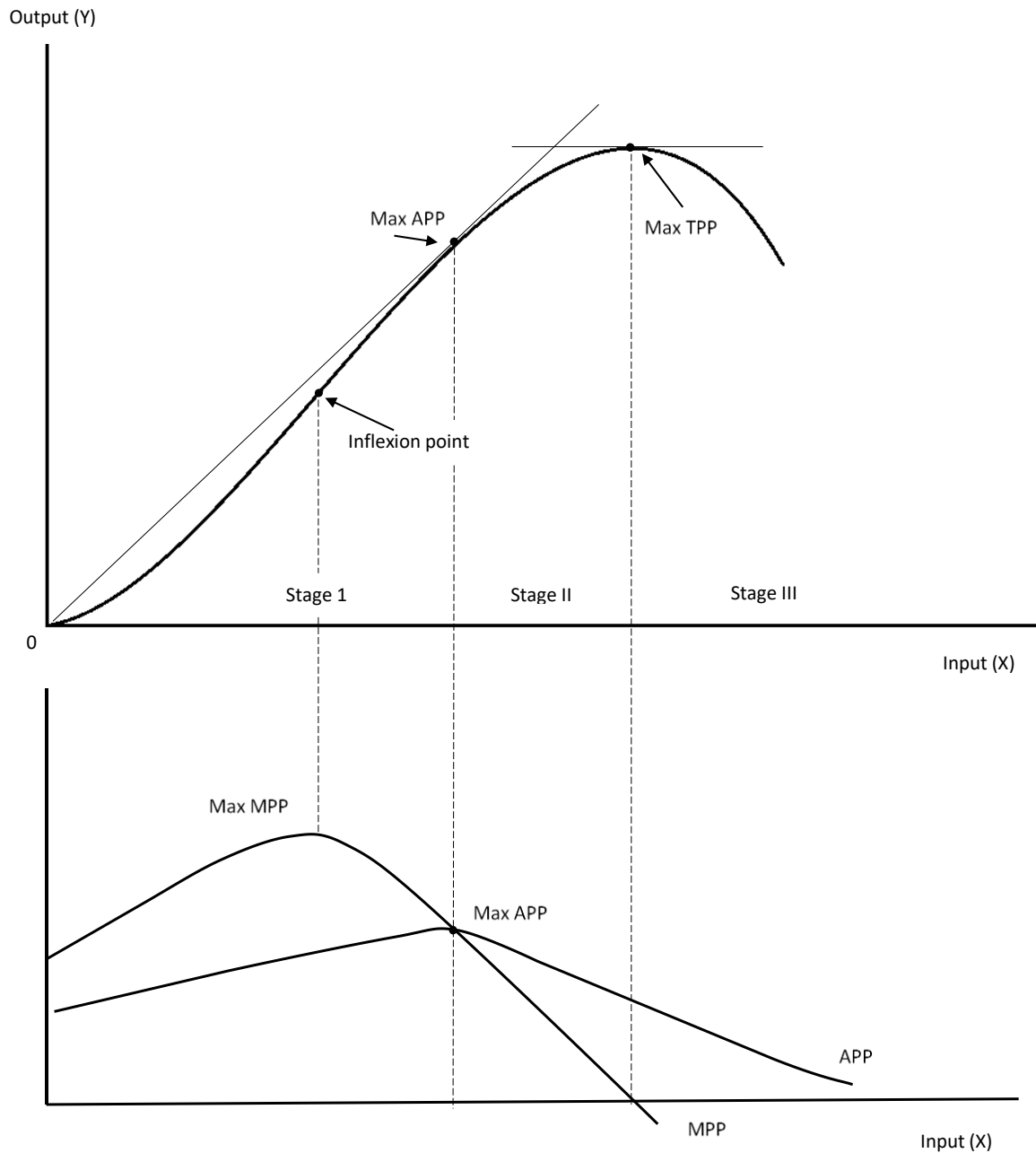


Figure 2.2: Neoclassical three-stage production function and marginal and average curves

Source: Own illustration adapted from Beattie & Taylor (1985) and Debertin (1986).

There are several important properties associated with production functions, among which the following four are critical: (1) non-negativity: the value of  $f(x)$  is a finite, non-negative, real number; (2) weak essentiality refers to the inability to produce positive output without the use of at least one input; (3) monotonicity: the use of additional units of an input will not result in a

decrease in output; and (4) concavity: if the production function is continuously differentiable, this assumption implies diminishing marginal productivity (Coelli *et al.*, 2005).

The law of diminishing marginal productivity is what causes the production function to be concave in relation to the horizontal axis. The application of these properties to Figure 2.2 yields some interesting information regarding the traditional three-stage production function. Firstly, in Stage I prior to the point of inflexion, the concavity assumption is violated due to the convex nature of the production function, brought about by increasing marginal productivity. Secondly, in Stage III, after the production (TPP) function has reached its maximum, the monotonicity assumption is violated since the use of an additional unit of input results in a reduction in output. Intuitively, Stage II is the economically feasible region of production, since none of the key assumptions are violated.

It is important at this point to differentiate between the assumptions of strict concavity, weak concavity (concavity) and quasi-concavity. Strict concavity and weak concavity (concavity) require that the production function is concave to the horizontal axis at all points whereas quasi-concavity is less restrictive and allows some portion of the function to be convex (Beattie & Taylor, 1985). The production function illustrated in Figure 2.2 satisfies the assumption of quasi-concavity but not strict or weak concavity.

### **2.3 Measuring efficiency**

The measurement of firm level efficiency has become commonplace with the development of frontier production functions (Beyers *et al.*, 2002). Current literature on the measurement of efficiency of production finds its origins in the early work of Farrell (1957) that introduced a conceptual framework for the measurement of technical and allocative efficiency. Defining technical efficiency (TE) as the ability of a firm to obtain maximum output from a given set of inputs, and allocative efficiency (AE) as the ability of a firm to use inputs in optimal proportions, given their prices, Farrell (1957) showed that economic efficiency (EE) may be calculated as the product of TE and AE (i.e.,  $EE = TE \times AE$ ) and, therefore, is defined as the capacity of a firm to produce a given level of output at minimum cost for a given level of technology.

According to microeconomic theory, production technology is represented by the production function that determines the maximum possible output that may be achieved from various

combinations of available inputs (Kalaitzandonakes *et al.*, 1992). Therefore, the production function essentially represents a best practice frontier indicating all efficient production possibilities. The deviations of a firm from the efficient frontier may, therefore, be regarded as measures of inefficiency (Førsund *et al.*, 1980; Kalaitzandonakes *et al.*, 1992; Mathijs & Vranken, 2001). Since, actual input and output levels are not known in reality, production functions must be empirically estimated using observed output and input data.

There are several alternative specifications used to estimate efficiency through frontier analysis, including primal (direct) and dual approaches (Coelli, 1995; Thiam *et al.*, 2001). The primal approach, which involves direct estimation of a production function, has been the most commonly used technique although it is subject to several drawbacks, the most severe of which is the possibility that parameter estimates may be biased and inconsistent if the behavioural assumptions of either profit maximization or cost minimization are valid (Coelli, 1995). This is a result of simultaneous equation bias that is caused by a lack of independence between inputs and the error term (Thiam *et al.*, 2001). An additional limitation of the primal approach is that only data on input quantities and not input prices may be considered; therefore, the impact of allocative efficiency cannot be measured (Førsund *et al.*, 1980; Coelli, 1995; Pingali & Evenson, 2010). Alternatively, dual forms of production technology, such as profit and cost functions, may be considered for the following reasons: 1) to account for alternative behavioural assumptions such as profit maximization or cost minimization; 2) to account for multiple outputs; and 3) to calculate both technical and allocative efficiency simultaneously (Coelli, 1995).

Of the two dual alternatives to the production function, the cost function is the most commonly used to represent a firm's production technology (Asche *et al.*, 2007). According to Schmidt & Lovell (1979), a production process can be inefficient in two ways. Firstly, it can technically be inefficient in the sense that actual output is less than the maximum possible output for a given input bundle which results in an equi-proportionate overutilization of all inputs. Secondly, it can be allocatively efficient in the sense that marginal revenue product of an input may not be equal to marginal cost of that input. This results in input utilization in the wrong proportions, given respective input prices. A major limitation of the stochastic production function is its ability to consider only technical inefficiency (Schmidt & Lovell, 1979; Kumbhakar *et al.*, 1989).



The development of the cost function approach overcame this limitation by considering both technical and allocative inefficiencies of the production process. Therefore, cost frontier approaches have the advantage of being able to facilitate the calculation of technical, allocative and economic efficiency (Bravo-Ureta & Pinheiro, 1997). Furthermore, the cost frontier approach accounts for exogenous outputs, endogenous inputs and can be extended to account for multiple outputs (Coelli, 1995). The assumption of cost minimization, which underpins the cost function approach, is generally considered appropriate in situations where output is regulated at a particular level (Coelli, 1995). This is often the case in regulated dairy industries where output supply is constrained by policy regulations or supply management quotas (see Richards & Jeffrey, 2000). The primary drawback of the cost function approach is that it requires price input data which are not readily available and difficult to collect, particularly over a number of time periods.

The production function approach to efficiency analysis may not be appropriate when estimating efficiency of individual producers since they may face different prices and have differing factor endowments. This translates to different best-practice production functions and hence different points of optimal operation (Ali & Flinn, 1989; Wang *et al.*, 1996). The desire to overcome the limitations of the traditional production function and consider farm-specific prices and resource endowments led to the formulation of the first profit functions (Ali & Flinn, 1989; Wang *et al.*, 1996). Although they were not responsible for the introduction of the concept of the profit function, Lau & Yotopoulos (1971) popularized the approach with an application to Indian agriculture.

Kumbhakar *et al.* (1989) advocated the use of a profit function approach in a study on the economic efficiency of Utah dairy farmers on the grounds that it allowed for the production process to be technically, allocatively and scale inefficient. Although the cost function approach considers technical and allocative inefficiency, it is not able to facilitate the calculation of scale inefficiency. A production process may be scale inefficient in the sense of not producing an output level by equating the product price with the marginal cost (Kumbhakar *et al.*, 1989). Kumbhakar & Bhattacharya (1992) extended the traditional profit function approach to a generalized (behavioural) profit function which could incorporate price distortions resulting from imperfect market conditions, socio-political and institutional constraints. Accounting for the effects of these restrictions is important because they determine to what extent the shadow prices paid by the farmer differ from observed market prices (Wang *et al.*, 1996).

Despite several limitations, the primal approach remains valid in several situations and provides the benefit of requiring only data on input quantities, which are more readily available than input prices. Zellner *et al.* (1966) have shown that the primal approach may be adopted under the assumption that producers maximize expected, rather than actual, profits. Various methods have been developed for the measurement of deviation from the best practice frontier. These methods may be broadly categorized into parametric and nonparametric approaches (Kalaitzandonakes *et al.*, 1992; Sharma *et al.*, 1999; Bravo-Ureta *et al.*, 2007; Tonsor & Featherstone, 2009).

### 2.3.1 Parametric methods

Parametric approaches differ from nonparametric methods in that they rely on a specific functional form. Parametric methods include deterministic and stochastic frontiers, both of which can be constructed using either programming or statistical procedures (Kalaitzandonakes *et al.*, 1992). Aigner & Chu (1968) were the first to extend the pioneering work of Farrell (1957) by specifying a Cobb-Douglas production function assuming all differences in technical efficiency would be captured by the disturbance (error) term. Afriat (1972) considered a similar deterministic model to that specified by Aigner & Chu (1968), except a gamma distributional assumption was imposed on the error term and estimation of the model parameters was executed using maximum likelihood (ML) methods. Further attempts to improve the deterministic frontier model were made by several authors (see Førsund *et al.*, 1980; Coelli, 1995, for more detailed reviews).

Deterministic frontiers are relatively easy to estimate and allow the production function to be expressed in a simple mathematical form (Førsund *et al.*, 1980). The primary limitation of the deterministic methodology is the assumption that any deviation from the production frontier is due to technical inefficiency (Kalaitzandonakes *et al.*, 1992; Bravo-Ureta *et al.*, 2007). This specification fails to account for deviations from the frontier due to statistical noise, which refers to unexplained variation within the sample due to measurement errors, omitted variables and other random phenomena (Fried *et al.*, 2002). The manner in which technical efficiency is defined means that estimated coefficients of deterministic frontier functions are susceptible to outliers (Ali & Chaudhry, 1990; Kalaitzandonakes *et al.*, 1992).

In an attempt to avoid the problem of spurious errors in extreme outlier observations, Timmer (1971) specified a probabilistic frontier. He adjusted the model of Aigner & Chu (1968) by either discarding a predetermined percentage of observations or by discarding outlier observations, one

by one, until the resulting estimated coefficients gained stability. Although the probabilistic frontier method has not been extensively followed, a few studies have adopted its methodology (Coelli, 1995). Bravo-Ureta (1986) considered an application of probabilistic frontier methodology in a study on the technical efficiency of milk producers in New England, Canada. Ali & Chaudhry (1990) specified a probabilistic frontier production function to determine farm efficiency in four irrigated cropping regions of the Punjab province in Pakistan. El-Osta & Morehart (2000) specified a deterministic parametric production frontier to investigate the effect of technology adoption on the production performance of a sample of dairy farms from several US states.

The assumption that any deviation from the production frontier is due to technical inefficiency alone is particularly unrealistic in agricultural studies. This is due to the nature of agricultural production, which involves a number of random factors that differ between producers, such as climate, weather, and soil fertility. These factors are likely to contribute towards the observed deviations from the frontier and should not necessarily be incorporated in the inefficiency term.

The stochastic frontier model, also known as the “error components” model, was independently developed by Aigner *et al.* (1977) and Meeusen & Van den Broeck (1977) to circumvent the inability of earlier deterministic models to account for random deviations from the frontier. The authors proposed the specification of a composite error term which allowed for the inclusion of random deviations from the frontier due to data error and statistical noise. The model of Aigner *et al.* (1977) may be expressed as follows:

$$y_i = f(x_i; \beta) + \varepsilon_i \quad (i = 1, \dots, N) \quad (2.1)$$

Where  $y_i$  represents the maximum output attainable from  $x_i$ , a vector of input, and  $\beta$  is a vector of unknown parameters to be estimated. This specification is similar to those used in the deterministic models of Aigner & Chu (1968) and Afriat (1972), with the exception of the disturbance term ( $\varepsilon_i$ ). Aigner *et al.* (1977) imposed the following error structure onto equation 2.1:

$$\varepsilon_i = v_i + u_i \quad (i = 1, \dots, N) \quad (2.2)$$

The composite error term ( $\varepsilon$ ) consists of a non-positive error component ( $u$ ), which reflects deviations from the efficient frontier due to firm inefficiencies, and a two-sided error component ( $v$ ), which captures random effects outside the control of the firm. The random component ( $v$ )

captures external factors such as climate, topography and machine performance as well as observational and measurement errors (Aigner *et al.*, 1977).

The primary strengths of the stochastic frontier approach lie in its ability to consider statistical noise and permit estimation of standard errors and tests of hypotheses. The main criticism of stochastic frontier models is the lack of *a priori* justifications regarding the distribution of the error terms (Coelli, 1995; Sharma *et al.*, 1999). The stochastic frontier model has been credited as the most appropriate methodology for application to agricultural studies due to its ability to account for statistical noise, allow for traditional hypothesis testing, and estimation of the inefficiency effects (Kumbhakar & Lovell, 2000, as cited by Cabrera *et al.*, 2010).

The model specifications in Aigner *et al.* (1977) and Meeusen & Van den Broeck (1977) both assume a distribution of  $u$  which has a mode at  $u=0$ . Stevenson (1980) highlighted the possible unfeasibility of such an assumption in reality and proposed a more general model, adopting a truncated-normal distribution of  $u$ , that allowed for the possibility of both zero ( $u=0$ ) and non-zero modes. Stevenson (1980) also specified a gamma distribution for  $u$  but did not consider an empirical application of this distribution in his work. Greene (1990) extended the restricted gamma distribution proposed by Stevenson (1980) in an empirical application, in which he combined a two-part gamma distribution with the stochastic frontier model. This specification was able to circumvent some of the practical shortcomings of one-sided disturbances due to the additional flexibility of a two-parameter (gamma) distribution (Greene, 1990).

Early stochastic frontier models, based on cross-sectional data, were subject to several major drawbacks. Early models permitted the calculation of average efficiency across all firms but failed to identify firm-specific inefficiency (Gong & Sickles, 1989). Jondrow *et al.* (1982) attempted to overcome this limitation by proposing a method to separate the composite error term of the model into its two components for each observation, thereby permitting firm-specific estimates of TE. These estimates are based on the conditional distribution of  $(u)$  given  $(\varepsilon)$ , and therefore require specific distributional assumptions for both error components ( $v$  and  $u$ ).

Schmidt & Sickles (1984) identified three major drawbacks to early stochastic frontier methods. Firstly, firm specific estimates of technical inefficiency may be estimated but not consistently. This may be attributable to the failure of Jondrow *et al.* (1982) to account for variability due to sampling error. Secondly, estimation of technical inefficiency, and its separation from statistical

noise requires specific distributional assumptions regarding the two error components ( $v$  and  $u$ ). Efficiency estimates may be sensitive to these distributional assumptions, which introduces uncertainty regarding the robustness of the resulting estimates. Thirdly, inefficiency is often assumed to be independent of the regressors (inputs) which may not be a realistic assumption since it may violate the behavioural assumptions of some firms (Schmidt & Sickles, 1984; Gong & Sickles, 1989).

Schmidt & Sickles (1984) recognized the potential advantages of modifying early stochastic frontier models to suit panel data applications. They proposed that the application of existing stochastic frontier models to panel data could potentially circumvent the problems associated with cross-sectional models. Seale (1990) attributed the inability of cross-sectional stochastic frontier models to estimate individual firm technical inefficiencies to a deficiency in degrees of freedom and considered panel data to be a potential remedy.

There are several potential advantages associated with the use of panel data over conventional cross-sectional data for frontier estimation. For instance, panel data usually provide a large number of data points which increases the degrees of freedom, reduces collinearity among the explanatory variables and improves the efficiency of econometric estimates (Hsiao, 2003). This provides consistent estimates of firm efficiencies, relaxes the need to make specific distributional assumptions regarding the inefficiency disturbance term, removes the assumption that technical inefficiency is independent of the regressors (Schmidt & Sickles, 1984; Coelli, 1995), and allows for the simultaneous consideration of technical change and technical efficiency over time (Coelli, 1995). Furthermore, the effects of missing or unobserved variables may be better handled in panel data situations as there is access to information on both intertemporal dynamics and individuality of firms (Hsiao, 2003).

The extension of Stochastic Frontier Analysis (SFA) to panel data allowed for the consideration of intertemporal variation which introduces the possibility of time-varying efficiency. As a result, the stochastic frontier analysis literature may be classified into models which assume technical efficiency is time-invariant and those which assume technical efficiency is time-variant (Khumbakhar *et al.*, 1997). Schmidt & Sickles (1984) and Gong & Sickles (1989) adopt the assumption of time-invariant technical efficiency in their applications of SFA to panel data. Gong & Sickles (1989) justify this assumption by regarding firm-specific inefficiency as an inherent

residual between observed data and the corresponding production frontier. The authors note that without inordinate changes in the economic environment (such as deregulation), firm-specific efficiency is not likely to experience substantial changes over a finite number of time periods.

Cornwell *et al.* (1990) identified time-invariant technical inefficiency as a strong assumption that may not be realistic and proposed the relaxation of this assumption in such a way as to retain the inherent advantages of panel data. Consider the standard stochastic frontier for panel data, specified as follows:

$$y_{it} = \alpha_i + X_{it}\beta + v_{it} \quad (2.3)$$

where the firm effect  $\alpha_i = \alpha - u_i$ ,  $y$  represents output,  $x$  represents inputs,  $v$  represents statistical noise and  $u$  is a firm effect representing technical inefficiency. Cornwell *et al.* (1990) allowed the firm specific effects to vary over time by replacing the firm specific effect ( $\alpha_{it}$ ) with a quadratic function of time, with coefficients varying across firms.

$$\alpha_{it} = \theta_{i1} + \theta_{i2}t + \theta_{i3}t^2 \quad (2.4)$$

Where  $\theta_{i1}$ ,  $\theta_{i2}$ ,  $\theta_{i3}$  are unknown parameters.

Battese & Coelli (1992) proposed a stochastic production function with a more simplistic, exponential specification of time varying firm effects where efficiency was specified as follows:

$$u_{it} = \exp[-\eta(t - T_u)]u_i \quad (2.5)$$

Where  $u_i$  is the firm specific inefficiency assumed to be independently and identically distributed as truncated normal and  $\eta$  is a single unknown parameter. This specification may be considered somewhat restrictive since TE must either increase at a decreasing rate, decrease at an increasing rate or remain constant. It is worth noting that the authors do specify a more flexible, two parameter alternative, which would permit firm effects to be convex or concave; however, no application of this model is considered. The selection of either time-invariant or time-variant technical inefficiency depends on factors such as the nature of technical rigidities and technical change within a specific sector. In reality, however, the specification of inefficiency is often based on convenience rather than on a specific inefficiency mechanism derived from well-developed theory (Khumbakhar *et al.*, 1997).

Empirical applications of stochastic frontier analysis using panel data have traditionally been based on balanced panel data, which assumes that each cross-sectional unit is observed for the same number of time periods (Kumbhakar & Heshmati, 1995). Early panel data models such as that of Schmidt & Sickles (1984) only permitted the use of balanced panel data. This assumption may be considered highly restrictive from a practical view, since sampled data are seldom balanced (Biørn, 2004). Furthermore, dropping observations from an unbalanced data set to make it balanced may result in substantial efficiency loss (Biørn, 2004).

In an attempt to relax the assumption of balanced data, Seale (1990) proposed an application of stochastic frontier analysis which allowed for direct estimation of technical and allocative efficiency from an unbalanced panel of data. Battese & Coelli (1992) considered an application of SFA to an unbalanced panel of data, assuming time-varying efficiency, for a sample of Indian paddy farmers. Kumbhakar & Heshmati (1995) further adapted the stochastic frontier model to consider a rotating panel of data. Rotating panel data refer to data collected using a rotational sampling design in which all units in the population are numbered consecutively. In each period a fraction of the sample selected in the previous period are replaced by new units from the population (Heshmati *et al.*, 1995).

Previously, stochastic frontier models failed to account for production risk, which is a critical aspect of the production process that is likely to affect technical efficiency estimates. Production uncertainty (risk) affects decisions concerning the choice of inputs and supply of outputs (Shankar, 2012); and the adoption and utilization of new technologies, which are a major source of productivity growth (Battese *et al.*, 1997). Since the concept of technical efficiency is essentially a measure of the degree of technology utilization in the production process, the inclusion of risk into stochastic frontier analysis should be considered (Battese *et al.*, 1997). As a potential solution, Battese *et al.* (1997) proposed an alternative model which incorporated the stochastic frontier production function within the framework of the flexible risk model of Just & Pope (1978). In an attempt to improve upon previous SFA risk models, Tiedemann & Latacz-Lohmann (2013) combined Just and Pope's framework with a stochastic frontier which was able to account for heteroscedastic error terms.

The estimation of traditional production, cost, or profit functions typically relies on the assumption of technological homogeneity, whereby the underlying technology is assumed to be the same for

all producers (Alvarez *et al.*, 2012). This assumption may not be appropriate since firms in a particular industry may use different technologies (technological heterogeneity), in which case the estimated underlying technology is likely to be biased (Orea & Kumbhakar, 2004; Alvarez *et al.*, 2012). Failure to account for these unobserved technological differences during estimation may result in them being incorrectly labelled as inefficiency (Orea & Kumbhakar, 2004).

Production heterogeneity can be addressed through the use of either two-stage or one-stage methods. The two-stage approach involves first separating the sample into several groups, based upon some a priori sample separation information, and then conducting separate analyses for each group (Orea & Kumbhakar, 2004). The one-stage method is an attractive alternative with the ability to separate the sample into groups and estimate the technology for each of these groups in one step (Alvarez & del Corral, 2010). A comparison of the one-stage approach, commonly referred to as a latent class (mixture) model, and the two-stage approach found the latent class model to be a superior method (Alvarez *et al.*, 2012). By incorporating the latent class model (LCM) into the stochastic frontier framework, Orea & Kumbhakar (2004), Alvarez & del Corral (2010) and Alvarez *et al.* (2012) were able to estimate efficiency, while accounting for technological heterogeneity.

Tsionas & Kumbhakar (2004) indicated that the latent class model may not be realistic in certain cases, drawing attention to the fact that there may be some persistence in the movement from one group to another and the lack of parsimony of the model. As a potential remedy, Tsionas & Kumbhakar (2004) proposed a stochastic frontier model with a Markov switching structure in which parameters were allowed to take a finite number of possible values, and at each time period there was a probability that the parameter values will remain unchanged or switch to something different. This method has the advantage of considering both cross-sectional and temporal heterogeneity, something the previous LCM's failed to achieve.

### 2.3.2 Nonparametric methods

Nonparametric frontier analysis involves the use of linear programming methods to construct a nonparametric piece-wise (frontier) surface over the data (Coelli *et al.*, 2005). Efficiency estimates are represented by the distance, which may be in terms of production, cost, profit or revenue, of a decision making unit (DMU) from this best-practice surface. Efficiency scores range between zero



and one, with zero representing the lowest efficiency measure and one representing optimum efficiency (equal to that of the best-practice firm) (Stokes *et al.*, 2007; Delis *et al.*, 2009). Efficiency scores lower than one indicate that the same vector of outputs could be produced with a smaller vector of input, therefore reflecting the presence of inefficiencies in production (Andersen & Petersen, 1993).

Nonparametric frontier methods originated from the work of Farrell (1957) which involved the use of linear programming techniques to construct a free disposal convex hull of the observed input-output ratios (Førsund *et al.*, 1980). This approach was extended by Charnes *et al.* (1978) who adopted a mathematical programming approach to efficiency analysis which is commonly known as Data Envelopment Analysis (DEA). Central to the DEA approach is the assumption of convexity of the production possibilities set (Delis *et al.*, 2009). The Free Disposal Hull (FDH) method is an extension of DEA that allows for nonconvex production possibility sets by assuming free disposability of inputs and outputs (Simar & Wilson, 1998; Delis *et al.*, 2009). Both approaches allow efficiency to vary over time.

DEA has the advantage of not requiring the specification of a production technology or distributional assumptions regarding the error term (Sharma *et al.*, 1999). Furthermore, it allows for the simultaneous use of multiple inputs and multiple outputs, each being measured with different units of measurement (Wadud & White, 2000). It is, however, criticized for its deterministic nature, attributing all deviation from the frontier to inefficiency. As a result, DEA is likely to be highly sensitive to measurement error and statistical noise (Sharma *et al.*, 1999).

DEA models may estimate efficiency with either input or output orientations (Stokes *et al.*, 2007; Murova & Chidmi, 2011). Input-oriented models measure technical inefficiency as a proportional reduction in input usage, holding output levels constant. Output-oriented models measure technical inefficiency as a proportional increase in output production, holding input levels constant (Coelli *et al.*, 2005). These two orientations provide equal estimates under the assumption of constant returns to scale (CRS) but not for variable returns to scale (VRS) (Delis *et al.*, 2009). There is a lack of consensus among the literature as to which orientation is the “best choice” (Delis *et al.*, 2009). Coelli *et al.* (2005) note that the choice of orientation depends upon the nature of the industry and should be selected according to which quantities (input or output) the firm has the greatest control over.

Early DEA models such as that of Charnes *et al.* (1978) assume CRS, which permits the estimation of an “overall” measure of technical efficiency. The CRS assumption that all firms operate at an optimal scale may not be appropriate since, in reality, a number of factors such as imperfect competition, government regulations and financial constraints cause a firm to operate at a non-optimal scale (Coelli *et al.*, 2005). Banker *et al.* (1984) extended the work of Charnes *et al.* (1978) to consider VRS, which permitted the separation of overall technical efficiency into pure technical efficiency and scale efficiency components. Furthermore, overall technical efficiency was found to be equal to the product of pure technical efficiency and scale efficiency. Analysis with the assumption of VRS is considered more flexible and envelopes the data in a tighter manner than CRS (Sharma *et al.*, 1999). One deficiency of the VRS measure of scale efficiency is that it fails to indicate whether the firm is operating under increasing or decreasing returns to scale (Coelli *et al.*, 2005). This can be determined by solving a non-increasing returns to scale (NIRS) DEA model (Sharma *et al.*, 1999). If the technical efficiency (TE) measure under NIRS is equal to that under CRS, there are increasing returns to scale. However, if the TE measure under CRS is less than that under NIRS, there are decreasing returns to scale (Färe *et al.*, 1994, as cited by Sharma *et al.*, 1999)

Simar & Wilson (1998) introduced the bootstrap method as a potential tool to analyse the sensitivity of measured efficiency scores to the sampling variation of the estimated frontier. The bootstrap method is based upon the idea of repeatedly simulating the data generating process (DGP), through resampling, and applying the original estimator to each of the simulated samples so that the resulting estimates mimic the original estimator’s sampling distribution (Simar & Wilson, 1998). This allows researchers to conduct traditional hypothesis tests and construct confidence intervals (Coelli *et al.*, 2005). Simulating the DGP, however, can prove difficult since the bootstrap method requires that a clearly defined model of the DGP is known, otherwise it is not possible to determine whether the bootstrap accurately mimics the sampling distribution of the original estimators (Simar & Wilson, 1998).

Two-stage DEA represents an attempt to simultaneously estimate farm level efficiency and explain the reasons for the resulting estimates of efficiency. This method involves estimation of the efficient frontier and firm level efficiency scores in the first stage (a conventional one-stage DEA). In the second stage, these efficiency estimates are regressed against a set of explanatory variables

in an attempt to explain observed inefficiency (Balcombe *et al.*, 2008; Johnson & Kuosmanen, 2012). Despite several applications in the literature (Wadud & White, 2000; Helfand & Levine, 2004), the two-stage DEA approach has fallen under criticism due to several key limitations. Firstly, studies which have applied the method are criticized for failing to describe the underlying DGP, therefore raising doubt as to the meaning of the estimates. Secondly, two-stage DEA estimates have been found to be serially correlated and as a result standard approaches to statistical inference are invalid (Simar & Wilson, 2007). Simar & Wilson (2007) proposed an application of the double bootstrap method to DEA as a means of overcoming these limitations.

In an attempt to circumvent the limitations of parametric stochastic frontier models, without foregoing their advantages, Kumbhakar *et al.* (2007) proposed a nonparametric stochastic frontier model based on the local maximum likelihood procedure (LML). This method adopts local modelling techniques which do not require strong assumptions regarding functional form and differ from traditional nonparametric approaches, such as DEA, in the sense they are able to provide efficiency estimates that account for random noise (Serra & Goodwin, 2009; Guesmi *et al.*, 2013). Furthermore, local modelling techniques can accommodate heterogeneity in the data by making the variances of both components of the error term observation specific (Serra & Goodwin, 2009). Due to the complexity involved in its implementation, this approach has received limited application in empirical studies (Guesmi *et al.*, 2013).

Dai (2016) proposed a fully nonparametric, three-stage method of efficiency estimation using the Richardson-Lucy blind deconvolution algorithm (RLb) to decompose firm specific inefficiency from their composite errors. In the first stage, the shape of the frontier is estimated using convex nonparametric least squares (CNLS) regression and the residuals are estimated. In the second stage, the expected inefficiency for all firms is estimated and used to correct the CNLS residuals estimated in stage one. Finally, stage three involves the estimation of firm specific efficiencies using RLb. This model does not require any distributional assumptions, is insensitive to statistical noise in the data and is robust to heteroscedasticity. Despite its potential advantages, RLb is sensitive to frontier estimation (the difference between the estimated and true frontier) and may be biased and thus should be applied with caution.

### 2.3.3 Semiparametric methods

In an attempt to extend the stochastic frontier model proposed by Aigner *et al.* (1977), Fan *et al.* (1996) proposed a semiparametric frontier model which aimed to relax parametric restrictions on the functional form representing production technology, through the application of nonparametric regression techniques. The model proposed by Fan *et al.* (1996) involved the construction of pseudo-likelihood estimators of the parameters based on kernel estimation of the conditional mean function. The advantage of the proposed semiparametric approach is that no particular functional form need be selected, hence, estimators are robust to possible misspecifications of the production frontier. One drawback of this approach, however, is the need to specify particular distributional assumptions on the composed error terms (Fan *et al.*, 1996).

Attempting to combine the nonparametric frontier with the composite error stochastic frontier model, Kuosmanen & Kortelainen (2012) proposed a two-stage semiparametric frontier model referred to as the stochastic non-smooth envelopment of data (StoNED) model. In the first stage, the shape of the frontier is estimated using convex nonparametric least squares (CNLS) regression, which identifies the function that best fits the data from a family of functions which satisfy monotonicity and concavity conditions. In the second stage, the conditional expectations of inefficiency are estimated from the CNLS residuals using method of moments (MM) or pseudo-likelihood techniques. The StoNED model essentially assumes that the observed data deviates from a DEA-style frontier production function due to a composite error term, consisting of noise and inefficiency components, such as that of the stochastic frontier model. It possesses the advantages of not requiring the specification of any particular functional form and extends traditional DEA methods in its ability to consider both inefficiency and noise components, thereby reducing sensitivity to outliers.

In a recent attempt to circumvent the limitation of specifying a particular functional form, as required in traditional SFA, Vidoli & Ferrara (2015) proposed a generalized additive model (GAM) framework for the estimation of stochastic production frontier models. The GAM fits a response variable using a sum of smooth functions of the explanatory variables. The additional flexibility provided by GAMs removes the need to impose a perfect linear relationship between the explanatory variables and the dependent variable and retains the ability to explain variability

of the dependent variable using an additive function of the inputs (Vidoli & Ferrara, 2015). For detailed literature on GAMs, see Hastie & Tibshirani (1986).

## **2.4 Flexible functional forms**

Investigating the relationship between a dependent variable and a set of independent variables is the primary objective of empirical research which generally requires two basic assumptions. The first assumption involves the specification of a functional form in which the dependent variable is represented by a function of the independent variables. The second assumption involves the specification of a probability distribution for the error (residual), which captures differences between actual and predicted values of the dependent variable (Sauer *et al.*, 2006). Stochastic frontier analysis is no exception and requires the specification of a parametric production technology through the selection of a particular functional form. Since economic theory often does not justify the imposition of a particular functional form, flexible functional forms are often used. These flexible functional forms often violate monotonicity, convexity (or concavity) and homogeneity conditions (Kuosmanen & Kortelainen, 2012). This may be due to the failure of most researchers to test whether the estimated function meets the required monotonicity and quasi-concavity conditions (Sauer *et al.*, 2006). To provide insight into the advantages and limitations of flexible functional forms, the properties underlying production functions need to be clearly defined.

Microeconomic theory highlights several properties which underpin production functions including: non-negativity, weak essentiality, monotonicity and concavity. It is important to note that these properties are not exhaustive and neither are they maintained under all conditions (Coelli *et al.*, 2005). The monotonicity property requires that production functions monotonically increase in all inputs, that is, the output quantity must not decrease if any input quantity is increased. If a production frontier is not monotonically increasing, the estimates of individual firm efficiency cannot be reasonably interpreted (Henningsen & Henning, 2009). This problem may be illustrated using an example of a non-monotone production frontier as in Figure 2.3. Firm A is below the best practice production frontier and therefore may be considered inefficient, while Firm B is on the frontier and may be considered technically efficient. Firm B, however, uses a larger quantity of input to produce the same quantity of output as firm A and therefore, by definition, is less

technically efficient than firm A. This highlights the potential errors that may arise through the interpretation of production frontiers that do not meet the monotonicity requirement.

In an attempt to avoid the problems associated with non-monotone production frontiers researchers often impose the monotonicity condition upon a production function. If the monotonicity condition is only violated at a few data points, this may be an appropriate course of action. However, if the condition is violated at many or all of the data points then the model is most likely misspecified and should be changed (Henningsen & Henning, 2009).

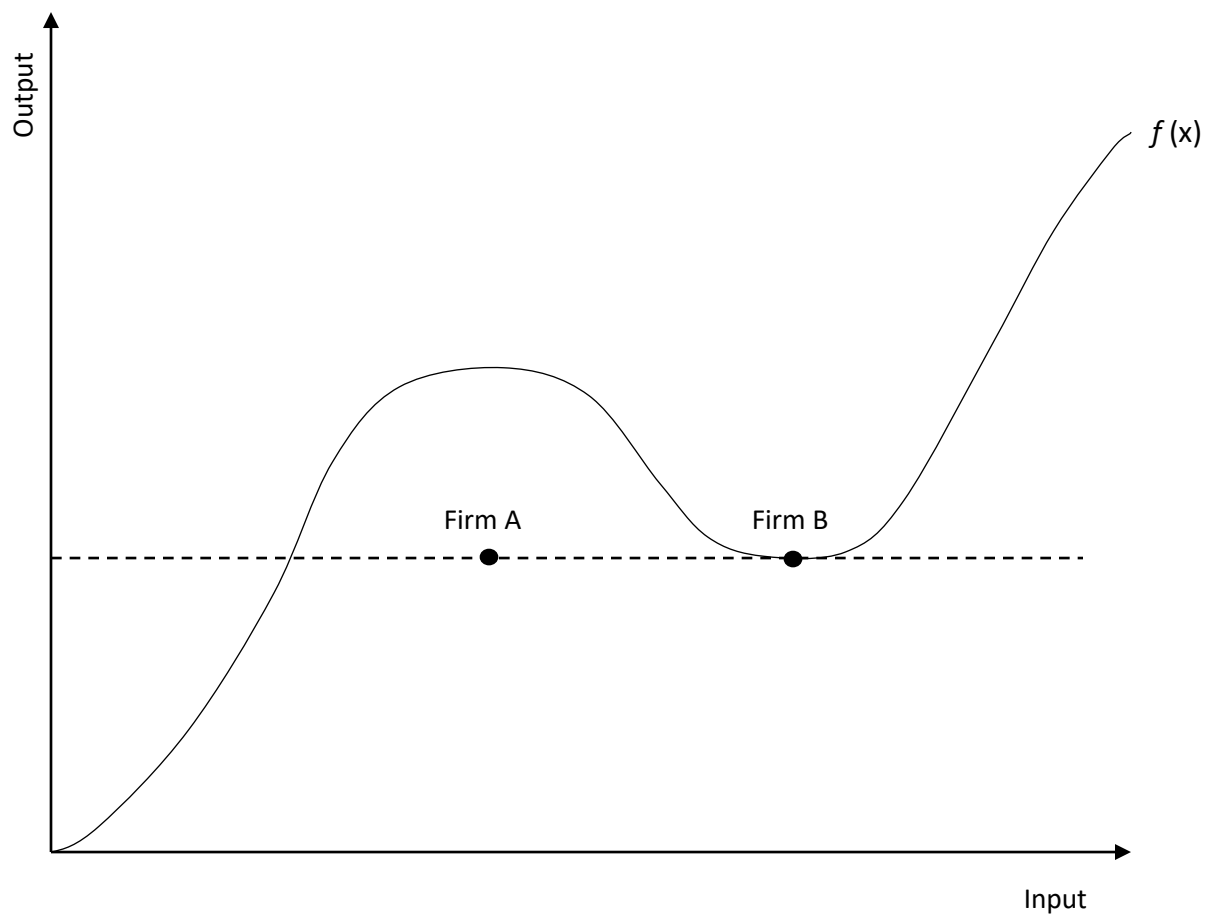


Figure 2.3: Non-monotone production frontier

Source: adapted from Henningsen & Henning (2009).

Apart from monotonicity, microeconomic theory often assumes that production functions are concave. This implies convex input sets and, hence, decreasing marginal rates of technical substitution (Henningsen & Henning, 2009). Furthermore, profit maximizing input levels can only be calculated from first-order equations if the production function is concave (Griffin *et al.*, 1987).

Production functions are generally quasi-concave if all inputs are perfectly divisible and different production activities can be applied independently (Henningsen & Henning, 2009). However, in reality, these assumptions may not hold and therefore the rationale behind the quasi-concavity assumption may not be necessary. As a result, Henningsen & Henning (2009) suggest that quasi-concavity should not be imposed when estimating production functions, but recommend checking for quasi-concavity after economic estimation, since some results of microeconomic theory (e.g. convex input sets) do not hold under non quasi-concavity.

Before investigating the flexible functional forms, it is important to note that flexibility is a multi-dimensional concept which does not possess one universal definition (Griffin *et al.*, 1987). The two commonly used definitions of flexibility highlight the differences between the notions of local flexibility and global flexibility. Local (Diewert) flexibility implies that an approximating functional form is a perfect approximation (with zero error) for an arbitrary function and its first two derivatives at a particular point. This flexible form places no restrictions on the value of the function or its first or second derivatives at this point (Griffin *et al.*, 1987). Global (Sobolev) flexibility is preferable to local flexibility since globally flexible functional forms, such as the Fourier form, possess desirable nonparametric properties (Thompson, 1988). Furthermore, globally flexible functional forms are theoretically well founded and allow for meaningful tests of significance (Sauer *et al.*, 2006). The relative complexity of specifying and estimating globally flexible functional forms has resulted in local flexibility becoming the more widely used definition (Thompson, 1988).

Flexible functional forms were first developed in an effort to reduce the econometric limitations of earlier forms, such as the Cobb-Douglas function (Thompson, 1988). When selecting a functional form for empirical application, there is a choice between forms which exhibit good behaviour globally and those that possess higher degrees of flexibility. Relatively simple functional forms, such as the Cobb-Douglas, lack flexibility and hence the ability to represent more complex technologies, but satisfy certain global regularity conditions, because of their simplicity. Relatively more complex functional forms, while possessing higher degrees of flexibility and the ability to model more complex technologies, are not globally well-behaved (Guilkey *et al.*, 1983).

The Cobb-Douglas production function, a derivative of the translog form, is the most applied functional form with respect to efficiency measurement. It is a first order (nonflexible) form which

is relatively simple, and thus globally theoretically consistent (Sauer *et al.*, 2006). This simplicity, however, comes at the cost of strong restrictions on the substitution possibilities (Mbagha *et al.*, 2003). The translog production function is a second-order Taylor series expansion, which is a frequently applied, locally flexible, functional form which imposes fewer restrictions on technology than the non-flexible forms (Mbagha *et al.*, 2003). As with many locally flexible functional forms, the translog form is susceptible to multicollinearity, due to the large number of interactions between the explanatory variables. The translog form is also susceptible to possible low degrees of freedom. Furthermore, theoretical consistency cannot be imposed globally upon the translog form without the loss of second-order flexibility.

Functional forms are data and model specific and differ not only in their convergence properties but also in their ability to approximate different technologies (Giannakas *et al.*, 2003). Since the appropriate functional form is case specific, there is no single functional form that performs best under all circumstances. Furthermore, the imposition of an inappropriate functional form may result in biased and inaccurate estimates and misleading statistical inferences (Giannakas *et al.*, 2003). This highlights the importance of selecting a functional form which is best suited to the data and least likely to result in biased and inconsistent estimates.

Determining the true functional form of an economic relationship is not possible, hence the challenge becomes the selection of the most appropriate functional form for the given relationship (Griffin *et al.*, 1987). This leads to the consideration of decision criteria, which assist in the selection of the most appropriate functional form. Before dealing with the problems associated with functional forms, it is important to distinguish between the ex-ante choice of functional form and the ex-post choice of functional form. The former refers to the selection of a particular functional form prior to actual estimation while the latter refers to the selection of a particular functional form, from a set of functional forms, estimated from the same data set, based on hypothesis tests and estimated results (Lau, 1986).

Lau (1986) identified five broad criteria for the ex-ante selection of a functional form for a particular economic relationship: (1) theoretical consistency: the functional form selected must be capable of possessing all theoretical properties required of the particular economic relationship for an appropriate choice of parameters. In the case of a production function, this means that monotonicity and convexity assumptions must hold (Sauer *et al.*, 2006). (2) Domain of



applicability: this most commonly refers to the set of values of the independent variables over which the functional form satisfies all requirements for theoretical consistency. (3) Flexibility: this refers to the ability of the functional form to approximate arbitrary but theoretically consistent economic behaviour through appropriate selection of parameters. The degree of flexibility required is dependent upon the economic relationship being investigated. In productivity analysis, flexibility generally means that the production, profit or cost function must be capable of generating output supply and input demand functions which have own and cross-price elasticities that can assume arbitrary values based only on the requirements of theoretical consistency, at any arbitrary set of prices, through the selection of an appropriate set of parameters. Flexibility of a functional form may be considered desirable since it allows the data to provide information about the important parameters. (4) Computational facility: this implies one or more of the following properties. The functional form and any functions of interest should therefore be: linear-in-parameters, with linear restrictions (if any), and represented in an explicit closed form and be linear in the parameters (explicit representability). Different functions in the same system should have the same functional form but should differ in the parameters (uniformity) and the number of parameters included in the functional form should be minimized, while maintaining flexibility (parsimony). (5) Factual conformity: this implies consistency of the functional form with known empirical facts.

## **2.5 Technological change**

When considering a production function from single period cross-sectional data, the underlying assumption is that the level of technology that existed at the time of data collection persists throughout that period. However, if time-series or panel data are available over several time periods, the effect of time, and more importantly technological change, may be considered (Debertin, 1968). The consideration of technological change is important as it has the potential to significantly affect the production process. Simply holding the level of technology constant is not acceptable. Although the potential effects of technological change cannot be denied, the definition and measurement of the concept are not free of problems (Chambers, 1988). One commonly accepted definition is that technological change represents a shift in the production function over time. The preceding definition may be expressed as follows:

$$y = f(x, t) \quad (2.6)$$

where:  $y$  represents output,  $f$  is a function,  $x$  is an input and  $t$  is time. In equation 1 technical change is measured by observing the change in output, holding inputs constant, as time changes. This equation assumes that technical change does not require new inputs and that the production function remains in the same basic form over time. This may be referred to as disembodied technical change (Chambers, 1988).

Despite its appeal, the preceding definition makes some stringent assumptions and may not always be an accurate representation of reality, as not all technological advancements fit this definition. Some technologies require such drastic changes in the methods and inputs required that they represent an entirely new technology. This results in the creation of a new production function, rather than a simple shift of the existing production function. The concept described above may be referred to as embodied technical change since the new technology must be acquired to access the potential benefits of that technology. Embodied technical change may be represented by differentiating the production function and input bundle with respect to time, which means production functions do not need to be of the same functional form and input bundles may vary over time. Although embodied technical change is an attractive concept which is consistent with reality, it is very difficult to apply in an analytical sense. For this reason, the more simplistic definition of disembodied technical change, represented by equation 2.6, is often adopted (Chambers, 1988).

The direct measurement of technical change over time is considered highly complex and researchers often rely upon the inclusion of simple time variables in a crude attempt to capture technological change (Debertin, 1968). Including a simple time trend variable into the production function is highly inaccurate but may be an improvement over a static model that fails to account for technological change in any way (Debertin, 1968). Furthermore, the inclusion of a time trend into the production function represents a workable alternative which may be easily applied (Chambers, 1988).

The Cobb-Douglas production function with simple disembodied technological change (smooth time trend) may be expressed as follows (Ahmad & Bravo-Ureta, 1996):

$$\ln Y_{it} = \beta_0 + \sum_k \beta_k \ln(x_{kit}) + \zeta T + (v_{it} - u_{it})$$

Where T is a time trend (t=1, 2, ..., T) and  $\zeta$  is a parameter to be estimated.

The translog production function can similarly be adjusted to account for disembodied technical change. In this instance, since the translog production function is a second-order flexible functional form, both T and T<sup>2</sup> are introduced into the equation. The resulting expression is given by:

$$y_{it} = \beta_0 + \sum_{k=1} \beta_k \ln(x_{kit}) + \frac{1}{2} \sum_{j=1} \sum_{k=1} \beta_{kj} \ln(x_{kit}) \ln(x_{jit}) + \zeta T + \frac{1}{2} \lambda T^2 + \sum_{k=1} \beta_{kt} \ln(x_{kit}) T + (v_{it} - u_{it})$$

Where T is a time trend (t=1, 2, ..., T),  $\lambda$  and  $\zeta$  are parameters to be estimated.

## 2.6 Productivity analysis in South Africa

Although there is an extensive body of literature concerning productivity analysis in countries such as the US, there is relatively little empirical research which considers productivity analysis of South African agriculture. Piesse *et al.* (1996) considered an application of data envelopment analysis (DEA), using farm level data, for small-scale farmers in three former Northern Transvaal homelands to investigate the productive efficiency of maize farmers. Total productivity is initially calculated and then decomposed into pure technical and scale efficiency components. Results indicated a wide dispersion of efficiency levels between farms, with inadequate farm size responsible for large proportions of inefficiency (Piesse *et al.*, 1996). Furthermore, the authors supplement their initial result with linear regression analysis in an attempt to determine the effects of the variables included in the DEA analysis on efficiency levels.

Gouse *et al.* (2003) applied DEA techniques, similar to that implemented by Piesse *et al.* (1996), in an efficiency analysis of insect-resistant (BT) cotton in South Africa. The study investigated and compared the technical efficiency of large-scale South African cotton farmers who adopted BT cotton varieties and those who did not. Results indicated that, on average, adopters of the BT cotton strains were more technically efficient than non-adopters.

Abu & Kirsten (2009) investigated the efficiency of small- and medium-scale maize milling enterprises based on a translog stochastic profit frontier model. Cobb-Douglass and translog model specifications were considered although likelihood ratio tests revealed the translog model as being

more suitable. Parameters of the models were estimated using maximum likelihood techniques and technical, allocative and scale efficiencies calculated. Results indicated that mills with larger capacities were generally more efficient than those with smaller milling capacity.

The above-mentioned studies have all considered applications of efficiency analysis, using either parametric or nonparametric techniques, to various agricultural commodities. Although these studies provide some insight into the methodologies employed in local studies and highlight some interesting findings, the focus must be brought back to milk production. There appears to be a limited number of South African studies which have investigated the productivity of milk production.

Beyers & Hassan (2001a) considered a long run average cost (LAC) curve approach in an analysis of economies of size and managerial ability in the South African dairy industry. The specification of a translog cost function was chosen due to its flexibility, conventional U-shape average cost curve and several other benefits. The results of the study indicate that substantial size economies exist in the South African dairy industry. Furthermore, better managerial practices were associated with lower average costs, higher levels of optimal output and larger herd sizes for all farm sizes. The use of cross-sectional data by Beyers & Hassan (2001a) is a distinct limitation of the study since the effects of the various factors cannot be analysed over time.

Beyers & Hassan (2001b) investigated the structure of milk production technology for a cross-section of South African dairy farms using a parametric approach. The study considered both Cobb-Douglas and translog functional forms within a profit function framework, although the translog model was selected according to likelihood ratio tests. Although a parametric profit function was specified and the profit share equations calculated, no efficiency measures were calculated, as in a stochastic frontier framework. Instead, Iterative Seemingly Unrelated Regression (ISUR) and full information maximum likelihood (FIML) procedures were used to estimate the parameters of the output supply and input demand equations. Both quantity constrained (Hicksian) and unconstrained (Marshallian) elasticities were calculated.

Mkhabela & Mndeme (2010) investigated the cost of producing milk in the KwaZulu-Natal (KZN) Midlands of South Africa using a LAC curve approach similar to that of Beyers & Hassan (2001a). Mkhabela & Mndeme (2010) improved upon the work of Beyers & Hassan (2001a) through the use of panel data, which contains both cross-sectional and time-series components and therefore

contains more information. The cost function specified by Mkhabela & Mndeme (2010) was, however, of a Cobb-Douglas form, and may be considered highly restrictive. Interestingly, the results of the study differed from that of Beyers & Hassan (2001a) in the sense that the cost curve was found to be L-shaped rather than U-shaped. Furthermore, in accordance with Beyers & Hassan (2001a), the authors noted the presence of size economies on the KZN Midlands dairy farms.

Mkhabela *et al.* (2010) investigated the efficiency of dairy farms in the KZN Midlands, using a gross input-output approach and a stochastic production function approach. Cobb-Douglas and translog production function parameters were estimated using maximum likelihood. The results of the efficiency analysis indicate that farms which are larger, have larger investments in capital equipment and have fewer cows not in milk have higher levels of technical efficiency. To the author's knowledge, this is one of the only applications of stochastic frontier analysis to the South African dairy industry.

## **2.7 Concluding remarks**

This review of the literature has provided an in-depth insight into the economic theory of productivity analysis, with particular focus on efficiency analysis. Economic theory and fundamentals underpinning the concepts of efficiency and productivity have been introduced, with an important distinction between productivity and efficiency being made. Although this study considers an application of parametric efficiency analysis, parametric, nonparametric and semiparametric approaches have all been reviewed in an effort to remain comprehensive and subjective. Throughout the chapter, the inherent strengths and limitations of each approach have been highlighted and applications of the abovementioned methodologies briefly discussed.

Following a detailed review of the various approaches to efficiency analysis, the concept of flexible functional forms was introduced, defined and discussed, with mention of various pros and cons associated with flexible functional forms. Concepts of local and global flexibility were also introduced. Following this discussion, the concept of technological change was introduced. Several approaches for the inclusion of technological change into the production function were introduced and their relative strengths and weaknesses highlighted. Simple time trends were applied to both a Cobb-Douglas and a translog production function for illustrative purposes.

Finally, a number of South African studies investigating productivity or efficiency analysis in South African agricultural industries were briefly reviewed. This review reveals the lack of South African literature on efficiency analysis and in particular on the dairy industry. While care has been taken to identify and briefly review all the relevant literature pertaining to productivity of the domestic milk market, the author acknowledges the possibility that some relevant studies may have been omitted. Early studies (such as Piesse *et al.*, 1996; Beyers & Hassan, 2001a; Beyers & Hassan, 2001b) may not accurately represent the current state of the dairy industry since these studies were conducted shortly after deregulation of the dairy market. Deregulation marked the start of significant structural change in the South African dairy industry, moving from a regulated market to an open market. The introduction of competition and an entirely new process of supply would undoubtedly have resulted in a new set of challenges for commercial milk producers. The process of adjustment to such a change is, in reality, not rapid and its effects can be expected to be lagged over a number of years. Taking this into consideration, caution should be exercised when comparing the findings of these studies to more recent findings, as applicability in today's milk market comes into question.

Inter-regional comparison is commonplace in the international literature, with a wealth of studies investigating variations in production between regions. However, in the South African context the majority of studies consider data from only one production region. It is also surprising that despite a wealth of literature on dairy productivity analysis and frontier analysis methodology internationally, there has been very limited research conducted on this front domestically. In fact, only one study by Mkhabela *et al.* (2010), which considers an application of stochastic frontier analysis to SA milk production, could be found.

The next chapter presents a review of the literature on latent variable analysis and structural equation modelling. The review begins with the introduction and definition of the concept of latent variable analysis and progresses to the introduction of latent variable modelling frameworks such as SEM and MIMIC. The chapter is concluded with a review of the literature on applications of the MIMIC to agricultural analysis.

## **CHAPTER 3: REVIEW OF LATENT VARIABLE ANALYSIS AND SEM TECHNIQUES**

### **3.1 Introduction**

A number of farm efficiency studies focus solely on the effect of technical efficiency on productivity (Tauer & Belbase, 1987; Kumbhakar & Heshmati, 1995; Sedik *et al.*, 1999; Diaz & Sanchez, 2008; Murova & Chidmi, 2011; Cabrera *et al.*, 2010). Bravo-Ureta & Rieger (1991) found that focusing only on technical efficiency substantially understates the potential gains from improvements in overall performance. Therefore, studies considering economic, allocative and technical efficiency effects on farm performance (Bravo-Ureta & Rieger, 1991; Bravo-Ureta & Pinheiro, 1997; Hansson, 2007) may be considered more comprehensive. However, calculation of allocative efficiency, hence economic efficiency, requires detailed input price and quantity data that are often not available in farm level agricultural data. Due to the imperfect nature of efficiency measures, it is posited that economic performance be defined as a latent variable for which there exist many imperfect indicators, including measures of efficiency (Richards & Jeffrey, 2000). This chapter begins with a brief literature review of latent variables, introducing the basic concepts of latent variable analysis. Fundamental concepts are then developed with a brief review of structural equation modelling, and a special case thereof, the Multiple-Indicators, Multiple-Causes (MIMIC) model. Finally, some applications are briefly reviewed to provide contextual background for model specification and analysis later on in this study.

### **3.2 Latent variables**

Before proceeding with a review of latent variable analysis and the various methodological frameworks that may be applied, it is prudent to first identify an unambiguous definition for the concept of a latent variable. Many different definitions of the concept exist, although the selection of the most appropriate definition depends on the context (Skrondal & Rabe-Hesketh, 2004). Schumacker & Lomax (1996) define latent variables as variables which are not directly observable or measurable, rather they must be observed or measured indirectly and, hence, are inferred. Skrondal & Rabe-Hesketh (2004) define a latent variable as a random variable whose realizations are hidden from us. Bowen & Guo (2011) define latent variables as measures of hidden or unobserved phenomena and theoretical constructs. Apart from minor differences, all of these definitions highlight the unobservable, or not directly observable, nature central to the concept of latent variables.

Since latent variables cannot be directly measured, they must be indirectly measured by observable indicator variables which can be directly measured (Schumacker & Lomax, 1996). These observed variables are modelled as functions of model-specific latent constructs and latent measurement errors (Bowen & Guo, 2011). The estimation of latent constructs using observed variables is the basis of structural equation modelling which will be discussed in the following section.

The conceptual framework behind latent variables analysis originates from the work of Spearman (1904), who developed factor analytic models for continuous variables in the context of intelligence testing (Borsboom *et al.*, 2003). The basic statistical idea of latent variable analysis is that if a latent variable underlies a number of observed variables, then conditionalizing on that latent variable will render the observed variables statistically independent, otherwise known as the principle of local independence. The primary challenge, however, is to find a set of latent variables that satisfies this condition for a given set of observed variables (Borsboom *et al.*, 2003).

Although the theoretical concepts behind latent variables are often rich, available indicators often fail to fully capture the substantive content behind these latent constructs (Treier & Jackman, 2008). This introduces the importance of content validity. Content validity exists when the scope of the latent construct is adequately represented by the indicators adopted for its measurement (Dunn *et al.*, 1994). The standard approach to this problem is to use statistical procedures to combine the information into multiple indicators of the latent concept (Treier & Jackman, 2008). If content validity does not exist, it can be argued that proceeding with further analysis is pointless since the latent construct is not sufficiently represented by the indicators considered (Dunn *et al.*, 1994). Information from multiple indicators can be combined in several ways, including the use of a linear additive scale, simply summing each indicator, or weighting or re-scaling each item so that the contributions of each item to the scale are equal (Treier & Jackman, 2008).

Another important consideration in the modelling of latent variables is that of substantive validity. Substantive validity refers to whether the items included to measure a construct are conceptually or theoretically linked to that construct. It differs from content validity in that it deals with each individual item (indicator) of a construct rather than with a set of items, as in the case of content validity. For a set of measurement items (scale) to have content validity, they must possess substantive validity (Dunn *et al.*, 1994). For a description of various other types of validity considered in latent variable analysis, refer to Dunn *et al.* (1994).



There are several studies that recognize the latency of variables for which proxy variables have traditionally been used. Gao *et al.* (1997) specified “consumer taste” as a latent variable in an analysis of the effect of consumer taste on the demand for beef in the US. Patterson & Richards (2000) adopted a latent variable model to determine the effect of newspaper advertisement characteristics on consumer preferences for apples and on the demand for different apple varieties, specifying “consumer preferences” as a latent variable. Winklhofer & Diamantopoulos (2002) investigated the effect of various forecast performance criteria, such as bias, accuracy and cost, on sales forecasting effectiveness, which they defined as a latent variable with a number of imperfect indicators and causes. Shehzad (2006) adopted a latent variable approach to the problem of health unobservability, specifying child health as a latent variable.

The application of latent variable analysis is not limited to any particular field of study and several studies have recognized the latency of variables in agriculture. Ford & Shonkwiler (1994) acknowledged the unobservable nature of management ability, relating a measure of farm financial success to three latent measures of “managerial ability”. These included financial, dairy and crop managerial ability. For each of these aspects of managerial ability, four observable indicators were specified in an attempt to ensure model identification. Kalaitzandonakes & Dunn (1995) adopted a similar approach in a study concerning technical efficiency, managerial ability and farmer education in Guatemalan corn production. Managerial ability was regarded to be a latent variable, with education, farming experience, and relevant personal attributes and talents specified as imperfect indicators.

Ivaldi *et al.* (1994) and Ivaldi *et al.* (1995) investigated productive efficiency on samples of French grain producers and fruit growers, respectively. Both studies consider variations of the traditional production function approach in which individual levels of productive efficiency are proposed to be latent variables. Both studies consider applications of covariance structure analysis to deal with the estimation of the stochastic production function, and the measurement of technical efficiency in the case of Ivaldi *et al.* (1994). These latent variable approaches are credited for their ability to solve the problem of correlations between input quantities and individual effects.

Eposti & Pierani (2000) proposed an alternative approach to the measurement of technical change, specifying the “level of technology” as a latent variable. Their analysis aimed to investigate the sources of growth of output and the rate of technical change in Italian agriculture through the

inclusion of latent technology level into an input demand system. Since the latent level of technology cannot be directly estimated from the input demand system the authors adopted a MIMIC model framework.

### **3.3 Structural equation modelling**

Structural equation modelling (SEM) may be viewed as a general model encompassing a set of multivariate statistical approaches to empirical data (Bowen & Guo, 2011). Kaplan (2000) defines SEM as a class of methodologies that aim to represent hypotheses about the means, variance, and covariances of observed data in terms of a smaller number of structural parameters defined by a hypothesized underlying model. SEM essentially represents a synthesis of two separate statistical methods, namely factor analysis, developed in the fields of psychology and psychometrics, and simultaneous equation modelling, developed primarily in the field of econometrics (Kaplan, 2000).

Schreiber *et al.* (2006) refer to SEM as a combination of confirmatory factor analysis and multiple regression since SEM is more of a confirmatory technique that can also be used for exploratory purposes. Before proceeding it is important to define and differentiate the concepts of confirmatory and exploratory factor analysis. Exploratory factor analysis (EFA) is used to determine the number or nature of factors that account for the covariation between variables when there is insufficient evidence to form an a priori hypothesis regarding the number of factors underlying the data. As a result, exploratory factor analysis is often considered to be a theory-generating procedure rather than a theory-testing procedure (Stapleton, 1997). Confirmatory factor analysis (CFA), unlike EFA, represents a theory testing procedure, in which a hypothesis is established prior to analysis. Confirmatory techniques aim to minimize the discrepancy between the observed and theoretical factor structures, in order to assess the goodness of fit of the fitted model to the data (Stapleton, 1997).

Structural equation models generally encompass two components: a measurement model and a structural model. The measurement model may be viewed as CFA, depicting the pattern of observed variables for the latent constructs, essentially linking the observed variables to latent variables (Schreiber *et al.*, 2006). The application of a CFA serves as a test of reliability, assessing how well the observed variables define the latent variables (Schumacker & Lomax, 1996; Kaplan, 2000). The measurement model is often used to examine the interrelationships and covariation among the latent constructs. This process involves estimation of factor loadings, unique variances,

and modification indexes to determine the most appropriate indicators of the latent constructs prior to estimation of the structural model (Schreiber *et al.*, 2006).

The structural model links the latent variables to each other through a system of simultaneous equations (Kaplan, 2000). These equations specify the prediction of the dependent latent variable(s) by the independent latent variable(s) (Schumacker & Lomax, 1996). One potential advantage of directly modelling the relationships between latent variables (as in the structural model) is that the negative effects of measurement error may be corrected (Skrondal & Rabe-Hesketh, 2004). Potential advantages of SEM include substantial flexibility and the ability to incorporate explicit measurement models into more general statistical models (Kaplan, 2000). Before proceeding further, it is important to introduce and define the concepts of endogenous and exogenous variables. Exogenous variables, similar to independent variables, represent constructs that have an influence on other constructs but are not influenced by other factors in the model. Endogenous variables, similar to dependent variables, are affected by both exogenous and endogenous variables in the model. Both endogenous and exogenous variables can be observed or unobserved (latent) depending on the model in question (Schreiber *et al.*, 2006).

Traditional SEM, with latent variables, may also be referred to as covariance structure analysis since the primary focus is on the covariance structure. In this instance, the mean structure is typically eliminated by subtracting the mean from each variable (Skrondal & Rabe-Hesketh, 2004). There are many possible formulations of SEM, although the LISREL model of Jöreskog (1973) is one of the most dominant specifications for SEM with latent variables.

### **3.4 The MIMIC model**

A popular SEM which contains observed covariates is the Multiple-Indicators, Multiple-Causes (MIMIC) model. The MIMIC model of Jöreskog & Goldberger (1975) considers the relationships among observable endogenous “indicator” variables, exogenous “cause” variables, and latent constructs. This approach allows for the identification and estimation of latent variable indices and the impact of various factors on these indices (Richards & Jeffrey, 2000).

The MIMIC model is a variation of SEM that has gained popularity as a research framework due to its flexibility in a wide range of research contexts (Thompson & Green, 2006, as cited by Finch & French, 2011). The notable advantages of SEM, including MIMIC, over observed variable

modelling are: 1) the ability to consider latent variables that cannot be estimated by any single measure; and 2) the ability to consider error due to measurement or omission, rather than assuming that measurements are made free of error (Finch & French, 2011).

Figure 3.1 provides an illustration of a basic MIMIC model in which a single latent variable ( $\eta$ ) is determined by several indicator variables, response items ( $X_q$ ), and observed “cause” variables, regressors ( $Y_p$ ).

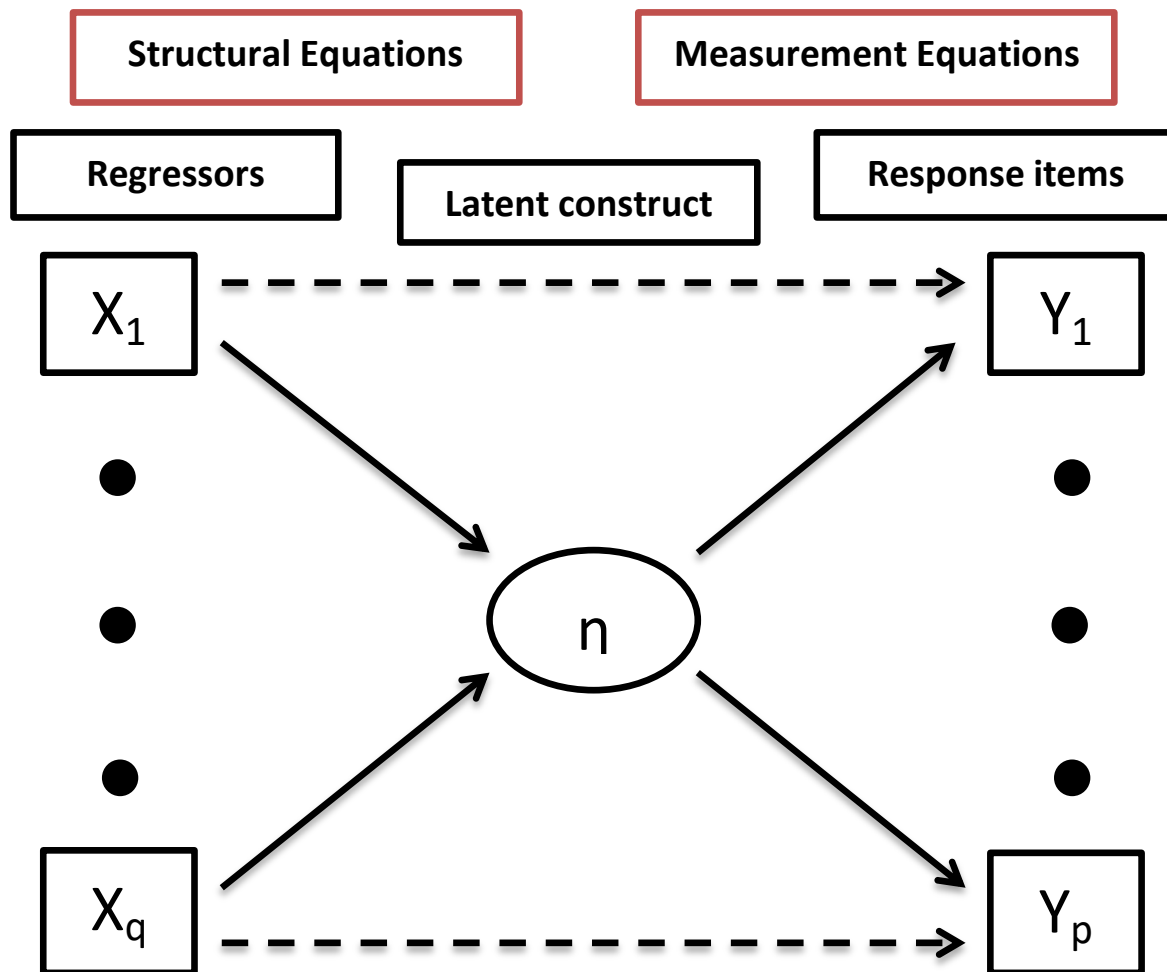


Figure 3.1: A one-factor MIMIC model

Source: Adapted from Muthén (1989)

The observable cause variables are generally regarded as some of the most important determinants of the latent variable (Dell’Anno, 2007). The relationship between the cause and indicator

variables and the latent dependent variable is captured through the specification of two separate equations. In the structural equation, the latent dependent variable is linearly determined by a set of observable exogenous causes ( $X_i$ ), while in the measurement equation, the latent dependent variable determines, linearly, a set of observable endogenous indicators ( $Y_i$ ). These two sets of equations are simultaneously solved, often using maximum likelihood (ML) estimation, to determine the effects of the various cause and indicator variables on the latent dependent variable (Jörëskog & Goldberger, 1975). It is important to note that there are no special rules of identification associated with the MIMIC model and estimation of model parameters proceeds in the same way as in general structural equation modelling (Kaplan, 2000).

Figure 3.2 shows a path diagram of a multiple-factor MIMIC model. In this specification, there are four latent variables ( $\eta$ ,  $X_1$ ,  $X_2$ ,  $X_3$ ), or factors, to be identified, whereby the latent response variable ( $\eta$ ) is determined by three latent constructs ( $X_1$ ,  $X_2$ ,  $X_3$ ), which represent “cause” variables. Each of these latent “cause” variables are then identified by three “indicator” variables ( $V_1$ ,  $V_2$ , ...,  $V_9$ ). For example: the latent “cause” variable  $X_1$  would be identified by  $V_1$ ,  $V_2$ , and  $V_3$ .

The MIMIC model has been a popular choice of model framework for latent variable analysis, which has been adopted extensively in a number of different disciplines, from behavioural psychology to marketing and economics (Macias & Cazzavillan, 2010). Proitsi *et al.* (2011) recently considered an application of the MIMIC model to assess the behavioural and psychological symptoms in dementia. The authors credited the MIMIC model for its ability to efficiently capture the complexity of inter-relationships between symptoms, factors and clinical variables considered in the study. Shehzad (2006) adopted a MIMIC model framework in his study on the determinants of child health in Pakistan. Results indicated that the use of MIMIC models allowed for a more comprehensive understanding of the determinants of child health compared to studies relying on single health measures. Furthermore, the unobservable nature of child health was successfully overcome using latent variable analysis.

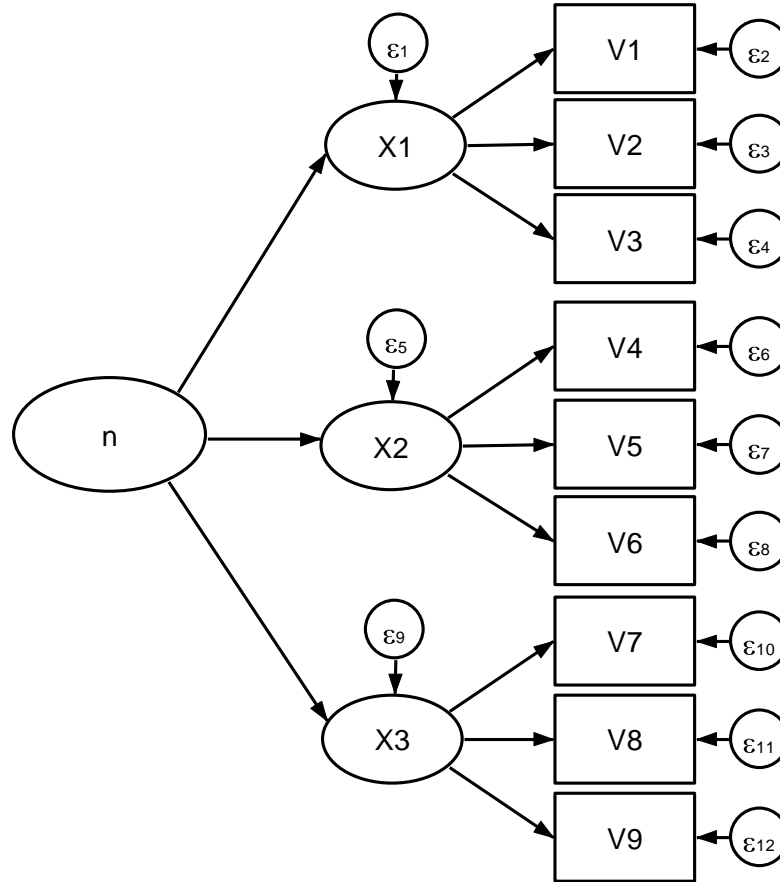


Figure 3.2: Path diagram for a multiple-factor MIMIC model

Source: own illustration adapted from Kaplan (2000)

The MIMIC model has received several applications in the analysis of the informal (underground) economy. Breusch (2005) adopted the MIMIC model in an attempt to quantify the underground economy of various countries. The attractiveness of the MIMIC model in this instance comes in the form of being able to represent the size of the underground (informal) economy as a latent, unobservable variable, which cannot be directly quantified but has a number of causes and effects which are observable. Dell’ Anno (2007), in a similar study, analysed the “shadow” economy in Portugal using a MIMIC model approach. The authors noted that the MIMIC model could be considered a useful methodology when taking other econometric alternatives into account.

More recently, Macias & Cazzavillan (2010) investigated the Mexican informal economy using a MIMIC model approach. Dell’ Anno (2007) and Macias & Cazzavillan (2010) highlighted two

potential limitations associated with the MIMIC, the first of which pertains to the difficulties that arise when undertaking time series analysis. Since the MIMIC model only provides a group of estimated coefficients that can be used to create an index, benchmarking or calibration techniques must be used to convert the resulting index into values that can be used to construct a time series (Dell' Anno, 2007). Secondly, assigning a specific meaning to the latent dependent variable is subjective since the actual meaning of the estimated latent variable may be conceptually different.

There have been a limited number of applications of the MIMIC model to farm level data. As mentioned in the opening subsection of this chapter, Ivaldi *et al.* (1994) and Ivaldi *et al.* (1995) implemented covariance structure analysis, with similar equation structure to the MIMIC method, to estimate stochastic production functions of French grain and fruit producers, respectively. As mentioned earlier in the chapter, Esposti & Pierani (2000) adopted a MIMIC model approach to the measurement of technical change and determine sources of output growth in Italian agriculture.

Richards & Jeffrey (2000) adopted a MIMIC model framework to estimate the efficiency and economic performance of a sample of Canadian dairy farmers, treating economic performance as a latent variable for which several imperfect indicators exist. Measures of technical, allocative and economic efficiency, estimated using a stochastic cost function framework, were then incorporated into the MIMC model as indicators of economic performance. Furthermore, the authors constructed latent quality indices to determine the effect of the quality of the breeding, feeding and labour programmes on latent economic performance.

## **CHAPTER 4: MILK PRODUCTION IN SOUTH AFRICA**

### **4.1 Introduction**

The South African (SA) dairy industry has undergone significant structural change since the promulgation of the Marketing of Agricultural Products Act of 1996. The shift from a market previously “protected” through state intervention to an open market system subject to competition posed a new set of challenges for SA milk producers. The most notable effects of deregulation include a reduction in profit margins, a geographical shift in the distribution of milk producers from inland to coastal regions, and consolidation and expansion of domestic dairy farms (Du Toit, 2009). Consolidation of the SA dairy industry is still ongoing, while mean herd size and national production continue to grow. The aims of this chapter are to provide a current snapshot of the SA dairy industry, the changes that have occurred in recent years, and the nature of milk production in the country. A brief overview of the dairy industry in each of the study areas is also provided for some contextual background.

### **4.2 The South African dairy industry**

The South African dairy industry is the fifth largest agricultural industry in the country, with gross value of production, including producers’ own consumption and on-farm usage, estimated at R12 544 million in 2013 (DAFF, 2014b). The total quantity of milk delivered to markets in 2014 was estimated at 2.8 billion litres (Coetzee & Maree, 2015).

The South African dairy industry may be disaggregated into two distinct sectors: the primary dairy sector, which refers to the production aspects of the dairy value chain and all associated factors, and the secondary dairy sector which refers to processing, distribution and marketing aspects of the dairy value chain. The remainder of this section will be dedicated to the description of, first, the primary and then the secondary sector of the South African dairy industry.

The South African dairy industry has, in recent years, experienced notable shifts in the geographic distribution of milk producers (Table 4.1). Currently, the vast majority of national milk production (81.3%) may be attributed to three of the country’s nine provinces, namely, The Eastern Cape, Western Cape and KwaZulu-Natal. The Eastern Cape, responsible for just 13.8% of national milk production in 1997, has become the largest contributor (27.7%) in terms of national milk production. The Western Cape, historically the leading province in terms of milk production,



remains a significant contributor to national milk production (26.8%). KwaZulu-Natal has experienced good growth in the primary dairy sector and currently contributes 26.8% of national milk production. The Free State, North West and Mpumalanga provinces have experienced substantial decreases in milk production from 18%, 12.6% and 11% in 1997 to 7.3%, 4.2% and 3.3% in 2014, respectively (Coetzee & Maree, 2009; 2015).

Table 4.1: Geographical distribution of South African milk producers, 1997-2014.

Province	Distribution of milk production (%)		
	Dec-1997	Mar-2008	Oct-2014
Western Cape	22.9	25.3	26.8
Eastern Cape	13.8	21.8	27.7
Northern Cape	1.2	0.7	0.8
KwaZulu-Natal	15.7	21.1	26.8
Free State	18	12.8	7.3
North West	12.6	7.1	4.2
Gauteng	4.4	3.1	2.3
Mpumalanga	11	7.6	3.3
Limpopo	0.4	0.5	0.8
Total	100	100	100

Source: Adapted from Coetzee & Maree (2009, 2015)

There has undoubtedly been an observed geographical redistribution of milk producers from inland provinces, such as Mpumalanga, Free State and Northwest provinces, to coastal provinces, such as the Eastern Cape, Western Cape and KwaZulu-Natal. This redistribution trend is most likely due to the increased reliance on pasture-based dairy production systems. In an effort to curb rising costs of production, mainly in the form of purchased feeds, many milk producers have increased their reliance on pasture-based dairying. These grazing oriented systems may be associated with improved animal health, in the form of reduced veterinary, breeding, and medicine costs per cow and greater income from the sale of animals (Hanson *et al.*, 2013). Despite the potential benefits for milk producers, pasture based dairy systems are limited by geographical location, land size, and the quality of land available. Furthermore, milk production per cow on pasture based dairy systems are typically lower than in total mixed ration (TMR) based systems. TMR systems refer

to production systems based entirely on mixed rations, typically consisting of a combination of purchased and home-grown feed, with no reliance on grazing.

Coastal areas are better suited to dairy production systems as mild temperatures and higher levels of rainfall support the growth of natural and artificial pastures necessary for optimal milk production. Artificial pastures refer to pastures created through human intervention, that would otherwise not occur naturally. Inland areas are, in comparison, less climatically favourable for dairying and require more intensive, higher cost production systems (DAFF, 2014b).

It is important to note that despite the guise of lower variable cost of milk production in coastal regions, the additional cost of transportation to markets should be considered (Mkhabela & Mndeme, 2010). According to Blignaut (1999), the effects of widely dispersed and low volume of production per producer in certain areas is reflected in the collection cost of milk. The author further noted that the collection cost of milk was notably higher in inland regions, due to lower milk production per square kilometre (density of milk production), while in coastal milk producing areas, collection costs were relatively low due to higher density of milk production. Although this information is dated, it is not unreasonable to assume, particularly in light of the redistribution trend, that coastal producers in regions with relatively high density of milk production are likely to benefit from lower collection costs in comparison to those producers in relatively low density regions.

There has been a significant decrease in the number of South African milk producers in recent years (Table 4.2). The total number of milk producers in the country has decreased from 7077 in 1997 to 1834 in January 2015, a 74% decrease. The largest decline in the number of producers has occurred in the inland provinces of Mpumalanga (-89%), Northern Cape (-89%), Northwest (-85%) and Limpopo (-81%) (Coetzee & Maree, 2009; 2015). This substantiates the relocation trend of milk production from inland to coastal regions. Despite the observed decline in the number of milk producers, annual domestic milk production has continued to increase. Total milk production for 2014 was 2.978 million tons compared to 2.559 million tons in 2007 (DAFF, 2015). Furthermore, the decline in the number of producers has been accompanied by an increase in the average herd size of milk producers (Table 4.3). The average national herd size per producer has increased from 151 cows in 2006 to 353 cows in 2014, translating to a 134% increase in nine years.

Herd size is a commonly used proxy for farm size in studies involving dairy farm analysis. The contemporaneous decrease in number of national producers and increase in average herd size is indicative of consolidation within the South African dairy industry whereby there are fewer, larger commercial milk producers. This situation is not unique to the South African context and has been highlighted in a number of studies concerning the dairy industries of important milk producing nations such as the United States, New Zealand and Australia (El-Osta & Morehart, 2000; Gloy *et al.*, 2002; Kompas & Che, 2003; Kompas & Che, 2006; Tauer & Mishra, 2006; Gillespie *et al.*, 2009; Hansson & Ferguson, 2011; Hanson *et al.*, 2013).

Table 4.2: Number of milk producers per province in South Africa, 1997 to 2015.

Province	Number of producers										% change
	1997	2007	2008	2009	2010	2011	2012	2013	2014	2015	
Western Cape	1577	827	815	795	754	683	647	573	529	533	-66
Eastern Cape	717	420	407	387	354	314	283	271	264	262	-63
Northern Cape	133	37	34	37	45	28	21	20	25	14	-89
KwaZulu-Natal	648	385	373	373	348	323	322	294	281	267	-59
Free State	1204	987	919	884	835	601	535	423	389	328	-73
North West	1502	596	549	540	507	386	352	253	233	222	-85
Gauteng	356	245	228	217	212	127	126	109	109	100	-72
Mpumalanga	866	357	302	286	248	201	164	119	117	94	-89
Limpopo	74	45	38	32	29	23	24	21	14	14	-81
Total	7077	3899	3665	3551	3332	2686	2474	2083	1961	1834	-74

Source: adapted from Coetzee & Maree (2009, 2010, 2014, 2015)

Given rising production costs and poor milk prices, South African dairy producers often look to increased milk production, either in the form of herd expansion, or improved milk production per cow, as a possible solution (Gertenbach, 2007). One possible driver behind the decision to increase total milk production may be a reduction in gross margin per cow. It is possible that farmers anticipate this change in two ways. Firstly, they may anticipate this as a reduction in the potential profitability of dairy farming and may opt to shut down their dairy enterprise and invest either off-farm or in another farming enterprise, which offers better returns to investment. Farmers with diversified farming portfolios, who derive only a portion of total farm income from the dairy

enterprise, are more likely to adopt this view as they are able to reallocate resources previously allocated to dairying to other farming enterprises. In this instance, the perceived loss associated with the decision to exit may be minimized.

Secondly, farmers may anticipate the change as an indication that they should expand production if they wish to remain profitable. Producers who are highly specialized in dairying and have large investments in this enterprise are more likely to avoid the decision to shut down as long as possible since the perceived losses associated with the decision to exit may be far larger than for smaller producers and non-specialized producers. It is, therefore, larger and more specialized dairy producers that are likely to remain in business due to asset fixity and attempting to exploit scale economies in order to maintain profitability.

Table 4.3: Mean herd size per producer, per province, for 2006 and 2014.

Province	Mean herd size (cows)		% Change
	2006	2014	
Western Cape	151	281	86
Eastern Cape	349	769	120
Northern Cape	67	76	13
KwaZulu-Natal	267	574	115
Free State	72	140	94
North West	68	90	32
Gauteng	225	117	-48
Mpumalanga	91	169	86
Limpopo	206	230	12
Total	151	353	134

Source: adapted from Coetzee & Maree (2009, 2015).

Conventional economic theory dictates that the decision to shut down, given perfect information and no adjustment costs, occurs when the product price falls below average variable costs (Tauer, 2006). However, in the case of farmers, standard shutdown theory does not apply since farmers anticipate a possible recovery of the milk price in the future and continue to operate despite average variable costs of producing milk exceeding the milk price. Furthermore, individual milk producers have different variable costs of production, therefore the decision to exit is farm specific.

According to Tauer (2006), small dairy farms are likely to exit at higher milk prices than larger dairy farms and hence are less likely to persist in the face of low milk prices.

Rahelizatovo & Gillespie (1999) investigated the factors affecting dairy farm exit in Louisiana, which was experiencing consolidation and overall decline in regional productivity. They found that milk prices, input prices, technology affecting milk productivity, agricultural policies incentivizing reduced milk production and early retirement, and farmer's financial conditions all significantly affected the structure of the local dairy industry.

Although the decision to exit dairy farming is often attributed primarily to low milk prices there are several other important factors that farmers may consider before deciding to exit the industry. Goetz & Debertin (2001) identified off-farm employment as an important determinant of farm exits in the US, finding that off-farm employment accelerated exits from production agriculture, only once the country had begun to experience a net loss of farmers. When deciding to exit farming, farmers compare the utility they expect to derive from remaining in farming with the utility derived from exiting and either becoming fully employed off-farm, retiring or relocating (Goetz & Debertin, 2001). Bragg & Dalton (2004) identified older producers, higher off-farm income, lower returns over variable cost and greater diversification of farm income as factors which significantly increase the likelihood of dairy farm exits.

The secondary dairy sector in South Africa consists of 153 registered milk buyers, of various size and processing ability, and 122 producer-distributors. Producer-distributors are defined as producers who are able to market produce directly to consumers or retailers (Coetzee & Maree, 2015). Of the 153 registered buyers there are several large milk buyers and processors including Clover, Parmalat, Woodlands Dairy, Lancewood and Nestlé. The remainder of the registered milk buyers represent smaller scale processing and marketing operations, operating more on a local basis.

The South African milk market may be divided into liquid and concentrate products whereby liquid products constitute 58% of the market and concentrate products constitute 42%. Pasteurized milk is the largest product of the liquid milk market (51%) followed by UHT milk (29%). Together they constitute 80% of the liquid milk market in South Africa. The South African concentrated products market is comprised primarily of hard & semi-hard cheese (44%), followed by other cheese (19%) and butter (12%) (Coetzee & Maree, 2015).

### **4.3 Dairying in KwaZulu-Natal**

KwaZulu-Natal is currently the second largest milk producing province in South Africa (alongside the Western Cape), responsible for 26.8% of national milk production as of October 2014. There are currently 267 milk producers registered with the milk producers' organization of KwaZulu-Natal (KZN), which is significantly lower than the 648 producers of 1997. Furthermore, KZN has experienced the second largest increase in average herd size per producer since 2006, with a 115% increase from 267 in 2006 to 574 in 2014 (Coetzee & Maree, 2009; 2015).

Dairy production systems are highly complex and may vary significantly between regions and producers. Pasture based systems and total mixed ration (TMR) systems represent opposite extremes, with any possible combination of the two representing partially pasture/TMR based systems. Milk production in KZN is primarily pasture based, with the majority of producers opting for the inclusion of formulated dairy concentrate rations to supplement any nutritional shortfalls and improve milk production as well as milk quality (Gertenbach, 2007).

The majority of milk produced in KZN is produced within the Midlands region due to high annual rainfall, between 800 and 1000mm per annum, moderate temperatures and good quality soils. These conditions promote the growth of good quality dry land pastures during the rainy summer months. Moderate temperatures promote the growth of irrigated ryegrass pastures during the dryer winter months. These conditions make the Midlands more suited to pasture based dairy systems than the majority of other regions in the province. The Northern areas of KZN, such as Zululand, are not conducive to commercial dairy farming due partly to high temperatures, which often result in heat stress of most dairy breeds (Mkhabela, 2011). East Griqualand is another important milk producing region within the KwaZulu-Natal province. East Griqualand is characterized as a summer rainfall region which typically receives an average of 620 to 816mm of rain per annum (Camp, 1997).

There are currently 17 milk buyers and 11 PD's registered with KZNMPO. The majority of milk producers in the EG study group supply to large multinationals such as Clover and Nestle while a few of have chosen to process their milk on site, using specialized equipment. There are very few producer distributors currently opting to market their own milk in EG (Bischoff, 2015).

#### **4.4 Dairying in the Eastern Cape**

The Eastern Cape is the largest milk producing province in South Africa, responsible for 27.7% of national milk production as of October 2014. Currently, there are 262 registered milk producers in the province, significantly less than the 717 milk producers registered in 1997. The Eastern Cape, like KZN, has experienced a substantial, 120%, increase in the average herd size of registered producers from 349 cows in 2006 to 769 cows in 2014 (Coetzee & Maree, 2009; 2015).

The majority of milk produced in the Eastern Cape province is produced under pasture based dairy systems in the cooler coastal regions such as Alexandria, Cookhouse, East London, Tsitsikamma, and Queenstown (Agri Eastern Cape, 2015). Cooler temperatures and relatively high rainfall, averaging between 500mm and 700mm per annum, facilitate the growth of high quality natural pastures and minimizes expenditure on expensive dairy concentrates. The majority of dairy farms in the coastal regions of the Eastern Cape are dryland farms, relying solely on rainfall for the growth of pastures. This is in contrast to KZN dairying, where the majority of dairy farmers have at least some proportion of their land under irrigation. Irrigated lands are commonly used for annual or perennial ryegrass pastures during the cooler winter months, in an effort to reduce reliance on costly concentrate feeds (Currie, 2015).

There are currently 12 registered milk buyers and 15 PD's in the Eastern Cape (Coetzee & Maree, 2015). The Alexandria study group markets the majority of its milk through large milk buyers such as Clover, Parmalat and Dairybelle while the remainder is supplied to Woodlands dairy, a large South African company which markets under the "Firstchoice" brand. The majority of milk produced by the Alexandria study group is marketed outside of the Eastern Cape Province with a large proportion being transported to Johannesburg in response to market demand. It is important to note that KZN milk producers may benefit from as much as 60c per litre transport advantage over EC milk producers (Currie, 2015).

## **CHAPTER 5: MODELLING TECHNICAL AND SCALE EFFICIENCY**

### **5.1 Introduction**

The modelling, estimation and application of stochastic frontier production functions to economic analysis has been a prominent area of focus in applied economic analysis over the past two decades (Ojo, 2003), with numerous applications to agricultural research. While much of this focus has been dedicated to the estimation of technical efficiency, very few applications have focused on the estimation of parametric scale efficiency. This chapter aims to surmount this limitation by modelling both technical and scale efficiency in a parametric framework. The chapter opens with a brief description of the study areas, data collected, and variables included in subsequent analysis and progresses into a preliminary analysis of the data. Several production functions are then specified. The final section of the chapter deals with the modelling of parametric scale efficiency.

### **5.2 Description of the study areas and the data collected**

#### **5.2.1 Data**

The data collected for the purposes of this study are detailed production and financial data from individual dairy farms, obtained from dairy consultants operating in the East Griqualand region of KwaZulu-Natal and the Alexandria region of the Eastern Cape, for the period 2007 – 2014. Data were collected on the dairy enterprise alone, hence, income and expenditures relate only to milk production and the dairy herd. Income from any value adding activities such as processing of milk into powdered milk, maas, cheese, yoghurt, etc., are not considered. Farms included in the sample are considered specialized dairy producers, deriving more than 80% of their income from milk production. A few noteworthy exceptions warrant mention. Dairy farms with value adding enterprises, such as those mentioned above, typically realise large revenues, attributable to their value adding enterprises, which negatively distorts the proportion of total income that may be attributed to milk production. These farms are still considered specialized dairy farms since these value adding processes are centred on the dairy enterprise.

The data consist of a combined panel of 26 commercial milk producers spanning a period of 8 years, from 2007-2014. The number of pooled observations for the study is 208. It is important to note that the appropriateness of sample size is linked to the ratio of the number of subjects to the number of parameters estimated (Tanaka, 1987). Therefore, it is difficult to determine, with



certainty, the appropriate sample size for a specific study. Boonsma (1983), as cited by Tanaka (1987), suggested sample sizes in excess of 200 are appropriate if maximum likelihood (ML) estimation is used. The pooled sample of 208 observations used in this study is therefore considered sufficiently large.

The original data from the East Griqualand study group consisted of 14 producers spanning the eight years from 2007 to 2014; however, due to one farm dropping out, an unbalanced panel of 104 observations was achieved. The original Alexandria study group comprised of 26 farms, although only 18 farms were consistent across the entire eight-year period. Furthermore, five farms from the Addo, Cookhouse and Tsitsikamma regions were considered outliers and were subsequently dropped from the sample to retain representability. This resulted in an unbalanced panel of 104 observations. It is important to note that the original data are in terms of current (nominal) prices and must be deflated to constant prices before any intertemporal comparisons may be made.

The resulting unbalanced panel of 208 observations was achieved by pooling the data from each respective production region. The unbalanced nature of the data is due to data omissions arising from incomplete farm records. Missing data analysis was conducted to determine the nature of the missing data and assist in the selection of an appropriate remedy. The results of the missing data analysis led to the use of multiple imputation, using the data augmentation technique, to construct a balanced panel of 208 observations. This will be covered in greater detail later in the chapter.

Data from Alexandria in the Eastern Cape are considered representative of above-average dairy farmers in the region (Currie, 2015). Farms in the Alexandria study group are all considered specialized dairy farms, earning 100% of total farm income from the dairy enterprise. Data for the East-Griqualand area of KwaZulu-Natal are also considered representative of above-average dairy farmers in the area (Bischoff, 2015). The East Griqualand study group is comprised of both dairy farms and mixed enterprise farms, although all farms included in the sample may be considered specialized in dairy, with upwards of 80% of total farm income attributable to the dairy enterprise.

### 5.2.2 East Griqualand

East Griqualand (EG) refers to southern parts of KwaZulu-Natal, such as Kokstad, and northern parts of the Eastern Cape, such as Matatiele and Cedarville. The entire EG region is characterized

by the grassland vegetation biome (Figure 5.1), which is comprised of two major grass types, namely sweetveld and sourveld, with mixed veld as an intermediate (Ellery *et al.*, 1995). Following the Bioresource Group (BRG) classifications of Camp (1997), the majority of the region may be classified as dry highland sourveld followed by moist highland sourveld. Mean annual rainfall ranges from 620 to 816mm for the former and 800 to 1265mm for the latter (Camp, 1997). Figure 5.2 illustrates that the mean annual rainfall for the KZN portion of East Griqualand ranges between 500mm and 800mm.

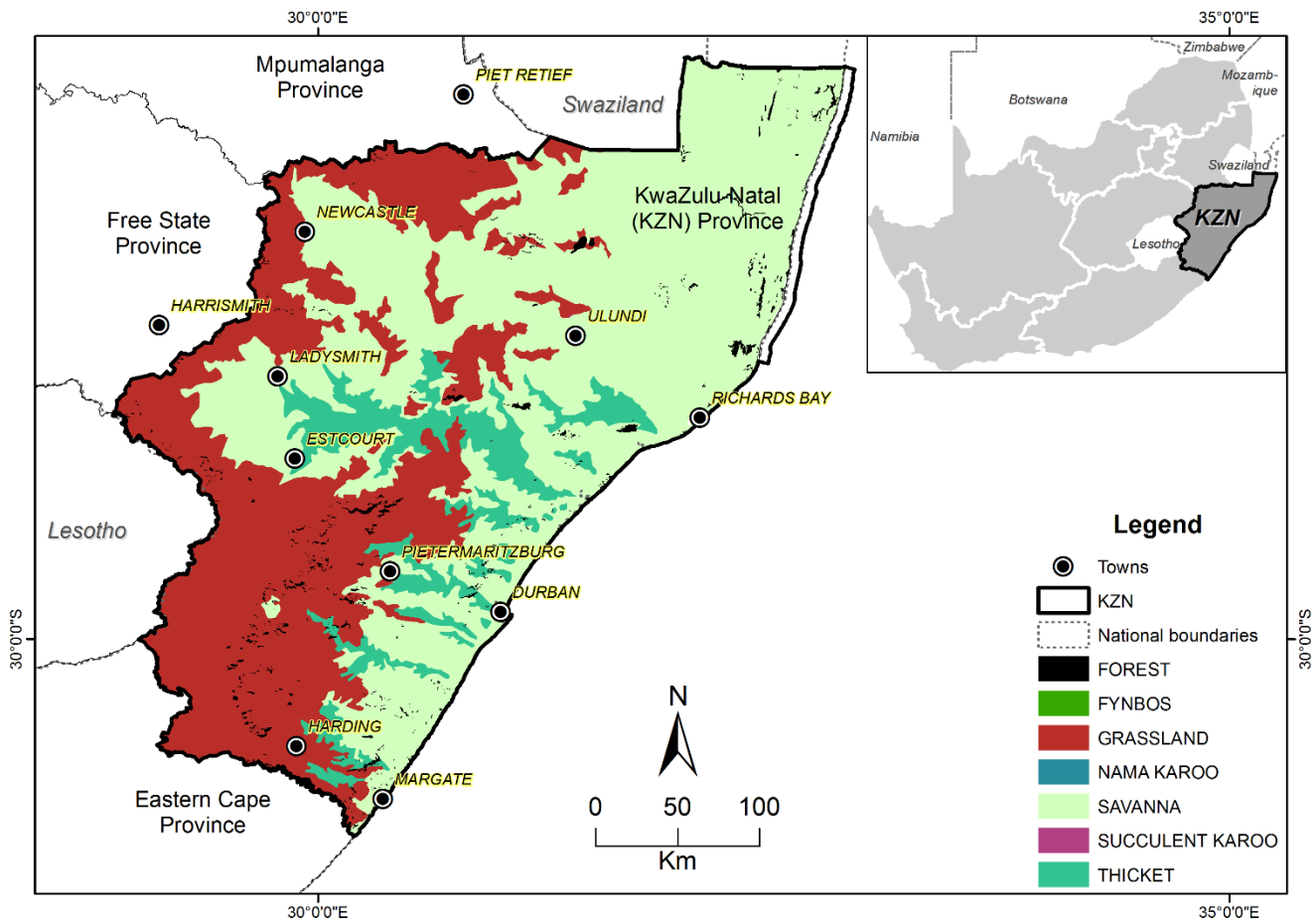


Figure 5.1: Map of vegetation biomes in KwaZulu-Natal, South Africa.

Source: Cartographic Unit, Geography Department, SAEES, University of KwaZulu-Natal, Pietermaritzburg, 2015.

East Griqualand is a summer rainfall region characterized by sourveld grazing conditions, which are restricted to summer and spring, providing approximately six to eight months of grazing per year. Despite a reasonable carrying capacity during spring and summer, sourveld becomes

relatively unpalatable to livestock during autumn and winter (Tainton, 1981). This has important implications for the type of farming systems that can be supported within the region. In the case of milk production, this variability in the fodder flow increases reliance on supplementary feed sources such as irrigated pastures, maize silage, and feed concentrates over the autumn and winter months. Additional costs associated with winter supplementation affect the overall cost structure of milk producers in the region and subsequently has an impact on profitability. Since feed costs are typically one of the largest costs for dairy farmers, it is reasonable to postulate that the ability to maintain fodder flow throughout the year, through the production of home grown feeds, is likely to be an important determinant of farm financial performance.

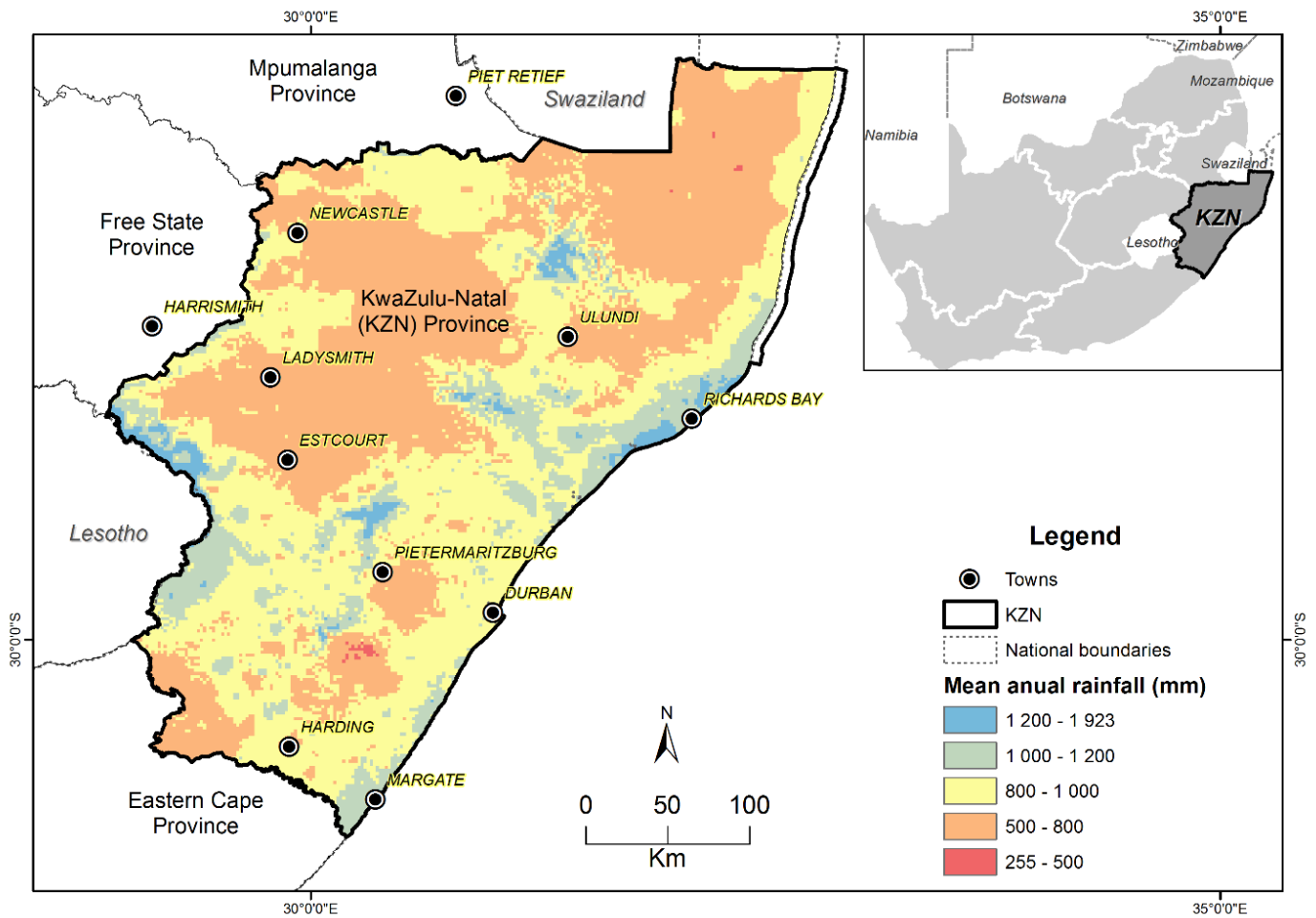


Figure 5.2: Mean annual rainfall map for KwaZulu-Natal, South Africa.

Source: Cartographic Unit, Geography Department, SAEES, University of KwaZulu-Natal, Pietermaritzburg, 2015

Milk producers within the EG study group rely predominantly on pasture based systems, due to lower input costs and higher potential profitability. Farmers rely on perennial ryegrass and clover pastures for the majority of the year although yields begin to decline in mid-summer at which point kikuyu pastures are introduced to supplement any shortfalls in dry matter. Turnips are planted in February and grazed during mid-winter in an effort to augment winter pastures. Maize silage is typically fed from May to September in order to balance out any shortfalls in dry matter requirement which may arise due to the relatively low nutritive value of pastures during the winter months (Bischoff, 2015). Furthermore, Bischoff (2015) indicated that EG milk producers should aim to produce 15kgs of dry matter per cow per day throughout the year (this figure refers to roughage requirement alone and excludes any dairy concentrates) and one hectare of maize silage for every ten dairy cows.

Mean annual temperature for the East Griqualand region ranges between 8.1 and 14.8 degrees Celsius. Referring to Figure 5.3, it is evident that the EG region experiences lower mean annual temperatures than most of the province, particularly the coastal regions. The northern reaches of KZN, in particular the North coast, experience significantly higher temperatures than traditional dairy farming areas, such as the Midlands and EG. These high average temperatures make northern KZN unsuitable for dairying.

Hot weather has been linked to an increased incidence of heat stress in dairy cattle, which typically results in decreased milk production and reproductive performance (Armstrong, 1994), particularly in cows with high genetic potential (Kadzere *et al.*, 2002). Heat stress occurs when any combination of environmental conditions (temperature, relative humidity, air movement and solar radiation) results in the effective temperature of the environment exceeding the thermo-neutral (comfort) zone of the animal (Armstrong, 1994). By minimizing heat stress, it is possible to reduce or eliminate yield and reproductive losses. The relatively cool climate characterizing the EG region not only facilitates the growth of good pastures but is likely to minimize the incidence of heat stress and associated productivity losses.

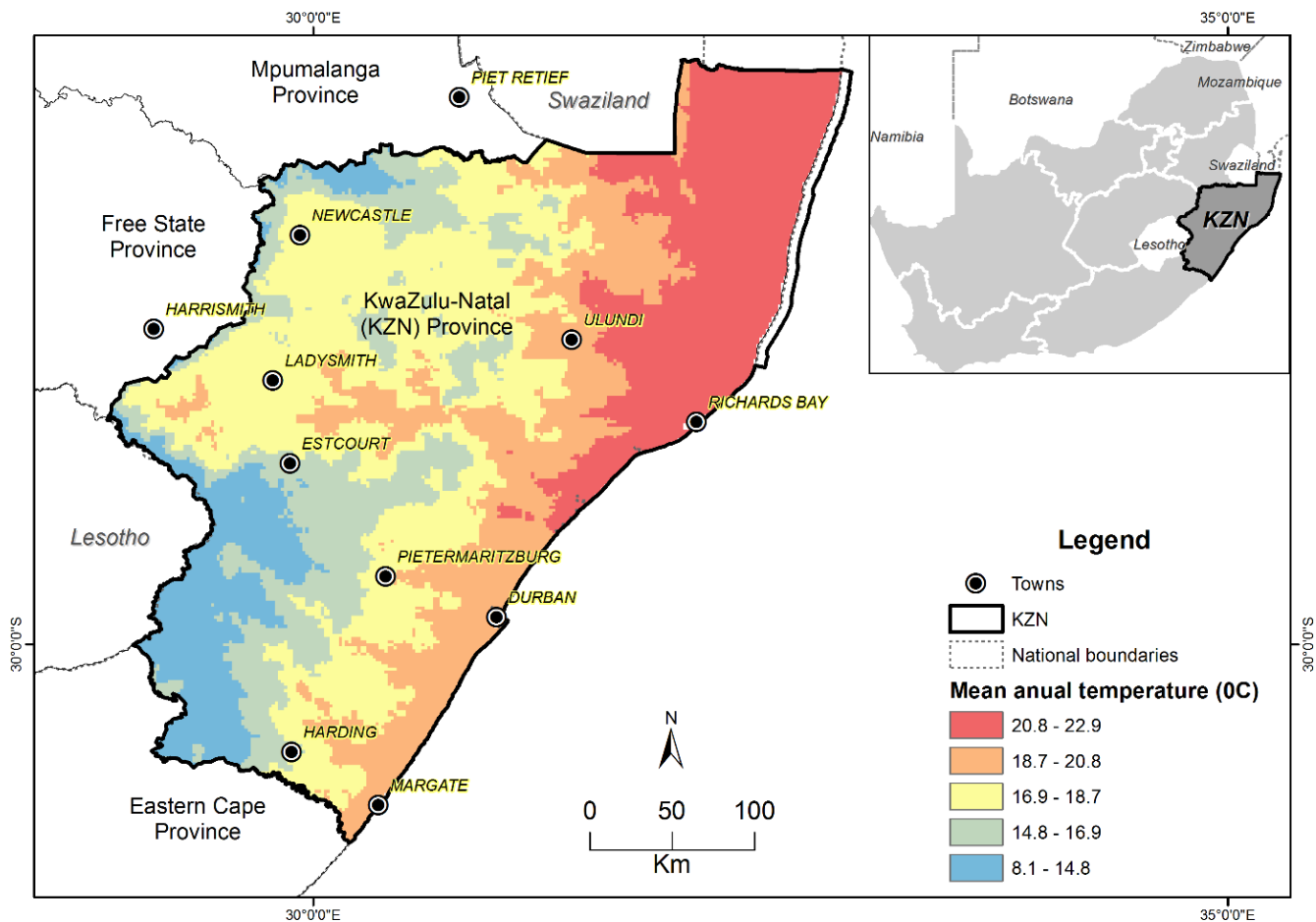


Figure 5.3: Mean annual temperature map for KwaZulu-Natal, South Africa

Source: Cartographic Unit, Geography Department, SAEES, University of KwaZulu-Natal, Pietermaritzburg, 2015

### 5.2.3 Alexandria

Alexandria is a small farming town located in the Ndlambe local municipality within the Cacadu, Sarah Baartman, district of the Eastern Cape. It is located in the south-western corner of the Eastern Cape Province in close proximity to the coastline (Sarah Baartman District Municipality, 2015). Figure 5.4 indicates that the coastal region between Port Elizabeth and East London is characterized by several different vegetation biomes including savanna, grassland, thicket and even areas of fynbos. Alexandria is most likely characterized by grassland and savanna vegetation which differs from the purely grassland vegetation of East Griqualand. Unfortunately, the lack of

available information on Eastern Cape vegetation did not permit the classification of the study area into specific Bioresource Groups (BRG)'s as in the case of the KZN study area.

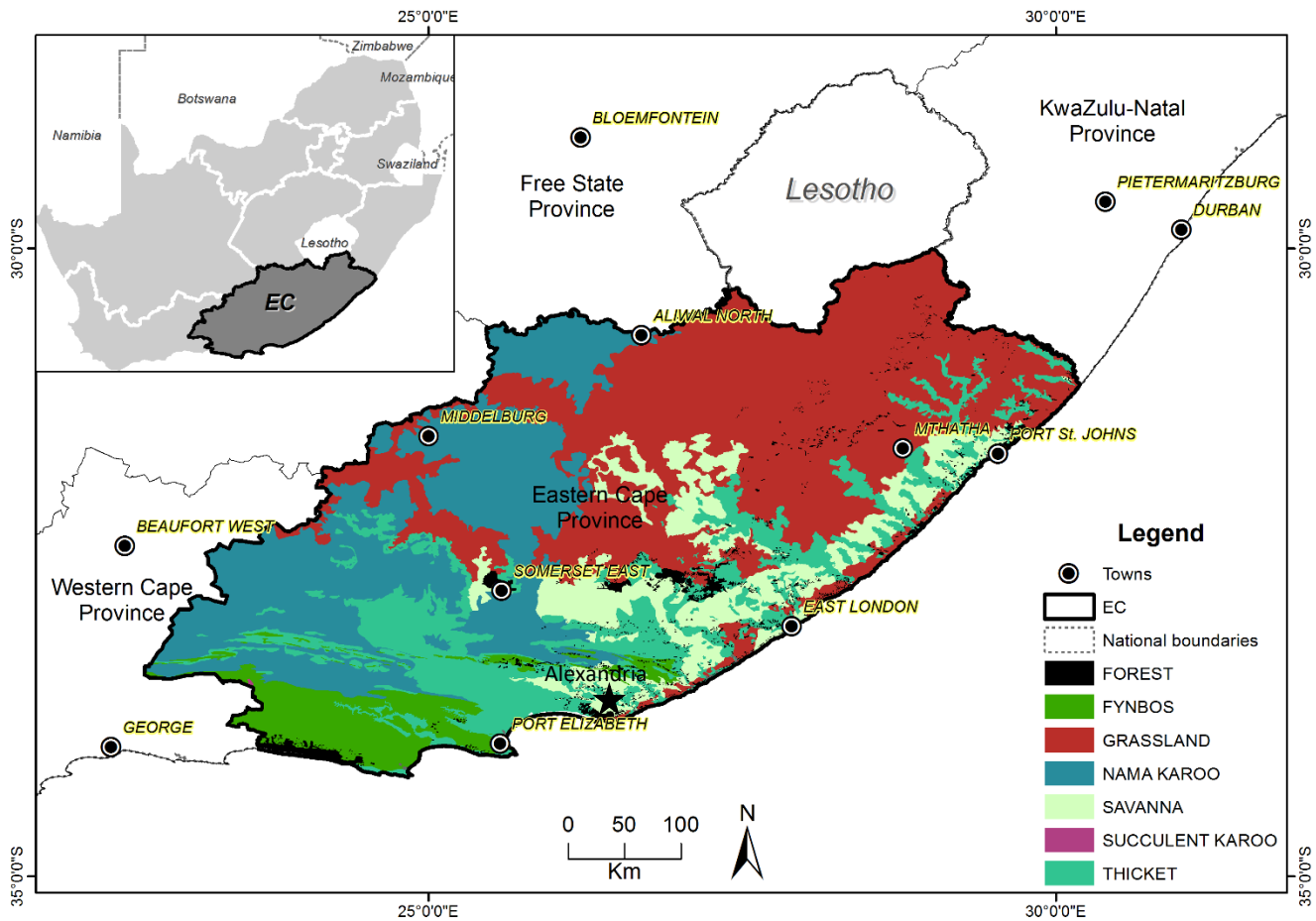


Figure 5.4: Map of vegetation biomes in the Eastern Cape, South Africa.

Source: Cartographic Unit, Geography Department, SAEES, University of KwaZulu-Natal, Pietermaritzburg, 2015.

Figure 5.5 indicates that mean annual rainfall for the Alexandria region ranges between 500mm and 700mm, similar to the figures reported for the EG region in KZN. It is evident that the northern stretch of coastline, between East London and Port St Johns experiences significantly higher rainfall than the Alexandria region. This former homeland known as the Transkei is, however, characterized by small-scale subsistence farming, with very little commercial agriculture taking place. Figure 5.6 indicates that the mean annual temperatures of the Alexandria region, and much of the Eastern Cape coastline, range between 17.7 and 20.6 degrees Celsius. This is significantly

higher than for the East Griqualand region, which experiences mean annual temperatures not exceeding 14 degrees Celsius.

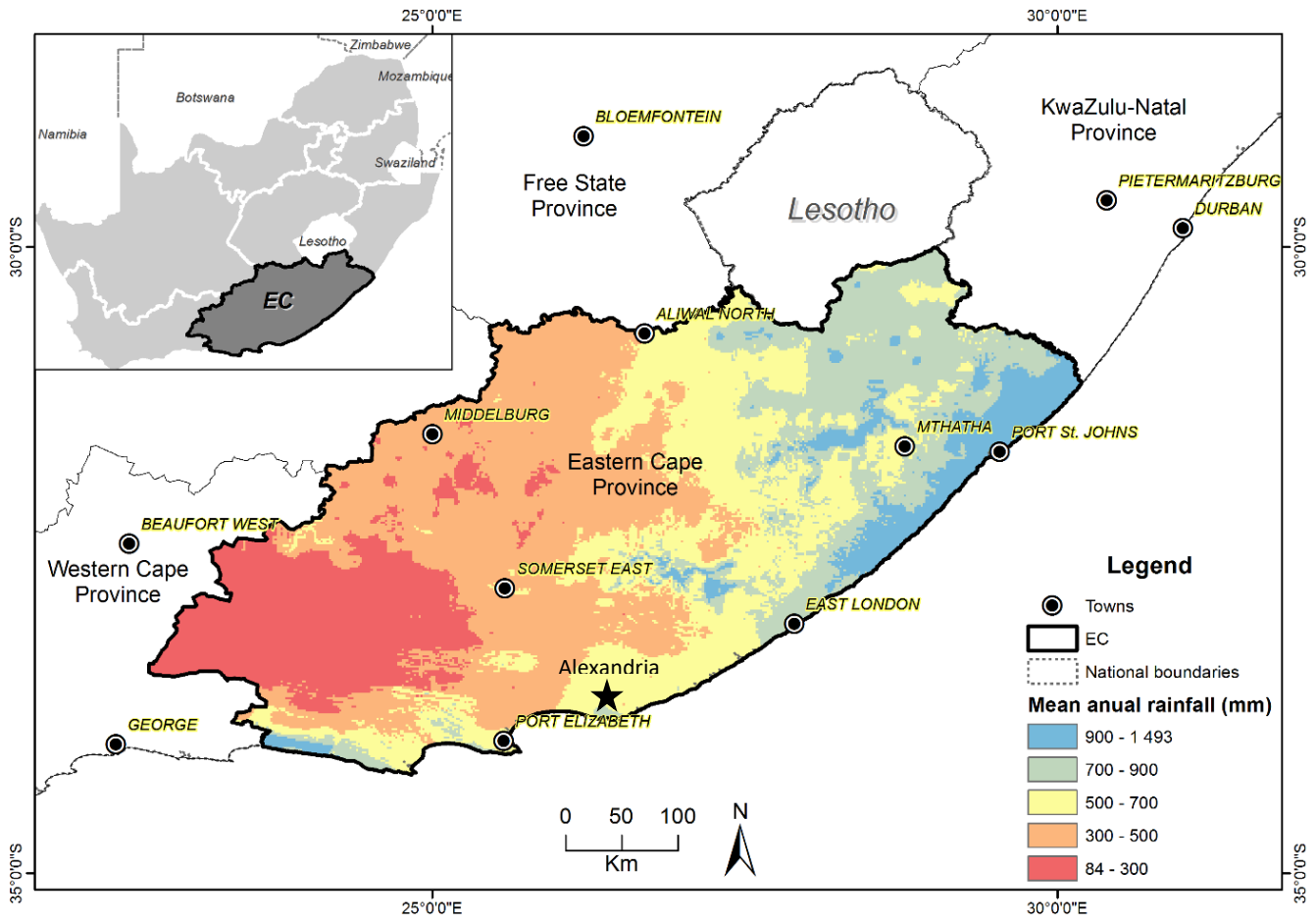


Figure 5.5: Mean annual rainfall map for the Eastern Cape, South Africa.

Source: Cartographic Unit, Geography Department, SAEES, University of KwaZulu-Natal, Pietermaritzburg, 2015.

The Alexandria study group consists entirely of dryland dairy farms which cannot facilitate the growth of conventional ryegrass pastures due to the lack of irrigation infrastructure. Relatively high mean annual temperatures limit the use of “traditional” dairy pastures such as clover, stouling rye and radish, which are more suited to cooler, wetter areas such as the KZN Midlands. Milk producers in the region therefore rely primarily on Kikuyu and K11 pastures to meet the dry matter requirements of the dairy animals.

Kikuyu is a palatable and nutritious tropical grass which grows well in warmer areas. It can tolerate heavy defoliation and provides relatively good foggage if left standing through the winter months (Bartholomew, 2015). K11, also called Coast Cross II, is a tropical Cynodon species which is well suited to warmer climates and is more drought resistant than Kikuyu. Young regrowth is palatable and nutritious although older growth may be relatively unpalatable. K11, unlike Kikuyu, is not well suited to foggaging (Bartholomew, 2015).

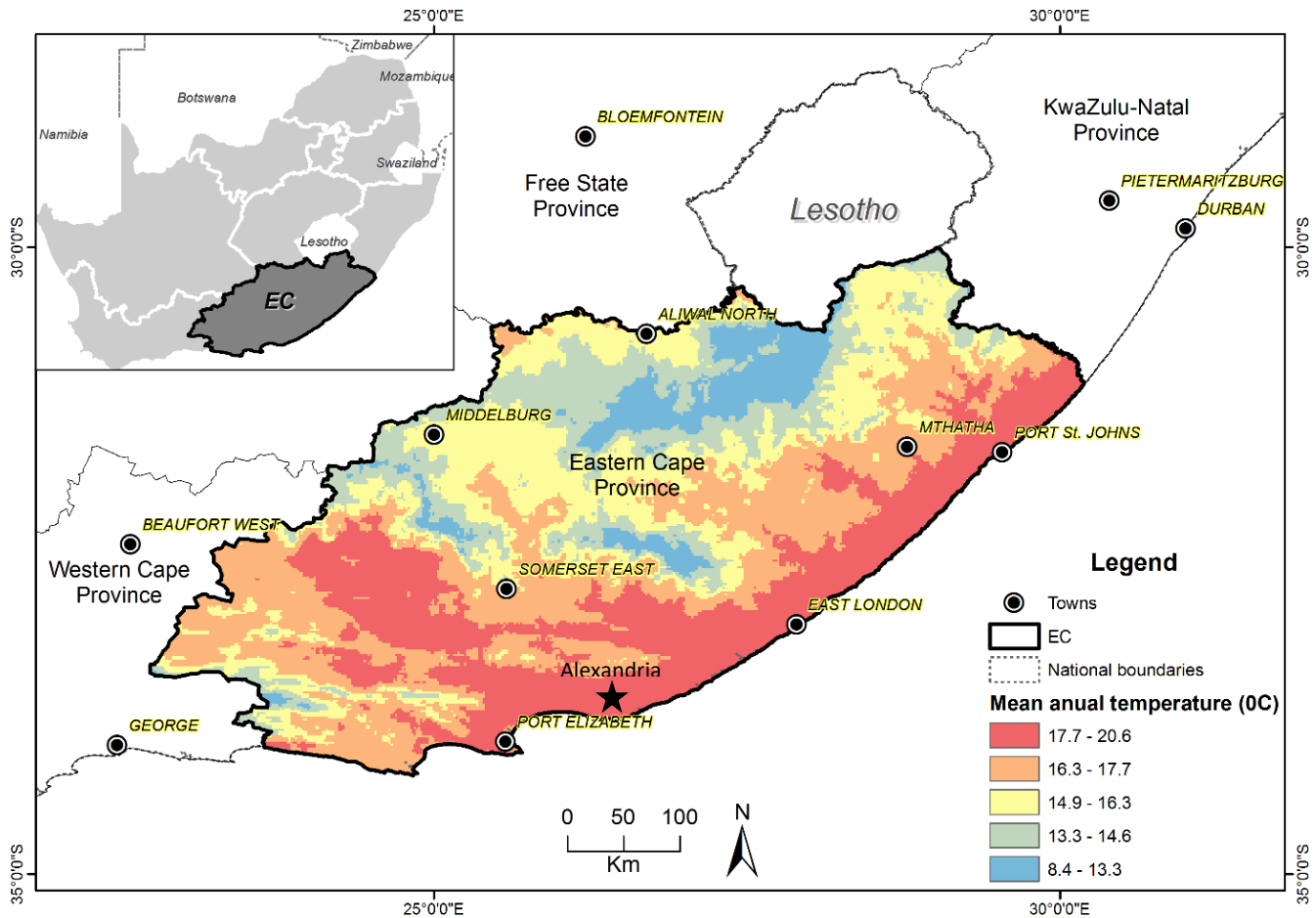


Figure 5.6: Mean annual temperature map for the Eastern Cape, South Africa

Source: Cartographic Unit, Geography Department, SAEES, University of KwaZulu-Natal, Pietermaritzburg, 2015

Due to relatively mild winters, Alexandria dairy farmers are able to maintain a relatively large portion of their pastures over the winter months (foggaging). Excess grass and hay is baled and wrapped to serve as supplementary roughage to be fed during the winter months. Local milk producers do not rely on maize silage but rather augment any shortfalls in roughage requirement



with citrus pulp which is readily available in the area and provides a cost-effective means of supplementation. Dairy concentrates are typically fed at a ratio of approximately 360g per litre of milk produced (Currie, 2015).

### **5.3 Variables used in the production function**

The variables considered in the production functions analyses are summarized in Table 5.1 with detailed descriptions of each to follow. This study considers one aggregated output variable and five individual factors of production, some of which have also been aggregated for the purposes of computational simplicity. All variables have been adjusted for inflation and are reported in 2014 Rands (2014 = 100).

#### *(i) Total dairy output (Y)*

The output variable in this study represents an aggregation of the two most significant outputs of the sampled dairy farms, namely, total income from the sale of milk and trading income. Total milk revenue represents total income from all milk sold to formal and informal (on-farm labour) markets as well as personal drawings. Trading income refers to the purchase and sale of livestock and may be defined as: stock sales + closing value - stock purchases - opening value.

Total milk revenue rather than physical output was considered as it has the advantage of accounting for inherent differences in quality (Abdulai & Tietje, 2007). The price received by each farmer is usually dependent on a number of milk characteristics including the butterfat content, protein content, and milk quality. Somatic cell count (SCC) is the most widely accepted measure of milk quality which assesses microbiological milk quality (coliform counts, plate counts, etc.) and mammary gland inflammation, associated with mastitis (Reneau, 2001). Although individual farm level prices are a function of several factors, it is reasonable to assume that price differences at the farm level capture at least some portion of inherent quality and compositional differences.

It is important to note that this assumption may not hold in the case of producer-distributors and producers supplying smaller milk buyers who fail to recognize quality and compositional differences through selective pricing. In this case milk prices are essentially at a “flat rate” and do not capture any quality or compositional differences between producers.

Table 5.1: Variables included in the production function

Variable	Code	Description	Unit
Output	Y	The combined value of total milk income and trading income.	Rand
Veterinary	V	Total expense on veterinary products and services including: veterinary visits; medicines, dips and tags; cleaning materials; milk recording costs and sundries.	Rand
Labour	L	Total wage bill for the dairy enterprise which accounts for differences in labour quality.	Rand
Feed	F	Total expense on feed including purchased feeds and home grown feeds.	Rand
Herd	H	Average number of cows in milk per year.	Cow
Capital	K	Total maintenance, depreciation and running costs associated with capital stock items such as fixed improvements and machinery.	Rand

(ii) *Total veterinary expense (V)*

High levels of production performance demanded by commercial dairy farmers requires that each milking cow's needs in terms of health, production performance, and breeding performance be met, particularly for the highest producing milk cows (best milkers). Achieving these performance requirements requires large expenditure on various aspects of veterinary products and services. Veterinary expense was included in an attempt to assess the importance of herd health on aggregate output, following Winsten *et al.* (2000) and Del Corral *et al.* (2011).

Veterinary expense is defined as all expenses relating to veterinary products and services including veterinary visits; medicine, dips and tags; artificial insemination costs; cleaning materials; milk recording costs and sundries. Following the findings of Del Corral *et al.* (2011), it is hypothesized that increased expenditure on veterinary products and services (V) will be correlated with improved herd health up until a certain point and therefore a positive relationship between veterinary expense and output is expected up until this point is reached. In other words, as veterinary expense increases production output is expected to increase up to a certain point, *ceteris paribus*.

(iii) *Labour (L)*

Commercial dairy farming requires a mix of relatively skilled workers, who have been trained in the use of the highly specialized milking equipment and/or production monitoring systems, and relatively unskilled labourers, such as stockmen and cleaners. Since information regarding the number of labour hours attributable to the dairy enterprise was not available, the labour variable is represented by the total wage bill for all staff employed in the dairy enterprise. The benefit of quantifying labour in terms of wage is the ability to account for differences in labour quality (Gloy *et al.*, 2002). Because an increase in labour is expected to result in increased output, in accordance with Kumbhakar *et al.* (1989), Jaforullah & Premachandra (2003), Hadley (2006), and Cabrera *et al.* (2010), a positive relationship between labour and output is hypothesized, *ceteris paribus*.

(iv) *Total feed expense (F)*

Expenditure on feed is typically one of the largest expenses of any dairy farmer, regardless of whether the majority of feed is purchased, or home grown. Following Abdulai & Tietje (2007), the feed variable is defined as the total rand value expenditure on all feeds, represented by the sum of purchased and home-grown feeds.

Expenditure on purchased feeds is represented by total expenditure on all feed purchased for cows, heifers, calves, and includes dairy concentrates. Expenditure on home-grown feeds is represented by the aggregation of all costs associated with the production of feeds grown *insitu*. This includes, but is not limited to, expenditure on fertilizer, seed, pesticides and herbicides, planting, and harvesting costs. It is important to note that by expressing feed in aggregate value terms, it is not possible to account for differences in feed quality and composition between farms. This may introduce some degree of heterogeneity into the data (Abdulai & Tietje, 2007). Feed cost (F) is hypothesized to have a positive and significant relationship with dairy output in line with Tauer & Belbase (1987), Bravo-Ureta & Rieger (1991), Alvarez & Arias (2003) and Mbagwa *et al.* (2003). In other words, as feed expense increases output is expected to increase, *ceteris paribus*.

(v) *Herd size (H)*

The herd size variable is represented by the average number of cows in milk per annum. It is included as a proxy for farm size, commonly measured in hectares. Herd size is considered more relevant than physical area measures of farm size since it intrinsically accounts for agricultural

potential of each farm. It could be argued that a farm with poor soils and low agricultural potential could achieve a large herd size through intensive feeding of purchased feeds, although the high cost of production associated with such a production system would most likely deem it unviable for South African milk producers. Furthermore, dairy farms from the two respective study areas are predominantly centred around pasture-based feeding systems, meaning that herd size is likely to represent the size of their farming enterprise reasonably well.

Because an increase in herd size is associated with increased production potential, it is hypothesized that the relationship between herd size and output will be strongly positive and significant. In other words, as herd size increases output is expected to increase, *ceteris paribus*. These expectations are in line with the findings of Kumbhakar *et al.* (1991), Jaforullah & Premachandra (2003), Gillespie *et al.* (2009) and Cabrera *et al.* (2010).

(vi) *Capital (K)*

Following Hadley (2006) and Mkhabela (2011), the cost of the capital variable is constructed in an effort to represent the flow of services originating from capital stock items. This approach is adopted since there was insufficient data on capital expenditure to calculate the capital stocks. Furthermore, Mkhabela (2011) noted that unless the level of capacity utilization is known, running costs associated with capital stock items have more explanatory power. Total maintenance, depreciation and running costs associated with capital stock items such as fixed improvements and machinery were aggregated to produce an input of total running cost of capital stock items.

In the modern dairy industry, capital investment has become an increasingly important part of production. Efforts to improve productivity, in the face of increasing herd sizes, has led to higher rates of technology adoption, much of it labour augmenting. Improved milking parlours, feeding systems, herd and production monitoring technologies are a few examples of increased capital investment. Kumbhakar *et al.* (1989), Von Bailey *et al.* (1989), Mbagha *et al.* (2003) and Jaforullah & Premachandra (2003) all reported a positive relationship between capital and dairy output. In line with the previous literature, it is hypothesized that the relationship between capital and output will be positive, *ceteris paribus*.

(vii) *Regional dummy variable (D)*

A regional dummy variable was included to differentiate between the two production regions and capture any variation in production due to regional differences. These may include climatic variations such as land quality, marketing variations, and differences in the production systems used in the two regions. Hence, East Griqualand = 1, and 0 if otherwise. Since inherent regional differences are expected to exist, the coefficient estimate of the regional dummy variable is hypothesized to be significant.

(viii) *Smooth time trend (T)*

A smooth time trend variable was introduced as a crude attempt to proxy technological progress over the study period. According to Debertin (1968), including a simple time trend variable into the production function is highly inaccurate but may be an improvement over a static model that fails to account for technological change in any way. Furthermore, the inclusion of a time trend into the production functions represents a workable alternative which may be easily applied (Chambers, 1988). Since new technologies such as rotary milking parlours, AI and genetic progress, and advanced production monitoring software are all expected to improve productivity, the time trend is hypothesized to have a positive relationship with dairy output, *ceteris paribus*.

## **5.4 Preliminary data analysis**

### **5.4.1 Missing data analysis**

Missing data are a prevalent issue for researchers using structural equation modelling (SEM) techniques (Enders & Bandalos, 2001). There is general consensus among the relevant literature that the effects of missing data need to be considered prior to statistical inference as it may affect research results (Lee, 2007; McKnight *et al.*, 2007). Researchers often fail to state the presence of missing data and resort to default methods, such as list-wise deletion, without acknowledgement, in an effort to avoid addressing the problem (Van Buuren, 2012). It is, therefore, considered prudent to analyse the missing data before proceeding with statistical estimation and inference.

When considering the impact of missing data on research results the pattern, amount and mechanism of missing data should be investigated. The pattern of missing data refers to the presence of any consistencies in the way that data are missing, while the amount of data missing

refers to the total number of missing observations. Generally, it is desirable to have less missing data, *ceteris paribus* (McKnight *et al.*, 2007).

The mechanism of, or process underlying, the missing data is of particular importance as it allows to classify missing data into one of three broad categories. Rubin (1976) defined the three categories as: missing completely at random (MCAR), missing at random (MAR) and missing not at random (MNAR). These mechanisms are related to the level of bias the missing data may exert on subsequent statistical analyses, whereby MCAR is considered to have a negligible potential impact and MNAR the largest potential impact (McKnight *et al.*, 2007). Data which are MCAR and MAR are considered ignorable (Enders & Bandalos, 2001), meaning there is no need to model the missing data mechanism as part of the estimation process (Allison, 2001). Data which are MNAR are non-ignorable, and may result in parameter bias and misestimation of standard errors (Finch, 2015). MCAR may be considered the “most desirable” classification since it indicates that there is no systematic process underlying the way in which the data are missing (there is no systematic relationship between missingness and either the observed or unobserved values in the data) (McKnight *et al.*, 2007).

Missing data analysis was conducted on the unbalanced, pooled dataset of 204 observations using R (R Core Team, 2015) to determine the amount, pattern and mechanism of the missing data. The results of the analysis indicated that 1.4% of the data were missing for each of the included variables, with the exception of the time trend variable. (Refer to Appendix 1 for detailed missing data analysis results.) To determine the underlying missing data mechanism, the null hypothesis that data are MCAR was tested using Little’s chi-square test. The resultant p-value of 0.164 indicates that the missingness process is indeed MCAR.

There are a number of conventional methods for handling missing data including: listwise deletion, pairwise deletion, dummy variable adjustment, simple imputation and maximum likelihood. Each of these methods is, however, subject to a number of limitations (refer to Allison, 2001, and Van Buuren, 2012, for further reading). Multiple imputation is an alternative approach which is considered the best general method for handling missing data in many fields (Van Buuren, 2012). This study considers an application of multiple imputation to surmount the issues associated with missing data.

#### 5.4.2 Multiple imputation

In an effort to retain all observations and create a balanced panel of data which is compatible with regular statistical methods, multiple imputation through the data augmentation technique was performed. Data augmentation is a type of Markov Chain Monte Carlo (MCMC) algorithm, which is a popular Bayesian method for finding posterior distributions (Allison, 2001). In short, MCMC is used to obtain the posterior distribution from which the imputed values for the missing observation are drawn. These imputed values replace the missing observations to create a new, independent data set. The imputation process is repeated  $m$  times to create  $m$  data sets (Finch, 2015). For the purposes of this study  $m$  was set to a maximum of 10 iterations and MCMC multiple imputation was executed using the SPSS statistical software package (IBM, 2013). It is important to note that the final imputed data set is identical to the original data set with the exception of the imputed values.

#### 5.4.3 Multicollinearity analysis

Stochastic frontier analysis involves an inherent trade-off between flexibility and the problem of collinearity among the explanatory variables. The use of flexible functional forms, such as the translog specification, are often better able to represent the underlying production technology than rudimentary functional forms, such as the Cobb-Douglas production function, due to the inclusion of more information (Reinhard *et al.*, 2000). Greater detail and added flexibility, however, come at a cost. The inclusion of additional cross products and squared terms in flexible functional forms often results in high degrees of collinearity among the explanatory variables. This in turn reduces the precision of the resulting parameter estimates and, hence, subsequent statistical inference (Mittelhammer *et al.*, 1980). It is important to note that the inclusion of a time trend variable, in an effort to measure technological change, is likely to exacerbate the problem of multicollinearity (Mittelhammer *et al.*, 1980).

Furthermore, the use of survey data often involves the collection variables that are highly correlated. The problem of collinearity often plagues analysts of survey data, and the presence of this problem encumbers precise statistical explanation of the relationships between predictors and responses (Liao & Valliant, 2012). Since the data used in this analysis are collected from farmers in a survey-like fashion, some degree of correlation is expected. The survey-like nature of the data, coupled with the inherent collinearity problems associated with flexible functional forms

(particularly those with a time trend variable), such as the full translog specification employed here, highlight the importance of assessing collinearity prior to estimation.

Inspection of the correlation matrix serves as a good indicator as to the number, and severity, of correlations present. The correlation matrix for the translog production function, shown in Appendix 2.1, reveals relatively few variables with high degrees of correlation. Ten of the 561 correlation coefficients were greater than 0.7. Considering the number of interaction terms included in the production function and the inclusion of a time trend variable, the degree of multicollinearity appears to be acceptably low.

To further explore the nature of this collinearity, the condition index and variance decomposition proportions were calculated (Appendix 2.1). The condition index serves as a means to identify possible multicollinearity. According to Belsley *et al.* (1980), condition index values greater than 30 may indicate collinearity problems and should be investigated further. The variance decomposition proportions associated with each condition index provide additional information to assist in identifying potential sources of collinearity. Generally, a large condition index associated with two or more variables exhibiting large variance decomposition proportions, is an indication that these variables are potential sources of correlation. Belsley *et al.* (1980) suggest that a large variance decomposition proportion may be 50% or higher.

The calculated condition indices for this study proved to be substantially larger than the yardsticks provided by Belsley *et al.* (1980), indicating the presence of collinearity in the data (see Appendix 2.2 for detailed results). One commonly employed solution to multicollinearity is the deletion of variables which are suspected to be the source of at least some portion of multicollinearity. This method may reduce the degree of collinearity but may result in a miss-specification problem (Herrero, 2005). Inspection of the variance decomposition proportions associated with relatively high condition indexes reveals that most correlation is between cross-product variables which contain the same explanatory variable.

For example, referring to Appendix 2.2, the condition index of 56.3 is associated with two variance decompositions of 0.31 and 0.34, corresponding to the variables  $\beta_{VK}$  and  $\beta_{VT}$  respectively. Clearly, this correlation may be explained by the common presence of V. The same conclusion may be drawn from  $\beta_{HL}$  and  $\beta_{LF}$ . The largest concern relates to the herd size variable (H) which has a large condition index of 142.3 and four variance decomposition proportions in excess of 0.3. Intuitively,



herd size, a proxy for farm size, is expected to be correlated with the majority of variables in the production process, since increased herd size will be correlated to increases in all related factors of production. Once again, the high variance decomposition proportions are attributable primarily to the interaction variables which contain herd size as a common variable ( $\beta_{HH}$ ,  $\beta_{HF}$ , and  $\beta_{HK}$ ). It is worth noting that these variables are correlated with  $\beta_{FK}$ , the interaction between feed and capital, although the variance decomposition proportion is relatively small (0.33).

Although formal testing reveals the existence of some degree of collinearity among the variables, it is the view of the author that omitting any of these variables from the production function would result in substantial miss-specification bias. It may be argued that herd size and its associated interaction variables display concerning levels of collinearity and should be removed. The counter argument put forward is that herd size is a crucial variable, serving as the primary means of differentiating between producers of different size. Its inclusion allows for comparisons between farms of various sizes, without which this analysis would be of limited value.

On these grounds, it is argued that the deletion of the herd size variable would most likely result in severe model miss-specification, the negative effects of which may be more significant than those associated with collinearity. In an effort to display the acceptability of the translog specification, a comparison between the Cobb-Douglas and the translog specification revealed that the translog model displayed lower condition indexes (see Appendix 2.3).

#### 5.4.4 Descriptive statistics

Table 5.2 presents the descriptive statistics for the East Griqualand study group, while descriptive statistics pertaining to the Alexandria study group are presented in Table 5.3. Investigation of the two tables indicates that the mean herd size for the two regions is very similar, with 491 milking cows noted in EG and 501 for Alexandria. The range between the smallest and largest producer, however, is substantially larger in the EG study group with 86 cows representing the smallest producer and 1253 cows representing the largest producer. In the case of Alexandria, a milking herd of 114 cows represents the smallest producer compared to 882 milking cows for the largest producer.

Interestingly, milk producers from both EG and Alexandria experienced notable increases in mean herd size over the study period. EG dairy farms experienced a 76% increase in mean herd size

from 345 milking cows in 2007 to 608 in 2014, while mean herd size on Alexandria dairy farms increased by 31% from 435 milking cows in 2007 to 570 in 2014. These findings are supportive of the data presented in Table 4.3, albeit by a lesser degree. This further substantiates that the panel of sampled farms included in this study appear to be reasonably representative of commercial dairy farms in EG, the Eastern Cape, and South Africa.

Table 5.2: Descriptive statistics for the East Griqualand study group

Variable	Code	Units	Mean value	Maximum value	Minimum value	Standard deviation
Aggregate output	Y	R/farm	9 452 082	26 928 560	1 131 934	6 463 285
Veterinary expense	V	R/farm	763 112	7 231 345	51 020	1 166 256
Cost of capital stocks	K	R/farm	1 969 767	5 911 411	347 380	1 334 597
Total labour cost	L	R/farm	612 406	1 618 863	149 457	360 664
Total feed cost	F	R/farm	4 031 528	12 572 750	426 347	2 727 504
Herd Size	H	cows/farm	491	1 253	86	300

Table 5.3: Descriptive statistics for the Alexandria study group

Variable	Code	Units	Mean value	Maximum value	Minimum value	Standard deviation
Aggregate output	Y	R/farm	12 821 370	24 376 640	1 933 729	4 992 348
Veterinary expense	V	R/farm	558 975	962 279	104 581	232 350
Cost of capital stocks	K	R/farm	1 526 239	2 993 069	324 263	635 077
Total labour cost	L	R/farm	641 543	1 361 075	159 659	265 228
Total feed cost	F	R/farm	6 933 405	16 195 190	929 626	2 826 097
Herd Size	H	cows/farm	501	882	114	165

Interestingly, average annual expenditure on all feeds, both purchased and homegrown, appears to be notably higher for Alexandria producers. One possible explanation could be that EG producers are, on average, better able to meet the nutritional requirements of the milking herd using available grazing and home-grown feeds. It is important to note that the data presented in Tables 5.2 and 5.3 are intended to provide a general overview of the average dairy farm in each of the two regions and are hardly conclusive. Average expenditure on labour, veterinary products and services, and capital stocks appear to all be reasonably similar between the production regions.

### **5.5 Stochastic frontier analysis**

Frontier models involve the estimation of a best practice frontier against which each and every producer may be compared. The technically efficient frontier represents all technically efficient input bundles that may be used to produce a given level of output. Therefore, producers who lie on the frontier are considered technically efficient in production, while those below the frontier are considered inefficient, indicating misallocation of resources (Førsund *et al.*, 1980).

There are several alternative specifications used to estimate efficiency through frontier analysis including primal (direct) and dual approaches (Coelli, 1995; Thiam *et al.*, 2001). The estimation of a primal production function has been justified by assuming that producers maximize expected profit or that profits are maximized with respect to anticipated output rather than actual output (Zellner *et al.*, 1966; Ahmad & Bravo-Ureta, 1996; Thiam *et al.*, 2001). Furthermore, there are often insufficient input price data to consider alternative dual approaches such as profit or cost functions.

Stochastic Frontier Analysis (SFA) requires the specification of a production technology by selecting a particular functional form. The choice of functional form is a contentious issue since many studies appear to arbitrarily select one functional form over another (Mbage *et al.*, 2003). Another requirement, and well-known downside, of SFA is the adoption of a particular distributional assumption regarding the error component that captures inefficiency. The selection of a specific distributional assumption also appears to be a factor that many researchers do not pay much attention to (Mbage *et al.*, 2003).

The general stochastic production frontier may be specified as follows:

$$y_{it} = f(x_{it}, t, \alpha) e^{(v_{it} - u_{it})} \quad (5.1)$$

where  $y$  is output of the  $i$ th firm at time  $t$ ;  $x_{it}$  is a vector of inputs;  $\alpha$  is a vector of parameters to be estimated;  $f(\cdot)$  is a suitable functional form;  $(v_{it} - u_{it})$  is a composed error term, where  $v_{it}$  represents a two-sided stochastic term accounting for statistical noise and  $u_{it}$  is a non-negative stochastic term representing inefficiency (Hadley, 2006).

There are a variety of functional forms that may be considered in frontier estimation, including Cobb-Douglas, translogarithmic, normalized quadratic, Generalized Leontief, Generalized Box-Cox, and Zellner-Revankar generalized production functions (Griffin *et al.*, 1987; Coelli, 1995). The Cobb-Douglas functional form is commonly adopted in frontier analysis due to its simplicity and ease of estimation. It is, however, highly restrictive in the sense that it is linear in logarithms and does not allow for interaction between variables in the production function. In order to better represent the true production technology, it may be desirable to consider the application of more flexible functional forms such as translogarithmic (TL), Normalized Quadratic (NQ), and Generalized Leontief (GL) specifications. Each of these second-order Taylor series expansions offers local flexibility and the ability to investigate a number of interactions between variables in the production function through the inclusion of squared terms and cross-products.

In an effort to identify the most appropriate model for the sample data, five different functional forms, each with two possible distributional assumptions, were specified. The fit of each of these models was then assessed using generalized likelihood ratio tests to determine the most appropriate model for the data. The five model specifications considered are based upon: i) Cobb-Douglas (CD) production function; ii) simplified translogarithmic production function (STL); iii) full translogarithmic production function (TL); iv) Generalized Leontief production function (GL); and v) Normalized Quadratic production function (NQ). A linear time trend was incorporated into each model in an attempt to account for technological progress over time.

In an attempt to ensure the most appropriate model is selected prior to the estimation of technical efficiency, the potential impact of different distributional assumptions is also considered. This is achieved by specifying two of the most common distributional assumptions to each of the functional forms and determining, via likelihood ratio tests, the most appropriate distribution for each. It is important, at this point, to differentiate between the error component  $v_{it}$  and  $u_{it}$ . The error component  $v_{it}$  is assumed to be independent and identically normally distributed with zero mean and constant variance [ $v_{it} \sim N(0, \sigma_v^2)$ ]. The error component  $u_{it}$  (quantifying technical inefficiency)

is assumed to follow either i) a non-negative truncated normal distribution (TN) with mean  $\mu$  and constant variance  $[\mu_{it} \sim |N(\mu, \sigma_u^2)]$ , or ii) a half normal distribution (HN) with zero mean and constant variance  $[\mu_{it} \sim |N(0, \sigma_u^2)]$ .

### 5.5.1 Cobb Douglas production function

The general functional form of a Cobb-Douglas production frontier with smooth technical change may be expressed as follows:

$$\ln Y_{it} = \beta_0 + \sum_k \beta_k \ln(x_{kit}) + \zeta T + D + (v_{it} - u_{it}) \quad (5.2)$$

Where Y represents output, X represents the inputs to production and subscripts i, k and t denote individual firms, inputs and years, respectively. D is a regional dummy variable (East Griqualand region =1, 0 otherwise); T represents a smooth time trend accounting for technological change (2007=1, ..., 2014=8);  $\beta_0, \beta_k, \alpha, \zeta$  are parameters to be estimated and  $(v_{it} - u_{it})$  is a composed error term, where  $v_{it}$  represents a two-sided stochastic term accounting for statistical noise and  $u_{it}$  is a non-negative stochastic term representing inefficiency.

The Cobb-Douglas production frontier specified in this study takes on the following form:

$$\ln Y_{it} = \beta_0 + \beta_1 \ln(H_{it}) + \beta_2 \ln(L_{it}) + \beta_3 \ln(V_{it}) + \beta_4 \ln(F_{it}) + \beta_5 \ln(K_{it}) + \zeta T + D (v_{it} - u_{it})$$

### 5.5.2 Simplified translog production function

A simplified translog (STL) production function with smooth technological change may be expressed as follows:

$$\ln y_{it} = \beta_0 + \sum_k \beta_k \ln(x_{kit}) + \sum_k \xi_k \ln(x_{kit})T + \zeta T + \lambda T^2 + D + (v_{it} - u_{it}) \quad (5.3)$$

Where the subscripts i, k and t denote individual firms, inputs and years, respectively. Y represents output, X represents the inputs to production, and D is a regional dummy variable (East Griqualand =1, 0 otherwise). T represents a smooth time trend accounting for technological change (2007=1, ..., 2014=8), and  $\beta_0, \beta_k, \xi_k, \zeta$  and  $\lambda$  are parameters to be estimated. Finally,  $(v_{it} - u_{it})$  is a composed error term, where  $v_{it}$  represents a two-sided stochastic term accounting for statistical noise and  $u_{it}$  is a non-negative stochastic term representing inefficiency.

As previously mentioned, the error component  $v_{it}$  in equations (5.2) and (5.3) is assumed independent and identically normally distributed  $[v_{it} \sim N(0, \sigma_v^2)]$ . The error component  $u_{it}$  is

assumed to follow either i) a non-negative truncated normal distribution [ $\mu_{it} \sim |N(\mu, \sigma_u^2)$  ]; or ii) a half normal distribution [ $\mu_{it} \sim |N(0, \sigma_u^2)$  ] and is equal to:

$$u_{it} = \eta_{it} u_i = e^{[-\eta(\tau(i)-T)]u_i} \quad (5.4)$$

Where  $\eta$  is an unknown scalar parameter and  $\tau(i)$  represents the set of  $T_i$  time periods among the  $T$  periods involved for which observations for the  $i$ th farm are obtained. Equations (5.3) and (5.4) can be estimated by first estimating the parameters of the model using maximum likelihood (ML) and then using the resultant estimates to calculate technical efficiency ( $TE_{it}$ ) at each data point assuming:

$$TE_{it} = \exp(-u_{it}) \quad (5.5)$$

### 5.5.3 Translog production function

A full translog (TL) production function may be specified as follows

$$\ln y_{it} = \beta_0 + \sum_{k=1} \beta_k \ln(x_{kit}) + \frac{1}{2} \sum_{j=1} \sum_{k=1} \beta_{kj} \ln(x_{kit}) \ln(x_{jit}) + \zeta T + \frac{1}{2} \lambda T^2 + \sum_{k=1} \beta_{kt} \ln(x_{kit}) T + D + (v_{it} - u_{it}) \quad (5.6)$$

Where the subscripts  $i$ ,  $k$  and  $t$  denote individual firms, inputs and years, respectively.  $Y$  represents output,  $X$  represents the inputs to production, and  $D$  is a regional dummy variable (East Griqualand =1, 0 otherwise).  $T$  represents a smooth time trend accounting for technological change (2007=1, ..., 2014=8) and  $\beta_0$ ,  $\beta_j$ ,  $\beta_{kj}$ ,  $\beta_{kt}$ ,  $\zeta$  and  $\lambda$  are parameters to be estimated. Once again,  $(v_{it} - u_{it})$  is the composed error term defined above.

It is important to note that before proceeding with estimation, data should be normalized by either the sample means or medians in order to make subsequent interpretation easier. The median may be more appropriate since it is less effected by outliers and hence provides a more precise approximation of the translog function (Farsi *et al.*, 2005).

The error term capturing technical inefficiency ( $u_{it}$ ) is equal to:

$$u_{it} = \delta_{ij} z_{it} + w_{it} \quad (5.7)$$

Where  $\delta$  is a vector of parameters to be estimated;  $z$  is a vector of explanatory variables associated with technical inefficiency over time; and  $w$  is a random variable defined by the truncation of the

normal distribution with zero mean and variance  $\sigma^2$  (Hadley, 2006). The unknown parameters of equations (5.6) and (5.7) may be simultaneously estimated by maximum likelihood.

#### 5.5.4 Generalized Leontief production function

A Generalized Leontief production function with technological change may be expressed as follows:

$$ly_{it} = \beta_0 + \sum_{k=1} \beta_k \sqrt[2]{x_{kit}} + \frac{1}{2} \sum_{j=1} \sum_{k=1} \beta_{kj} \sqrt[2]{(x_{kit})(x_{jit})} + \sum_{k=1} \beta_{kt} \sqrt[2]{x_{kit}} T + \zeta T + \frac{1}{2} \lambda T^2 + D + (v_{it} - u_{it}) \quad (5.8)$$

Where the subscripts i, k and t denote individual firms, inputs and years, respectively. Y represents output, X represents the inputs to production, and D is a regional dummy variable (East Griqualand =1, 0 otherwise). T represents a smooth time trend accounting for technological change (2007=1, ..., 2014=8),  $\beta_0$ ,  $\beta_j$ ,  $\beta_{kj}$ ,  $\beta_{kt}$ ,  $\zeta$  and  $\lambda$  are parameters to be estimated, and  $(v_{it} - u_{it})$  is the composed error term defined above.

#### 5.5.5 Normalized Quadratic production function

A normalized quadratic production function with technological change may be expressed as follows:

$$lny_{it} = \beta_0 + \sum_{k=1} \beta_k x_{kit} + \frac{1}{2} \sum_{j=1} \sum_{k=1} \beta_{kj} (x_{kit})(x_{jit}) + \zeta T + \frac{1}{2} \lambda T^2 + \sum_{k=1} \beta_{kt} (x_{kit}) T + D + (v_{it} - u_{it}) \quad (5.9)$$

Where the subscripts i, k and t denote individual firms, inputs and years, respectively. Y represents output, X represents the inputs to production, and D is a regional dummy variable (East Griqualand =1, 0 otherwise). T represents a smooth time trend accounting for technological change (2007=1, ..., 2014=8),  $\beta_0$ ,  $\beta_j$ ,  $\beta_{kj}$ ,  $\beta_{kt}$ ,  $\zeta$  and  $\lambda$  are parameters to be estimated, and  $(v_{it} - u_{it})$  is the composed error term defined above.

### 5.6 Parametric scale efficiency

The analysis of scale efficiency (SE) is commonly associated with agricultural studies involving applications of nonparametric techniques (Chavas & Aliber, 1993; Piesse *et al.*, 1996; Muchena *et al.*, 1997; Sharma *et al.*, 1999; Gouse *et al.*, 2003; Tonsor & Featherstone, 2009). The use of nonparametric, typically DEA, techniques allows total technical efficiency (TE) to be decomposed into “pure” TE and SE components (Piesse *et al.*, 1996). Under the assumption of constant returns

to scale (CRS), TE is represented holistically. It is only through the relaxation of this assumption, to that of variable returns to scale (VRS), that TE can be decomposed. This forms the basis for the calculation of nonparametric scale efficiency, in which estimates of TE obtained under the assumption of CRS are divided by estimates obtained under the assumption of VRS. Unfortunately, this approach is not transferable to a parametric framework.

Attempting to surmount this limitation, Ray (1998) proposed a model for the estimation of scale efficiency in a parametric framework. Despite its potential operational advantages, this model has seen very few applications in agricultural studies (Madau, 2011). In fact, reviews by Coelli (1995), Thiam *et al.* (2001) and Bravo-Ureta *et al.* (2007) do not cover any studies dealing with the analysis of parametric scale efficiency. The methodology proposed by Ray (1998) represents a simple approach to the analysis of parametric efficiency that has the added benefit of being suitable for flexible functional forms, such as the translog production function. Ray's (1998) approach allows scale efficiency scores to be calculated from the estimated parameters of the fitted production function and the associated estimates of scale elasticity. The methodology proposed by Ray (1998) may be expressed as follows:

$$SE_{it}^0 = \exp \left[ \frac{(1-E_{it})^2}{2\beta} \right] \quad (5.10)$$

Where  $E_{it}$  refers to scale elasticity and is simply the sum of production elasticities defined as

$$E_{it} = \sum_{j=1}^n (\beta_j + \sum_{k=1}^l \beta_{jk} x_{kit} + \beta_{jt} t) \quad (5.11)$$

And

$$\beta = \sum_{j=1}^n \sum_{k=1}^n \beta_{jk} \quad (5.12)$$

$\beta$  ensures that the resulting scale efficiency estimates are bound between zero and one, in other words ( $0 < SE_{it}^0 < 1$ ). From (5.10) it is apparent that scale efficiency and scale elasticity are related but are ultimately two different measures relating to the returns to scale of a technology at any specific point on the production function. Scale elasticity may be defined as the ratio of the proportionate change in output to a small equi-proportionate change in all inputs (Ray, 1998). Scale elasticity then provides an indication of whether the production technology exhibits



increasing, decreasing or constant returns to scale based on whether its value is greater, less than, or equal to unity. Scale efficiency, however, measures the ray average productivity at the observed input scale relative to what is attainable at the most productive scale (MPSS), i.e. where scale elasticity is equal to one (Ray, 1998).

It is important to note that at the most productive scale, where constant returns to scale prevail, both scale efficiency and scale elasticity are equal to unity. At any other point, where the observed input bundle is not at optimal scale (MPSS), their magnitudes differ and the value of scale elasticity does not directly reveal anything about the level of scale efficiency (Ray, 1998; Karagiannis & Sarris, 2005). In other words, scale efficiency will be less than unity, regardless of whether scale elasticity is greater than or less than unity.

The empirical results of the technical and scale efficiency analyses are presented in the next chapter.

## **CHAPTER 6: EMPIRICAL RESULTS OF TECHNICAL AND SCALE EFFICIENCY ANALYSES**

### **6.1 Introduction**

The estimation of TE, within a Stochastic Frontier Analysis (SFA) framework, requires the specification of a production technology by selecting a particular functional form. The selection of functional form is a dataset specific challenge, a fact that is often overlooked in productivity analysis. Researchers commonly impose a specific functional form onto a dataset without any attempt to assess the suitability of the particular form to the data. The selection of functional forms often relies on *ad hoc* selection criteria such as flexibility, computational convenience, theoretical consistency, factual conformity and plausibility of estimated elasticities (Lansink & Thijssen, 1998). The imposition of an inappropriate functional form may result in biased and inaccurate estimates and misleading statistical inferences (Giannakas *et al.*, 2003). This chapter aims to minimize the potential drawbacks associated with the selection of an unsuitable functional form by modelling several common functional forms, with selection of the most appropriate form based on likelihood ratio testing. The most appropriate functional form is then used to specify the production function and generate estimates of technical efficiency for each milk producer. Technical efficiency estimates are then interpreted, with temporal and inter-regional components being discussed. The remainder of the chapter is dedicated to interpretation and discussion of parametric scale efficiency estimates, calculated from the estimated production function parameters and associated elasticities, following Ray's (1998) methodology.

### **6.2 Choice of functional form and distributional assumption**

In an effort to minimize potential bias resulting from the imposition of an unsuitable functional form, five common functional forms were modelled, four of which represent second-order Taylor series expansions, commonly referred to as flexible functional forms. Furthermore, since the choice of distributional assumption is another requirement of stochastic frontier analysis in which researchers do not seem to invest much time or effort (Mbaga *et al.*, 2003), the suitability of two distributional assumptions was formally assessed for each of the five functional forms. In addition, the assumption of either time variant or time invariant efficiencies was modelled for each of the above-mentioned models, resulting in a total of 20 possible milk production functions. Table 6.1

presents a summary of the resulting 20 model specifications to be subjected to formal model testing.

Each of these 20 models was specified and estimated within the stochastic frontier analysis software package *frontier* (Coelli & Henningsen, 2013), using the R statistical package (R Core Team, 2015). A series of likelihood ratio tests were then conducted to determine the most suitable model for the data. These likelihood ratio tests can be classified into two categories. The first may be classified as within-model likelihood ratio tests, conducted to determine the most suitable model within each functional form. The second, summarized in Table 6.2 may be classified as between-model likelihood ratio tests, used to compare the most suitable models from each functional form and ultimately determine the most appropriate functional form for the given data set.

Table 6.1: Summary of modelled milk production technologies.

Model	Functional form	One-sided distribution	Nature of efficiency
1	Cobb-Douglass (CD)	HN	Time invariant
2		TN	Time invariant
3		HN	Time variant
4		TN	Time variant
5	Simplified Translog (STL)	HN	Time invariant
6		TN	Time invariant
7		HN	Time variant
8		TN	Time variant
9	Translog (TL)	HN	Time invariant
10		TN	Time invariant
11		HN	Time variant
12		TN	Time variant
13	Generalized Leontief (GL)	HN	Time invariant
14		TN	Time invariant
15		HN	Time variant
16		TN	Time variant
17	Normalized Quadratic (NQ)	HN	Time invariant
18		TN	Time invariant
19		HN	Time variant
20		TN	Time variant

\*HN = half normal, TN = truncated normal

The within-model likelihood ratio tests, presented in Appendix 3, involve comparisons of each model to the ordinary least squares (OLS) equivalent. This is done to confirm if any significant production inefficiencies are present. The results, shown in Appendix 3, indicate that all 20 models are significantly different from their OLS equivalents. This implies that most of the sampled milk producers operated below the efficient production frontier. Therefore, the average production function, with no inefficiency, is considered to be an inadequate representation of the milk production technology (Karagiannis & Sarris, 2005). It is worth noting that the TN distribution appears to be significantly better than the HN distribution for each and every functional form. TL and GL functional forms provided some interesting results in that time variant and time invariant models were not significantly different. It was expected that models able to account for variation of efficiencies over time would be more appropriate than the more rudimentary time invariant models.

The results presented in Table 6.2 indicate that the simplified translog (STL), Normalized Quadratic (NQ) and the Generalized Leontief (GL) were not significantly different from the Cobb-Douglas (CD) functional form. The translog (TL) models with TN distributions were, however, significantly different from the CD models with TN distributions and are, therefore, considered an improvement. Furthermore, results indicate that the TL models with truncated normal distribution were significantly better than CD, STL, NQ and GL models with truncated normal distribution. This is true for both time variant and time invariant efficiency models.

In addition to subjecting each of the above-mentioned models to likelihood ratio tests, each of the five functional forms were modelled in R using linear equation methods to determine the relative fit of the various functional forms to the data. In an attempt to gauge the suitability of each functional form, several residual plots (histograms) were generated to provide a graphical representation of goodness of fit (see Appendix 4). In total, ten separate plots were generated, with two for each functional form. For each plot, the Y-axis represents function specific (fitted) output and the X-axis represents actual output. Plots therefore represent the ability of a particular functional form (production technology) to model actual dairy output. Referring to Appendix 4, plots depicted on the right-hand side of the page are simply logarithmic representations of those on the left. This comparison of “fitted” output to actual output provides insight into the goodness of fit of each possible functional form.

Table 6.2: Between-model likelihood ratio tests

Likelihood Ratio Tests							
	Model	# DF	LogLik	Df	Chisq	Pr>(Chisq)	Decision
CD VS STL	CDtnVAR	12	205,1				
	STLtn	17	209,13	5	8,0631	0,1528	NSD
	CDtnVAR	12	205,1				
	STLtnVAR	18	210,67	6	11,13	0,08443	NSD
CD VS TL	CDtnVAR	12	205,1				
	TLtnVAR	33	228,13	21	46,056	0,001256	** TLtnVAR
	CDtnVAR	12	205,1				
	TLtn	32	226,78	20	43,357	0,001833	** TLtn
CD VS GL	CDtnVAR	12	205,1				
	GLtn	32	199,63	20	10,932	0,948	NSD
	CDtnVAR	12	205,1				
	GLtnVAR	33	200,57	21	9,0577	0,9888	NSD
CD VS NQ	CDtnVAR	11	201,02				
	NQtn	32	204,99	21	7,9447	0,9954	NSD
	CDtnVAR	12	205,1				
	NQtnVAR	33	206,41	21	2,6211	1	NSD
STL VS TL	STLtn	17	209,13				
	TLtn	32	226,78	15	35,294	0,002233	** TLtn
	STLtn	17	209,13				
	TLtnVAR	33	228,13	16	37,993	0,001517	** TLtnVAR
	STLtnVAR	18	210,67				
	TLtn	32	226,78	14	32,227	0,003719	** TLtn
NQ VS TL	STLtnVAR	18	210,67				
	TLtnVAR	33	228,13	15	34,926	0,002519	** TLtnVAR
	NQtn	32	204,99				
	TLtn	32	226,78	0	43,572	2,20E-16	*** TLtn
	NQtn	32	204,99				
	TLtnVAR	33	228,13	1	46,272	1,03E-11	*** TLtnVAR
GL VS TL	NQtnVAR	33	206,41				
	TLtn	32	226,78	-1	40,736	1,74E-10	*** TLtn
	NQtnVAR	33	206,41				
	TLtnVAR	33	228,13	0	43,435	2,20E-16	*** TLtnVAR
	GLtn	32	199,63				
GL VS TL	TLtn	32	226,78	0	54,288	2,20E-16	*** TLtn
	GLtn	32	199,63				
	TLtnVAR	33	228,13	1	56,988	4,39E-14	*** TLtnVAR
	GLtnVAR	33	200,57				
	TLtn	32	226,78	-1	52,415	4,49E-13	*** TLtn
	GLtnVAR	33	200,57				
	TLtnVAR	33	228,13	0	55,114	2,20E-16	*** TLtnVAR

Significance codes: \*\*\*=<0.0001, \*\*=0.001, \*=0.05, ". "=0.1

NSD = No significant difference, VAR = time variant inefficiencies

Visual inspection of the plots reveals that CD, STL, and TL specifications appear to display acceptable levels of fit, with all three production technologies representing the actual data reasonably well. GL and NQ specifications displayed very poor levels of fit. Both production technologies failed to model the actual data with any reasonable degree of accuracy.

### 6.3 Maximum likelihood results and discussion

Table 6.3 presents the estimated parameters for each of the 20 model specifications, estimated by maximum likelihood. Since likelihood ratio testing revealed the translog model with truncated normal distribution and time variant inefficiency to be the most suitable approximation of the true underlying dairy production technology, only coefficient estimates pertaining to this model will be discussed. Coefficients with a negative sign indicate that an increase in the value of the associated variable results in a decrease in milk output, whereas a positive value represents an increase. Based on the estimated results there are several important issues to address: (1) output elasticities for inputs in the production function; (2) significance and interpretation of translog parameter estimates; (3) interpretation of technical efficiency estimates and inter-regional comparison; and (4) interpretation of parametric scale efficiency, calculated from the estimated production function parameters and associated elasticities, following Ray's (1998) methodology.

#### 6.3.1 Elasticity and parameter estimates

Since all variables in the production function have been expressed in logarithmic form, estimated coefficient values may be interpreted as partial output elasticities, the sum of which provide an indication of returns to scale (Cabrera *et al.*, 2010). Estimated output elasticities conform to *a priori* expectations regarding their signs, with the exception of labour ( $\beta_L$ ), which is negative. The estimated coefficients for labour and veterinary expense were statistically insignificant at the 10% level of probability. Parameter estimates for feed ( $\beta_F$ ), herd size ( $\beta_H$ ) and capital ( $\beta_K$ ) were statistically significant at the 1% level. Of these inputs, feed had the greatest effect on productivity with a partial elasticity of 0.5. This is interpreted as, a 1% increase in aggregate feed expenditure would result in an estimated increase in dairy output of 0.5%, *ceteris paribus*.

The next highest elasticity was for herd size (0.342) followed by capital (0.214). In other words, a 1% increase in herd size and capital expenditure would result in a 0.342% and 0.214% increase in output, respectively, *ceteris paribus*. Scale elasticity, represented by the summation of output

elasticities, totalled 1.09 indicating slightly increasing returns to scale. This result is comparable to Tauer & Belbase (1987) and Hadley (2006), but contradictory to the findings of Kompas & Che (2006) and Cabrera *et al.* (2010) who reported constant returns to scale for Australian and US dairy farms.

Concerning the elasticities of production, Hadley (2006) reported similar findings for a sample of dairy farms from England and Wales, with elasticities for feed cost (0.199), capital (0.123) and herd size (0.293) constituting the largest portion of total output elasticity. In this instance, herd size was found to have the greatest effect on productivity, rather than total feed cost, as indicated by the results of this study.

Table 6.3: Maximum likelihood estimates of the specified production functions, East Griqualand and Alexandria Dairy Farms, 2007 - 2014

Parameter	Cobb-Douglas								Simplified Translog							
	Time invariant				Time variant				Time invariant				Time variant			
	HN		TN		HN		TN		HN		TN		HN		TN	
$\beta_0$	2.279	***	2.423	***	2.504	***	2.589	***	0.150	**	0.198	***	0.144	**	0.161	***
$\beta_V$	-0.006		-0.006		0.001		-0.003		0.084	.	0.084	.	0.077	.	0.081	.
$\beta_L$	0.196	***	0.193	***	0.179	***	0.184	***	0.084		0.086		0.061		0.053	
$\beta_F$	0.477	***	0.496	***	0.465	***	0.483	***	0.412	***	0.450	***	0.462	***	0.455	***
$\beta_H$	0.276	***	0.270	***	0.345	***	0.323	***	0.358	***	0.329	***	0.371	***	0.360	***
$\beta_K$	0.169	***	0.147	***	0.145	***	0.128	***	0.190	**	0.152	*	0.156	*	0.162	**
$\zeta$	-0.010	**	-0.009	**	0.000		0.004		0.001		-0.002		0.005		0.005	
$\lambda$									-0.002		-0.001		-0.001		-0.001	
$\beta_{HT}$									-0.023		-0.020		-0.019		-0.020	
$\beta_{LT}$									0.023	*	0.024	.	0.031	**	0.031	**
$\beta_{VT}$									-0.011	.	-0.012	.	-0.011	.	-0.011	.
$\beta_{FT}$									0.010		0.006		-0.002		0.003	
$\beta_{KT}$									-0.003		0.000		0.000		-0.004	
$\alpha$	0.049		0.062	.	0.016		0.033		0.047		0.054		0.001		0.030	
$\sigma^2$	0.025	**	0.012	***	0.042	*	0.016	***	0.025	**	0.012	**	0.048	*	0.016	***
$\gamma$	0.731	***	0.480	***	0.847	***	0.614	***	0.757	***	0.535	***	0.878	***	0.645	***
$\mu$			0.153	***		*	0.201	***			0.162	***			0.204	***
time					-0.098	*	-0.087	.					-0.095	*	-0.075	*
TE	0.893		0.853		0.893		0.854		0.890		0.844		0.883		0.847	

Significance codes: \*\*\*=<0.001, \*\*=0.001, \*=0.05, ". "=0.1

$\zeta$  = time trend,  $\lambda$  = time trend<sup>2</sup>,  $\alpha$  = regional dummy

Parameter	Translog								Generalized Leontief							
	Time invariant				Time variant				Time invariant			Time variant				
	HN		TN		HN		TN		HN		TN	HN		TN		
$\beta_0$	0.169	***	0.204	***	0.164	***	<b>0.192</b>	***	-0.253	.	-0.068		-0.276	*	-0.116	
$\beta_V$	0.07		0.083	.	0.065		<b>0.079</b>		0.215		0.209		0.191		0.170	
$\beta_L$	-0.017		-0.030		-0.028		<b>-0.045</b>		0.431		0.344		0.391		0.333	
$\beta_F$	0.454	***	0.478	***	0.483	***	<b>0.500</b>	***	-0.297		-0.364		-0.341		-0.413	
$\beta_H$	0.328	***	0.333	***	0.332	***	<b>0.342</b>	***	-0.124		-0.193		0.124		0.097	
$\beta_K$	0.225	***	0.209	**	0.215	**	<b>0.214</b>	**	0.389		0.356		0.271		0.182	
$\beta_{LL}$	-0.336	*	-0.383	**	-0.359	*	<b>-0.426</b>	**	-0.716	*	-0.723		-0.767	*	-0.787	
$\beta_{VV}$	-0.021		-0.018		-0.03		<b>-0.028</b>		0.033		0.031		0.024		0.018	
$\beta_{FF}$	-0.57	***	-0.569	***	-0.558	***	<b>-0.589</b>	***	-1.367	***	-1.317	**	-1.367	***	-1.345	***
$\beta_{HH}$	-0.488		-0.446		-0.678	.	<b>-0.609</b>		-0.911		-0.585		-1.264	.	-1.088	
$\beta_{KK}$	-0.088		-0.087		-0.145		<b>-0.122</b>		-0.85	.	-0.659		-0.955	*	-0.801	
$\beta_{HL}$	-0.075		-0.128		-0.085		<b>-0.166</b>		-0.67		-0.778		-0.645		-0.715	
$\beta_{HV}$	-0.15	*	-0.148	*	-0.15	*	<b>-0.146</b>	*	-0.215		-0.216		-0.185		-0.172	
$\beta_{HF}$	0.551	**	0.544	**	0.596	***	<b>0.612</b>	***	2.709	***	2.593	**	2.881	***	2.84	***
$\beta_{HK}$	0.023		0.044		0.117		<b>0.129</b>		0.87		0.462		1.122		0.864	
$\beta_{LV}$	0.021		0.027		0.03		<b>0.038</b>		-0.19		-0.174		-0.184		-0.147	
$\beta_{LF}$	0.149		0.186	.	0.156		<b>0.22</b>	*	0.966	*	1.083	*	0.933	*	0.973	.
$\beta_{LK}$	0.067		0.107		0.085		<b>0.129</b>		0.892		0.956		1.001	.	1.092	
$\beta_{VF}$	0.07		0.081		0.067		<b>0.077</b>		0.335		0.354		0.334		0.407	
$\beta_{VK}$	0.075		0.055		0.081		<b>0.06</b>		-0.094		-0.125		-0.099		-0.186	
$\beta_{FK}$	-0.075		-0.096		-0.109		<b>-0.145</b>		0.06		0.055		0.013		0.019	
$\zeta$	0.008		0.003		0.008		<b>0.006</b>		0.014		0.015		0.015		0.025	
$\lambda$	-0.005		-0.004		-0.003		<b>-0.002</b>		-0.005		-0.004		-0.004		-0.002	
$\beta_{HT}$	-0.004		-0.003		-0.003		<b>-0.001</b>		-0.014		-0.003		-0.013		-0.007	
$\beta_{LT}$	0.036	**	0.038	**	0.04	**	<b>0.043</b>	***	0.059	.	0.059	.	0.07	*	0.07	*
$\beta_{VT}$	-0.007		-0.008		-0.006		<b>-0.007</b>		-0.01		-0.008		-0.008		-0.006	
$\beta_{FT}$	-0.007		-0.008		-0.013		<b>-0.013</b>		-0.02		-0.029		-0.031		-0.039	
$\beta_{KT}$	-0.013		-0.017		-0.013		<b>-0.02</b>		-0.024		-0.029		-0.024		-0.033	
$\alpha$	0.047		0.052	.	0.024		<b>0.032</b>		0.061		0.061		0.036		0.038	
$\sigma^2$	0.018	***	0.009	***	0.027	*	<b>0.012</b>	***	0.024	***	0.012	**	0.032	*	0.016	***
$\gamma$	0.717	***	0.435	***	0.809	***	<b>0.575</b>	***	0.713	***	0.455	***	0.793	***	0.593	***
$\mu$			0.125	***			<b>0.166</b>	***			0.148	**			0.195	**
time					-0.071		<b>-0.077</b>	.					-0.059		-0.069	.
TE	0.91		0.878		0.909		<b>0.873</b>		0.879		0.826		0.876		0.819	

Significance codes: \*\*\*=<0.001, \*\*=0.001, \*=0.05, ". "=0.1

$\zeta$  = time trend,  $\lambda$  = time trend<sup>2</sup>,  $\alpha$  = regional dummy



Parameter	Normalized Quadratic							
	Time invariant				Time variant			
	HN		TN		HN		TN	
$\beta_0$	-0.054		0.050		-0.073		0.007	
$\beta_V$	0.083		0.084		0.065		0.065	
$\beta_L$	0.262	*	0.221	.	0.234	*	0.192	.
$\beta_F$	0.545	***	0.529	***	0.549	***	0.536	***
$\beta_H$	0.207		0.197		0.315	.	0.287	
$\beta_K$	0.217	.	0.172		0.168		0.137	
$\beta_{LL}$	-0.439	***	-0.432	**	-0.470	***	-0.460	***
$\beta_{VV}$	0.017		0.014		0.015		0.009	
$\beta_{FF}$	-0.724	***	-0.710	***	-0.742	***	-0.735	***
$\beta_{HH}$	-0.637	.	-0.536		-0.851	*	-0.717	.
$\beta_{KK}$	-0.431	*	-0.387	.	-0.481	*	-0.429	*
$\beta_{HL}$	-0.060		-0.095		-0.064		-0.103	
$\beta_{HV}$	-0.042		-0.039		-0.039		-0.032	
$\beta_{HF}$	0.571	***	0.557	***	0.620	***	0.600	***
$\beta_{HK}$	0.280		0.215		0.359	.	0.291	
$\beta_{LV}$	-0.032		-0.034		-0.032		-0.032	
$\beta_{LF}$	0.141		0.159	.	0.144		0.165	.
$\beta_{LK}$	0.164		0.211	.	0.189		0.234	*
$\beta_{VF}$	0.067		0.075		0.078		0.090	
$\beta_{VK}$	-0.034		-0.037		-0.040		-0.045	
$\beta_{FK}$	0.019		0.017		0.008		0.007	
$\zeta$	0.008		0.010		0.010		0.017	
$\lambda$	-0.003		-0.003		-0.002		-0.001	
$\beta_{HT}$	-0.009		-0.002		-0.008		-0.004	
$\beta_{LT}$	0.036	*	0.034	*	0.044	**	0.042	**
$\beta_{VT}$	-0.007		-0.006		-0.005		-0.004	
$\beta_{FT}$	-0.018		-0.021	.	-0.025	*	-0.027	*
$\beta_{KT}$	-0.011		-0.014		-0.012		-0.018	
$\alpha$	0.044		0.046		0.009		0.020	
$\sigma^2$	0.025	***	0.012	***	0.037	*	0.016	***
$\gamma$	0.746	***	0.502	***	0.831	***	0.631	***
$\mu$			0.156	***			0.204	***
time					-0.072	.	-0.073	.
TE	0.874		0.820		0.871		0.816	

Significance codes: \*\*\*=<0.001, \*\*=0.001, \*=0.05, ". "=0.1

$\zeta$  = time trend,  $\lambda$  = time trend<sup>2</sup>,  $\alpha$  = regional dummy

In an application of stochastic frontier analysis to estimate the TE of German dairy farms, Abdulai & Tietje (2007) reported total expenditure on dairy feeds to have the largest output elasticity followed by herd size. These findings are supportive of elasticities reported in Table 6.3. Mbagala *et al.* (2003), in a cross-sectional study of TE on Quebec dairy farms, reported an output elasticity for capital of 0.185 for a Generalized Leontief production function with truncated normal distribution. This is broadly comparable to the value of 0.214 estimated in this study.

It is important to note that the variables included in the production functions of Hadley (2006) and Abdulai & Tietje (2007) were expressed in aggregate value terms, as were the production function variables in this study. Expressing these variables in value terms introduces several potential limitations, which will be discussed later in the chapter. This distinction becomes important when attempting to compare the results of different studies. Intuitively, similar studies with a reasonable degree of homogeneity represent acceptable benchmarks against which comparisons may be made. On the other hand, if two studies adopt different methodologies, use different variables or modelling techniques, the results should not be considered comparable. As such, results presented in Hadley (2006) and Abdulai & Tietje (2007) are considered acceptable benchmarks against which to compare the results of this study.

The relatively large partial elasticity estimate associated with the feed expense variable is not evident in some of the previous literature such as Tauer & Belbase (1987) and Cabrera *et al.* (2010), who reported partial elasticities for feed of 0.288 and 0.059, respectively. The large partial feed elasticity observed in this study is most likely due to the nature of its construction. For the purposes of this study, feed expense is expressed as total rand value expenditure on both purchased and home-grown feeds. Home grown feeds are a function of several costs, including but not limited to, fertilizer, seed, planting, harvesting and herbicide and pesticide costs. Purchased feed is expressed as total rand value expenditure on all dairy, heifer and calf meal, and dairy concentrates. Intuitively, the inclusion of both purchased and home-grown feed components is likely to account for a large portion of the variability in dairy output. Studies considering only one of these aspects are likely to report smaller elasticities. The elasticities of Tauer & Belbase (1987) and Cabrera *et al.* (2010) are evidence of this as feed expense in these studies is defined in terms of purchased feed alone. Abdulai & Tietje (2007), on the other hand, express feed expense as the sum of costs

originating from both purchased and homegrown aspects, hence the relatively large reported elasticity for feed of 0.381.

The statistical insignificance of the veterinary expense variable ( $\beta_v$ ) may be explained, in part, by the nature in which it is calculated. Veterinary expense was included in an attempt to capture farm-level variations in animal health and breeding practices, such as artificial insemination (AI). However, due to lack of a comprehensive cost break-down of veterinary services, all veterinary expenses were pooled together into total veterinary expense.

The downside to expressing variables as aggregate values is a possible loss of information. For example, the effects of increased expenditure on AI, representing improved breeding practices, cannot be disentangled from expenditure on unhealthy or non-productive animals. To illustrate, consider two farmers who spend the same amount on veterinary services over the same period. One farmer may have dedicated most of his resources to improving breeding performance, in an effort to positively affect milk output. The other farmer, however, may have dedicated most of his resources to maintaining health among poor producers and sickly animals, which is unlikely to stimulate milk output in the same manner. The resulting effect on milk production for these two scenarios is expected to be very different, although, due to lack of information, they cannot be disentangled from one another.

It is proposed that the insignificance of the labour variable may be attributable, in part, to the capital-intensive nature of dairy farming. Commercial dairy farms typically require large investments in capital infrastructure such as milking parlours and machinery and farm implements for the production of home grown feeds. Investment in advanced production management systems is another investment which many commercial dairy farmers make. Investment in equipment of this nature generally has a labour augmenting effect and typically requires fewer, more skilled labourers to operate the equipment. It is possible that the aggregate wage bill does not have a significant effect on milk output due to the large costs associated with other factors of production, such as capital and feed. Another possible explanation for the insignificance of the labour variable may be a lack of variation in the wage data.

Of the remaining parameter estimates, two squared terms and four cross-products are statistically significant at the 95% level. Negative signs on the squared terms indicate decreasing returns to labour and feed. These results are contradictory to *a priori* expectations and the findings reported

in the previous literature. According to Wadud & White (2000) and Alvarez & Arias (2003), the squared labour and feed terms are expected to be of positive sign, indicating increasing returns to labour and feed. The coefficient of the regional dummy variable ( $\alpha$ ) was positive but statistically insignificant, indicating limited variability in the data between the two production regions. This indicates that farms in East Griqualand and Alexandria are reasonably homogeneous.

Broadly, similar temperature and rainfall conditions mean both regions can facilitate the growth of good nutritional pastures. It is possible that farmers in these two regions have adopted similar milk production and feeding structures, centred primarily around grazing, with purchased feeds and concentrates fed to supplement nutritional shortfalls. Given that sampled farms in both regions are considered specialized dairy producers, it is not unreasonable to postulate that diffusion of technology may have occurred at similar rates within these areas. As a result, the levels of technology in these two regions may be relatively similar, resulting in similar production potential for a given set of inputs. Another important consideration is that sampled dairy farms all benefit from the services of a professional agricultural consultant. It is, therefore, possible that despite geographical differences, farms may share a number of similarities in operations, feeding regimes, technology and labour productivity.

The parameter  $\sigma^2$  represents the sum of the variances  $u$  and  $v$  ( $\sigma_u^2 + \sigma_v^2$ ) and  $\gamma$  represents the ratio of the variance of  $u$  to  $\sigma^2$  ( $\sigma_u^2/\sigma^2$ ) (Jaforullah & Premachandra, 2003). Each of the coefficient estimates is statistically significant at the 1% level. The significance of  $\sigma^2$  is consistent with *a priori* expectations and suggests that a conventional average production function is not an adequate representation of the data (Theodoridis & Psychoudakis, 2008).

The statistical significance of  $\gamma$  indicates that technical inefficiency is important in explaining part of the variation in observed dairy output. The estimated value of 0.545 implies that 54.5% of total variation in dairy output may be attributed to technical inefficiency. This is marginally lower than the 61.6% reported by Theodoridis & Psychoudakis (2008) and the 64.4% and 65.4% reported for variable and constant returns to scale models reported by Jaforullah & Premachandra (2003).

Finally, concerning technological change, the estimated parameters  $\zeta$  and  $\lambda$  incorporated into the production function to account for smooth technological change were statistically insignificant at the 10% level. Although this time trend was expected to capture at least some portion of variability in dairy output attributable to technological change, the results suggest that technological change

was not a significant determinant of dairy production output. This result should, however, be interpreted with caution as the inclusion of a simple time trend variable to capture technological progress is a crude and somewhat rudimentary approach that may be unable to effectively capture true technological progress. Another possible explanation is that technological progress, or adoption of new technology, in these areas may have been very slow over the study period. Perhaps most farmers have already adopted relatively new technologies, and continue to benefit from them, which is why no significant technological advancement can be identified in the data.

### 6.3.2 Technical efficiency

The results presented in Table 6.4 indicate that the average level of TE is 86.5% for the East Griqualand study group and 88% for the Alexandria study group. These results are well within the bounds of those found in similar studies, concerning TE of dairy farms. Bravo-Ureta & Rieger (1991), using cross-sectional data for 1984, estimated technical, allocative and economic efficiency for a sample of 511 New England dairy farms. Efficiency measures were estimated from a Cobb-Douglas stochastic cost frontier. Mean TE for the study ranged from 72.6% to 87.7%, with a mean of 83%. These findings are similar to the results presented in this study, despite the use of a more simplistic Cobb-Douglas functional form.

Mbaga *et al.* (2003) used a 1996 cross-sectional sample of 1,143 specialized dairy farms (deriving more than 80% of revenue from the dairy enterprise) to assess TE for Quebec dairy farms. The sample was separated into farms located in areas suitable and not suitable for maize production. Cobb-Douglas, Translog and Generalized Leontief productions functions were specified, each with Half normal, Truncated normal and exponential distributional assumptions. Efficiency scores were presented for the Generalized Leontief model with a truncated normal distribution, selected via likelihood ratio testing. For non-maize regions TE ranged between 80.1% and 98.9%, with a mean of 94.5%. For maize regions, TE ranged between and 84.2% and 98.7% with a mean of 94.9%. Mean efficiency scores presented by Mbaga *et al.* (2003) are larger than those presented in this study; however, some important similarities can be identified upon examining the range between maximum and minimum levels of efficiency. The range between maximum and minimum TE presented in Mbaga *et al.* (2003) was 18.78% for non-maize regions, and 14.5% for maize regions. This is broadly comparable to the ranges of 17.1% for the East Griqualand region and 18.2% for the Alexandria region found in this study. This indicates a reasonably similar degree of

homogeneity between the sampled dairy farms in both studies. That being said, there appears to be a slightly higher degree of homogeneity among the sampled East Griqualand dairy farmers.

Table 6.4: Descriptive statistics of mean technical efficiency per year, East Griqualand and Alexandria Dairy Farms, 2007 – 2014.

East Griqualand									
TE (%)	2007	2008	2009	2010	2011	2012	2013	2014	Mean
90-100	5	5	5	3	2	2	2	2	3
80-90	8	8	8	10	11	9	7	6	8
70-80	0	0	0	0	0	2	4	5	1
60-70	0	0	0	0	0	0	0	0	0
Min.	85.30	84.30	83.10	81.90	80.60	79.20	77.80	76.20	81.10
Mean	89.60	88.90	88.00	87.10	86.20	85.20	84.10	83.00	86.50
Max.	98.60	98.50	98.40	98.20	98.10	97.90	97.80	97.60	98.10
Range	13.30	14.20	15.30	16.30	17.50	18.70	20.00	21.40	17.10

Alexandria									
TE (%)	2007	2008	2009	2010	2011	2012	2013	2014	Mean
90-100	8	8	8	6	4	3	2	1	5
80-90	5	5	5	7	8	8	9	10	7
70-80	0	0	0	0	1	2	2	2	1
60-70	0	0	0	0	0	0	0	0	0
Min.	83.80	82.70	81.40	80.10	78.70	77.20	75.60	73.90	79.20
Mean	90.80	90.10	89.40	88.60	87.70	86.80	85.90	84.80	88.00
Max.	98.00	97.90	97.70	97.50	97.30	97.10	96.90	96.60	97.40
Range	14.20	15.20	16.30	17.40	18.60	19.90	21.30	22.70	18.20

The high degree of homogeneity identified by Mbagia *et al.* (2003) and subsequently observed in this study is not all that surprising considering sampled dairy farms in both studies are classified as specialized dairy farms, deriving at least 80% of revenue from the dairy enterprise. Furthermore, in this study all sampled farmers are among the top producers in their respective regions, with both study groups comprised of “above-average” milk producers, all of whom benefit from the services of professional agricultural consultants.

Theodoridis & Psychoudakis (2008) investigated farm-level TE using a cross-sectional sample of 165 Greek dairy farms for the period 2003-2004. TE was estimated through Maximum Likelihood estimation of a Cobb-Douglas stochastic production frontier. Mean TE for the sample was reported at 81.21%, which is slightly lower than the result reported here. The reported maximum (94.09%) and minimum (51.95%) efficiencies, resulting in a range of 42.14%, indicate a high degree of heterogeneity among Greek dairy farms. This observation does not correlate with the findings of this study.

Finally, Cabrera *et al.* (2010) estimated TE for a cross-sectional sample of 273 Wisconsin dairy farms for the 2007 calendar year. Farms in the sample were identified as being specialized in dairy production, with most of their farm output coming from the dairy enterprise. Mean TE, originating from a Cobb-Douglas production function, was 88%, almost identical to the findings of this study. It is important to highlight similarity in sample composition between this study and that of Cabrera *et al.* (2010), whereby both studies consider samples comprised of farms specialized in dairy production.

The comparisons above have all involved studies using cross-sectional data. Since this study considers panel data, and hence incorporates the dynamics of time and technological change, the models are not directly comparable. Estimated TE levels are, however, reasonably similar and thus provide useful insight into the result presented herein. To ensure a comprehensive comparison, it is important to compare homogeneous studies, using similar approaches and estimation procedures. The comparisons below represent panel data studies with broadly similar approaches to those adopted in this study.

Kompas & Che (2006) estimated TE for an unbalanced panel of 252 farms in New South Wales and Victoria, Australia, for the years 1996, 1998, 2000. As in the case of Mbagala *et al.* (2003), all farms included in the sample dataset are considered specialized dairy producers, deriving more than 80% of income directly from dairy products. Likelihood ratio tests, used to select the most appropriate functional form, revealed the log-linear Cobb-Douglas production function as the most suitable functional form for the data. The resulting mean technical efficiencies were 88.4% for New South Wales and 86.8% for Victoria. These findings are highly comparable to those presented in this study, although it should be noted that the Cobb-Douglas functional form is considerably more restrictive than other flexible functional forms, such as translog, and may not adequately

represent milk production technology. The Cobb-Douglas production function does, however, have the benefit of being less prone to multicollinearity problems that often plague flexible functional forms.

Hadley (2006) considered a large panel of farm survey data for various farm types in England and Wales for the years 1982 to 2002. Dairy farmers were defined as those deriving more than 60% of total annual farm income from the dairy enterprise. The sample comprised of 1,431 dairy farms in total. Dairy technology was modelled in a translog production function framework with the inclusion of a linear time trend to account for technological change over time. The resulting mean efficiency estimate of 89.7% is comparable to the results presented in Table 6.4. The range between maximum (97.2%) and minimum (58.4%) TE of 38.8% is markedly higher than that reported in Table 6.4. This may be explained, in part, by the different selection criteria used to select the dairy farm samples. Intuitively, one would expect to see a larger discrepancy between the most and least efficient farms with the use of a broader sampling criteria; i.e. a relatively lower degree of homogeneity between farms.

Abdulai & Tietje (2007) used a balanced panel of data for 149 dairy farms, observed over the period 1997 to 2005, to estimate TE of dairy farms in northern Germany. Selection criteria for dairy farmers was that more than 75% of farm returns be realized from the dairy enterprise. Several popular panel data estimation techniques were reported in the study, although the results emanating from the Battese & Coelli (1995) model are of particular relevance since the methodology underlying their calculation is comparable to that adopted in this study. Mean TE was reported to be 92% with a maximum of 97.7% and a minimum of 68.8%, resulting in a range of 28.9%. The mean TE is higher than reported in this study and the range between maximum and minimum efficiency indicates a lower degree of homogeneity between the sampled dairy farms.

Finally, Mkhabela *et al.* (2010), using an unbalanced panel of data for the period 1999 to 2007, estimated technical efficiencies for 37 dairy farms located in the KwaZulu-Natal Midlands of South Africa. Farms included in the sample were identified as highly specialized dairy farms, deriving at least 90% of total revenue from the dairy enterprise. Three separate models were specified, each with slightly different assumptions regarding the inclusion of herd size as an input in the production function. The preferable model, selected via likelihood ratio testing, resulted in mean technical efficiencies of between 70.2% and 80.7% for the nine years under study.



Interestingly, these findings are lower than the mean TE scores presented in Table 6.5. Holding all else constant, it appears that sampled farms from East Griqualand and Alexandria exhibit higher levels of TE than dairy farms in the KZN Midlands. This result should be interpreted with caution as the methodology, underlying assumptions and estimation procedures adopted in the two studies vary, and as such, results are not directly comparable.

It is important, at this stage, to mention a possible limitation of this study. Due to data limitations, and insufficient detail regarding physical quantities, output and input variables are expressed in value terms. The type of analysis to be conducted often depends upon the nature of the data collected. For instance, do the available data contain sufficient information to facilitate an investigation into the effect of price (allocative efficiency) as well as quantity (technical efficiency), or do they limit analysis to only one of the above? In parametric TE analysis, variables included in the production function are typically expressed in terms of physical quantity, as this allows TE, free from the influence of price, to be investigated.

In this study, the financial data collected were represented in aggregate value terms, providing information only on total rand value expenditure per farm. In this instance, the effect of price and quantity are both captured, but cannot be disseminated without additional information on either. Due to a lack of information on price and quantity, variables incorporated into the production function are expressed in total annual rand value, in line with Hadley (2006) and Abdulai & Tietje (2007). Defining the output variable in value terms, rather than physical output, has implications for the interpretation of inefficiency effects ( $u$ ) as  $u$  accounts for any factors associated with production inefficiency, including technical inefficiency (Battese & Coelli, 1995). This has important implications for model interpretation and subsequent policy and management recommendations. While this is acceptable practice, it is important to note that this approach is subject to several drawbacks, two of which are of particular importance to this paper.

Firstly, inherent quality and compositional differences cannot be identified and disentangled from one another. In the case of the labour variable, represented by the total wage bill, there is no way to determine what portion of total wage is attributable to managers, skilled workers or unskilled workers. Secondly, and more importantly, variables expressed in rand values need to be price deflated to neutralize the effect of price changes (inflation) over time. Representing these variables in aggregate value terms results in the inherent inclusion of price effects into TE analysis, therefore

conflating the concepts of technical and allocative efficiency to some degree (Hadley, 2006). It must therefore be disclosed that some of the movements in the mean efficiency scores may have been influenced to some extent by price changes over time. It is important that this be borne in mind when attempting to interpret results and structure recommendations for policymakers and dairy farm decision makers alike.

Referring to Table 6.4, it is possible to segregate sampled milk producers into three broad categories based on their relative efficiencies. The first, referred to as “highly-efficient”, denotes producers with mean TE values between 90 and 100%. The second, referred to as “efficient”, refers to producers with mean TE values between 80 and 90%. The final group is referred to as “reasonably-efficient” and encompasses all producers with mean TE values between 70 and 80%. Results indicate that from 2007-2012, Alexandria had a higher proportion of dairy farms in the highly-efficient group, particularly for the years 2007-2010. Alexandria also had a lower proportion of dairy farmers in the reasonably efficient group, particularly for 2013 and 2014. This leaves East Griqualand with the highest proportion of farms in the efficient group. It is interesting to note that, for both regions, the distribution of farms shifted from higher to relatively lower efficiency groups over time. This implies that the average farm is becoming relatively less efficient over time, in comparison to the best practice farm (representing the frontier).

The fundamentals of microeconomics dictate that the relationship between TE and time should be positive, with efficiency improving as technology progresses, enabling greater production potential with the same level of inputs. This is no different for milk production technology which has seen the adoption of a range of new technologies in recent years. Improved milking systems, such as rotary parlours, result in significant time saving as well as a reduction in the number of labourers required per cow. Advanced production monitoring software allows farmers to monitor their herds closely, feeding custom rations per each cow’s needs. This ensures wastage is minimized and milk yield is optimized by allocating the highest quality rations to the best milkers. Cost may also be reduced by feeding lower quality, cheaper rations to relatively poor milkers and dry cows.

Concerning the temporal pattern of efficiency, results presented in Table 6.4 indicate that mean TE has generally decreased over time in the two study samples, while the range between minimum and maximum efficiency has widened. These results may seem counter intuitive at first, but it is

important to remember that the production frontier represents the best-practice farm and subsequently mean TE is calculated in relation to the best practice frontier. Therefore, if some farms can adopt newer technology or make better use of existing technologies than others, it is reasonable to assume that the average farm will lag further behind the best practice farm (representing the frontier), assuming farms are equally weighted.

Kumbhakar *et al.* (1997) illustrated this concept in a study on cement plants, suggesting that in an industry characterized by rapid technological progress, one would expect to see a negative relationship between mean TE and time. This is based on the notion that rapid technological progress would result in the average lagging further behind the best practice firm, representing the frontier, therefore generating lower mean efficiency values over time. In other words, as the frontier shifts outward over time, the gap between the average farm and the best practice farm will widen. Supporting evidence can be found in Ahmad & Bravo-Ureta (1996), who reported a gradual decline in mean TE over the period 1971 to 1984 for a panel of 96 Vermont dairy farms, using a simplified translog production function with a smooth time trend and truncated normal distribution.

Hadley (2006) reported similar findings for a panel of English and Welsh dairy farmers, in which farms became more efficient over time due to technical change, however annual mean levels of TE were found to decrease over time. This trend was further substantiated by Abdulai & Tietje (2007), who reported that the mean level of TE on a panel of German dairy farms were found to decrease over time. In contrast, Mkhabela *et al.* (2010) reported that mean TE values increased over the period 1999 to 2007 for a panel of South African dairy farmers. This suggests that the average farm became more efficient relative to the best practice frontier, possibly by making better use of existing technology.

There has been considerable focus on determining the relationship between farm size and TE in recent years, with a wealth of literature providing different results. Given the continuation of industry consolidation, it is hardly surprising that it remains a topic of interest. The results presented in Table 6.5 suggest that over the whole study period, mean TE values for the Alexandria study group appear to increase with farm size, as indicated by Von Bailey *et al.* (1989) and Tauer & Mishra (2006). The largest milk producers, with milking herds of 626-896 cows exhibited a mean TE of 88.9%. Small farmers, milking 86-356 cows, exhibited a mean TE of 87.0%, while

medium size farmers, milking 356-626 cows, exhibited a mean TE of 88.1%. On a year-to-year basis it is evident that the difference in mean TE score between farms of different size is notably small. This implies that for the sampled Alexandria farms, mean TE scores are not sensitive to the size of operation. It is interesting to note that none of the sampled Alexandria farms increased herd size beyond 896 milking cows over the study period. In fact, the frequency distribution per farm size did not change drastically as is the case with the East Griqualand study group.

For East Griqualand, the average TE levels for farms in different size categories, measured by herd size, does not indicate a positive relationship between farm size and TE as has been found in the previous literature (Von Bailey *et al.*, 1989; Tauer & Mishra, 2006). For the years 2007, 2009, 2012 and 2014 the highest levels of mean TE are associated with the largest farmers in the sample. With the exception of 2014, this pertains to large farms, milking 896-1166 cows. For the remaining years, medium sized farms, milking 356-626 cows appear to have the highest TE. On average, over the whole period of study, medium sized farms exhibited the highest levels of mean TE, 89.1%, followed by large farms, 88.5%, with medium-large farms, milking 626-896 cows, associated with the lowest levels of TE in the sample. Although this result does not conform with the reported findings of Von Bailey *et al.* (1989) and Tauer & Mishra (2006), there are several possible explanations for the nonlinear relationship between farm size and TE.

Firstly, the sample is comprised of a small number of farms with less than ten farms representing each size category. In some instances, as in the case of farms milking above 1,166 cows, there are only two farms representing this size category, and only for the year 2014. This hardly constitutes a large enough sample to be deemed representative, and as such, the relationship between farm size and TE should be interpreted with caution. Secondly, the continual growth of herd size must be considered. From Table 6.5 it is evident that several farms have increase in size over the study period, moving into subsequently larger size categories. Growth in herd size may appear simple but in reality, it requires a change in a number of factors. Increased herd size requires greater quantities of feed, more resources during milking, including labour and time, greater expenditure on veterinary products and services and most likely more capital investment. The two most important factors limiting the rate of growth are most likely available pasture (land) and milking infrastructure (capital investment).

Table 6.5: Frequency distribution of mean technical efficiency scores per farm size and region, East Griqualand and Alexandria Dairy Farms, 2007 – 2014.

<b>Farm size</b>	<b>Herd Size</b>	<b>Farms</b>	<b>TE (%)</b>	<b>Farms</b>	<b>TE (%)</b>	<b>Farms</b>	<b>TE (%)</b>
	<b>2007</b>	<b>Total</b>		<b>East Griqualand</b>		<b>Alexandria</b>	
Small	86-356	14	89.27	10	89.42	4	88.90
Medium	356-626	8	91.64	-	-	8	91.64
Medium-Large	626-896	4	90.65	3	90.37	1	91.50
Large	896-1166	-	-	-	-	-	-
Very Large	1166 +	-	-	-	-	-	-
	<b>2008</b>						
Small	86-356	11	87.88	9	87.52	2	89.50
Medium	356-626	10	90.86	1	98.50	9	90.01
Medium-Large	626-896	5	90.24	3	89.67	2	91.10
Large	896-1166	-	-	-	-	-	-
Very Large	1166 +	-	-	-	-	-	-
	<b>2009</b>						
Small	86-356	9	87.59	7	87.27	2	88.70
Medium	356-626	12	89.20	3	89.00	9	89.27
Medium-Large	626-896	4	88.38	2	86.35	2	90.40
Large	896-1166	1	94.00	1	94.00	-	-
Very Large	1166 +	-	-	-	-	-	-
	<b>2010</b>						
Small	86-356	10	86.67	7	86.31	3	87.50
Medium	356-626	10	89.13	2	90.95	8	88.68
Medium-Large	626-896	4	86.63	2	83.55	2	89.70
Large	896-1166	2	89.85	2	89.85	-	-
Very Large	1166 +	-	-	-	-	-	-
	<b>2011</b>						
Small	86-356	8	85.48	5	84.78	3	86.63
Medium	356-626	13	88.13	4	88.45	9	87.99
Medium-Large	626-896	2	85.05	1	81.40	1	88.70
Large	896-1166	3	87.17	3	87.17	-	-
Very Large	1166 +	-	-	-	-	-	-
	<b>2012</b>						
Small	86-356	6	85.17	4	84.75	2	86.00
Medium	356-626	13	86.47	5	85.94	8	86.80
Medium-Large	626-896	4	85.55	1	80.10	3	87.37
Large	896-1166	3	86.27	3	86.27	-	-
Very Large	1166 +	-	-	-	-	-	-
	<b>2013</b>						
Small	86-356	6	84.10	4	83.68	2	84.95
Medium	356-626	11	85.58	4	86.20	7	85.23
Medium-Large	626-896	6	84.70	2	79.30	4	87.40
Large	896-1166	3	85.23	3	85.23	-	-
Very Large	1166 +	-	-	-	-	-	-
	<b>2014</b>						
Small	86-356	5	83.32	3	82.93	2	83.90
Medium	356-626	11	84.88	5	84.62	6	85.10
Medium-Large	626-896	8	82.58	3	78.77	5	84.86
Large	896-1166	-	-	-	-	-	-
Very Large	1166 +	2	85.45	2	85.45	-	-

To illustrate, consider a farmer milking 800 cows with an observed TE of 90%. If the farmer wishes to increase herd size to 1000 milking cows but keeps all other fixed resources the same, the available resources are placed under more stress. A greater number of cows are now expected to graze the same pastures resulting in each cow receiving a lower percentage of its daily nutritional requirement from grazing. This in turn requires more supplementation, either in the form of maize silage or purchased feeds, to meet the demanding nutritional requirements of the herd. Furthermore, milking times will be extended to deal with the increased number of animals, requiring additional labour hours. This shift to a larger herd size will undoubtedly alter the cost structure faced by the farmer and most likely alter input utilization. In this case, observed TE may decrease, despite increased herd size.

### 6.3.3 Scale efficiency

Frequency distributions of scale efficiency scores are presented in Table 6.6. During the period 2007-2014, mean scale efficiency was 95.2 %. This implies sampled milk producers could have, on average, increased their output by 4.8% had they operated at optimal scale. Table 6.6 shows that the vast majority of farms achieved scale efficiency scores between 90-100 %. This indicates that the majority of sampled dairy farms are operating near optimal scale and do not experience any substantial loss in output due to scale efficiency problems. Generally, very few farms achieved scale efficiency scores lower than 90% for most of the study period. With the exception of 2011 and 2012, less than four of the 26 sampled farms achieved scale efficiency scores below this level. Several farms operated at 100% scale efficiency over the study period, particularly prior to 2010, after which the number of farms achieving scale efficiency decreased notably.

The highest number of farms to operate under scale efficiency was seven, for the year 2009, followed by five farms in 2007 and 2010. Table 6.6 indicates that after 2010 the number of scale efficient milk producers did not increase beyond three, and in the final year of study only one farm achieved scale efficiency. The difference between the highest and lowest levels of scale efficiency, indicated as “range” in Table 6.6, is also of importance. For most of the study period, the range between the most and least scale efficient farms was 11% to 26%, although for the years 2011 and 2012 this range increased to 43.8% and 37.2 %, respectively. Reasons for the large shift of farms during 2011, and 2012 to some degree, to relatively lower levels of scale efficiency are unclear.

Table 6.6: Descriptive statistics of mean scale efficiency per year, East Griqualand and Alexandria Dairy Farms, 2007 – 2014.

Scale efficiency (%)	2007	2008	2009	2010	2011	2012	2013	2014	Mean
50-60	0	0	0	0	1	0	0	0	0
60-70	0	0	0	0	0	1	0	0	0
70-80	0	0	0	1	5	0	1	0	1
80-90	2	1	1	3	9	6	1	1	3
90-100	19	23	18	17	10	17	21	24	19
100	5	2	7	5	1	2	3	1	3
Total	26	26	26	26	26	26	26	26	26
Min.	82.28	88.55	87.28	78.64	56.17	62.8	73.66	88.98	77.30
Mean	97.11	97.63	98.46	94.96	86.52	93.49	96.21	97.23	95.20
Max.	100	100	100	100	100	100	100	99.98	100
Variance	0.24	0.07	0.08	0.34	0.99	0.63	0.34	0.08	0.35
Range	17.72	11.44	12.71	21.36	43.83	37.2	26.34	11.00	22.70

Jaforullah & Whiteman (1999) reported similar findings in an analysis of scale efficiency, using DEA techniques, on a sample of 264 New Zealand dairy farmers. The reported mean scale efficiency of 94% is very similar to the 95.2% reported in this study, despite the nonparametric approach to the measurement of scale efficiency. Minimum scale efficiency was reported to be 45%, while 50% of sampled farms achieved scale efficiency. While reported minimum scale efficiency is broadly comparable to the results reported in Table 6.6, the proportion of scale efficient farms is substantially higher. Using an input distance-function approach to stochastic frontier analysis, Rasmussen (2010) estimated technical and scale efficiencies for several Danish farming enterprises, including dairying, for the period 1985-2006. Mean scale efficiency for the sample period was 89%.

In an application of DEA to a sample of French and Hungarian dairy farmers for the period 2001-2006, Fogarasi & Latruffe (2009b) reported mean scale efficiencies of 94% and 95% for French and Hungarian dairy farmers, respectively; 8% of French dairy farmers and 27% of Hungarian dairy farmers were scale efficient. Furthermore, only 9% of French dairy farmers operated at CRS, where scale elasticity equals unity. This finding is comparable to the results of this study, in which, on average, 11% of the sampled South African dairy farmers were found to be scale efficient and

exhibited CRS. Finally, in an analysis of technical and scale efficiency for a sample of 165 Greek dairy farms using DEA, Theodoridis & Psychoudakis (2008) reported mean scale efficiency of 92.7% for the sampled farms. This is once again a comparable result; however, minimum scale efficiency was 29.8%, substantially lower than the 56.2% reported in this study. This implies there is a greater degree of homogeneity regarding the size of South African dairy farms sampled.

Concerning the relationship between scale efficiency and scale elasticity, Table 6.7 indicates the vast majority of sampled farms exhibit increasing returns to scale. That is, they are operating at a suboptimal scale and could benefit by increasing output, thereby moving towards optimal scale. Suboptimal scale is characterized by scale elasticities greater than unity and scale efficiencies below unity. There are relatively few farms operating at supra-optimal scale, which is characterized by scale elasticity below unity, evidence of decreasing returns to scale. Farms operating at supra-optimal scale can benefit by reducing the scale of the operations. Table 6.7 reveals that farms operating at supra-optimal scale, on average, achieved greater scale efficiency scores than farms operating at suboptimal scale. Furthermore, mean levels of scale efficiency associated with supra-optimal farms appear to be much closer to unity. In other words, the gap in mean scale efficiency between farms operating at supra-optimal and optimal scale is notably narrower than the gap between farms operating at suboptimal and optimal scale.

This implies that scale inefficiency is primarily attributable to farms operating at suboptimal scale and these farms must have adjusted output levels to a greater extent than the farms operating at supra-optimal scale. These findings are in line with Karagiannis & Sarris (2005), who estimated scale efficiency for a sample of Greek tobacco farmers using the methodology proposed by Ray (1998) and Madau (2011), who estimated scale efficiency for a sample of Italian citrus growing farms using the same methodology.

Eliminating the supra-optimal scale would potentially increase the output of three dairy farms by an average of only 0.45 % from 99.55% to 100%. Eliminating the suboptimal scale, on the other hand, would potentially increase output by 5.2% from 94.8% to 100%. According to Jaforullah & Whiteman (1999), this would suggest that if it is desirable to improve production efficiency then, from an agricultural policy viewpoint, encouraging the trend towards larger dairy farms is better than discouraging it. Although this observation pertains to the New Zealand dairy industry, given



the observed structural shift towards fewer, larger dairy farms in the South African dairy industry, it remains highly relevant.

Table 6.7: Efficiency scores and scale, East Griqualand and Alexandria Dairy Farms, 2007-2014.

Returns to scale	Number of farms	Scale elasticity	Scale efficiency	Technical efficiency
2007				
Supra-optimal	9	0.97	99.87	91.27
Optimal	1	1.00	100.00	93.70
Suboptimal	16	1.12	95.65	89.65
2008				
Supra-optimal	1	0.92	99.45	98.50
Optimal	-	-	-	-
Suboptimal	25	1.10	97.56	89.12
2009				
Supra-optimal	7	0.91	99.21	88.80
Optimal	-	-	-	-
Suboptimal	19	1.07	98.18	88.66
2010				
Supra-optimal	4	0.91	99.09	86.80
Optimal	4	1.00	100.00	91.15
Suboptimal	18	1.14	94.21	88.05
2011				
Supra-optimal	-	-	-	-
Optimal	-	-	-	-
Suboptimal	26	1.22	86.52	86.97
2012				
Supra-optimal	1	0.95	99.71	88.40
Optimal	1	1.00	100.00	84.10
Suboptimal	24	1.15	93.24	85.91
2013				
Supra-optimal	1	0.98	99.95	82.23
Optimal	-	1.00	100.00	77.80
Suboptimal	24	1.13	95.72	85.36
2014				
Supra-optimal	-	-	-	-
Optimal	-	-	-	-
Suboptimal	26	1.11	97.23	83.92

Concerning the relationship between scale efficiency and technical efficiency, there does not appear to be any discernible trend in the results presented in Table 6.7. For the years 2007 and

2010 farms operating at optimal scale appear to be associated with higher levels of technical efficiency; however, for the remainder of the study period this does not hold true. In fact, for 2012 and 2013, farms operating at optimal scale appear to be associated with below-mean values of technical efficiency. This indicates that improved scale efficiency does not necessarily translate to higher levels of technical efficiency, *ceteris paribus*.

Concerning the temporal pattern of scale efficiency, there appears to be no discernible relationship between scale efficiency and time for the sampled dairy farms. Initially, between 2007 and 2009, mean scale efficiency increases linearly with time, before decreasing over the period 2010-2011. Following this, it begins to increase again until the end of the study period in 2014. This provides further evidence of 2010 and 2011 results going against findings in other years, essentially pointing to these as outliers.

Table 6.8 presents a frequency distribution of scale efficiencies per farm size, with results generally indicating a positive correlation between the number of milking cows and the mean level of scale efficiency. For most of the years under study, larger farms are associated with higher mean levels of scale efficiency. The years 2007, 2011 and 2012 are the exceptions to this trend. For 2007, farms of medium size, milking 356-626 cows, was associated with the highest mean level of scale efficiency and the largest farm, milking 626-896 cows, the lowest. 2011 once again proved to be an outlier with the smallest farms, milking 86-356 cows, exhibiting the highest levels of mean scale efficiency. For 2012, the highest level of mean scale efficiency was associated with medium-large farms, milking 626-896 cows. Interestingly, for many of the years mean technical efficiency appears to be highest for those farms of medium size, milking 356-626 cows.

Considering the regional level results, for East Griqualand herd size and mean scale efficiency do not display a clear correlation. A positive relationship between herd size and mean scale efficiency is evident for the years 2009, 2010, 2013, and 2014. For the remaining years there is no evidence of a clear trend. It should be noted that the sample size at each respective farm size is not sufficiently large to draw concrete conclusions but does provide valuable insight into the relationship between scale efficiency and farm size, as measured by herd size. Alexandria dairy farms show a positive relationship between herd size and mean scale efficiency for the years 2009, 2012, 2013, and 2014.

Table 6.8 Frequency distribution of mean scale efficiency scores per farm size and region, East Griqualand and Alexandria Dairy Farms, 2007-2014.

Farm size	Herd Size	Farms	SE (%)	Farms	SE (%)	Farms	SE (%)
	<b>2007</b>	<b>Total</b>		<b>East Griqualand</b>		<b>Alexandria</b>	
Small	86-356	14	96.82	10	95.62	4	99.82
Medium	356-626	8	99.37	-	-	8	99.37
Medium-Large	626-896	4	93.60	3	91.59	1	99.66
Large	896-1166	-	-	-	-	-	-
Very Large	1166 +	-	-	-	-	-	-
	<b>2008</b>						
Small	86-356	11	97.18	9	96.79	2	98.94
Medium	356-626	10	97.90	1	99.45	9	97.73
Medium-Large	626-896	5	98.10	3	98.18	2	97.98
Large	896-1166	-	-	-	-	-	-
Very Large	1166 +	-	-	-	-	-	-
	<b>2009</b>						
Small	86-356	9	97.28	7	98.64	2	92.51
Medium	356-626	12	98.89	3	99.30	9	98.75
Medium-Large	626-896	4	99.46	2	99.68	2	99.23
Large	896-1166	1	99.99	1	99.99	-	-
Very Large	1166 +	-	-	-	-	-	-
	<b>2010</b>						
Small	86-356	10	95.01	7	94.26	3	96.75
Medium	356-626	10	94.21	2	95.48	8	93.89
Medium-Large	626-896	4	94.58	2	96.40	2	92.76
Large	896-1166	2	99.22	2	99.22	-	-
Very Large	1166 +	-	-	-	-	-	-
	<b>2011</b>						
Small	86-356	8	89.07	5	88.72	3	89.66
Medium	356-626	13	85.81	4	92.14	9	83.00
Medium-Large	626-896	2	80.86	1	82.30	1	79.42
Large	896-1166	3	86.53	3	86.53	-	-
Very Large	1166 +	-	-	-	-	-	-
	<b>2012</b>						
Small	86-356	6	89.23	4	87.00	2	93.69
Medium	356-626	13	94.59	5	93.03	8	95.56
Medium-Large	626-896	4	96.34	1	96.14	3	96.41
Large	896-1166	3	93.46	3	93.46	-	-
Very Large	1166 +	-	-	-	-	-	-
	<b>2013</b>						
Small	86-356	6	96.50	4	98.12	2	93.26
Medium	356-626	11	94.30	4	92.17	7	95.53
Medium-Large	626-896	6	97.66	2	96.18	4	98.41
Large	896-1166	3	99.69	3	99.69	-	-
Very Large	1166 +	-	-	-	-	-	-
	<b>2014</b>						
Small	86-356	5	97.33	3	97.22	2	97.50
Medium	356-626	11	95.85	5	95.45	6	96.19
Medium-Large	626-896	8	98.44	3	99.72	5	97.67
Large	896-1166	-	-	-	-	-	-
Very Large	1166 +	2	99.76	2	99.76	-	-

On average, over the entire study period, however, the mean scale efficiency of Alexandria dairy farms appears to be relatively stable across different farm sizes. The difference in mean scale efficiency scores between the largest and smallest farm

size classifications for East Griqualand is 17.4%. For Alexandria, this difference is marginally more pronounced, with a 20.4% difference in mean scale efficiency between the largest and smallest farm size classification. This implies, that in terms of scale of operation, there is a higher degree of homogeneity among East Griqualand farmers than among Alexandria farmers.

The next chapter deals with modelling the economic performance of dairy farms in the East Griqualand and Alexandria regions.

## CHAPTER 7: MODELLING THE ECONOMIC PERFORMANCE OF DAIRY FARMS

### 7.1 Introduction

Structural equation modelling (SEM) is a technique used extensively in the social sciences due to its ability to capture the relationships between latent (unobserved) variables and observed indicator or cause variables (Macias & Cazzavillan, 2010). When compared to similar techniques such as confirmatory factor analysis (CFA), SEM extends the possibility of relationships among the latent variables by considering both structural and measurement models. The structural model encompasses the relationships between latent constructs and observable variables in several linear equations, similar to the concept of simultaneous regression. The measurement model shows the pattern of observed variables for the hypothesized latent constructs and may be used to analyse covariation among the latent constructs (Schreiber *et al.*, 2006). The Multiple-Indicators, Multiple-Causes (MIMIC) model of Joröskog & Goldberger (1975) adopted in this study represents a special case of SEM in which the hypothesized model may contain multiple indicators and multiple causes of the latent (unobserved) variables (Esposti & Pierani, 2000).

Applications of SEM, and the MIMIC model, are typically found among the social sciences literature, due to the unobservable nature of the variables under study. There have been only a limited number of applications of these techniques in agricultural productivity studies. This study proposes the use of SEM techniques to model economic performance as a latent variable. The supporting argument is that studies investigating farm performance have typically reported various measures of efficiency as the sole indicator of farm performance. These efficiency measures, as highlighted in earlier chapters, are not free of problems and do not encompass all aspects pertaining to the relative performance of a farm.

Furthermore, following Macias & Cazzavillan (2010), it is posited that by treating farm economic performance as a latent variable, the MIMIC model is less constrained by a lack of information and can make use of a greater number of variables, allowing for a more robust set of causal relationships to be covered. The inclusion of technical and scale efficiency as indicators of economic performance, in addition to the hypothesized cause and indicator variables, represents an attempt to investigate farm performance at a more integrated level than has been adopted traditionally. In addition, latent indices for breeding, feeding and labour management were

constructed in an effort to determine the effect of these three critical aspects of dairy farm management on relative economic performance (Figure 7.1).

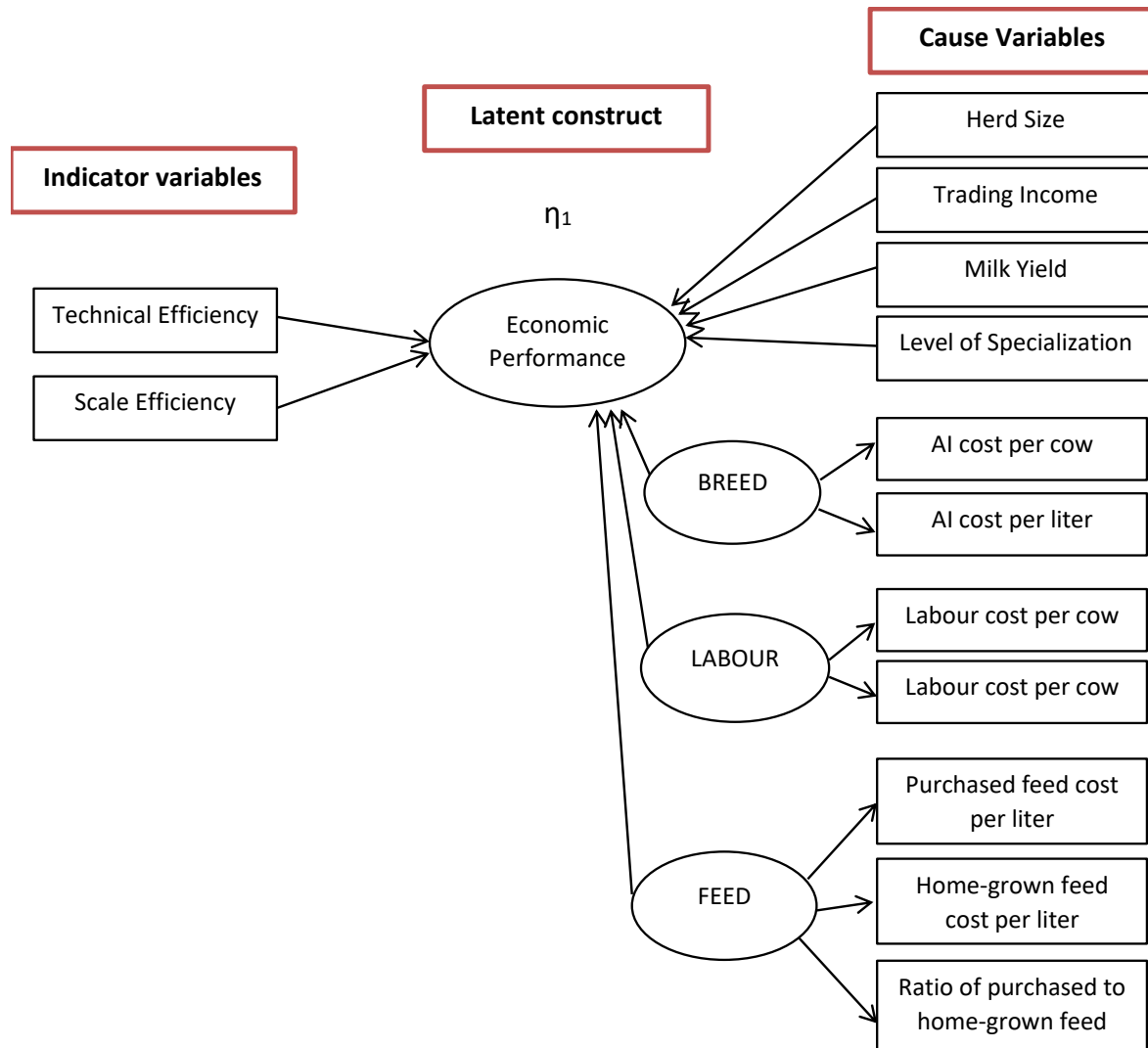


Figure 7.1 Path diagram of the proposed MIMIC model

Estimating economic performance, and its key determinants, requires the identification of several “cause” and “indicator” variables and their subsequent inclusion into the MIMIC model framework. Causal variables refer to variables which have a direct relationship with farm performance such as herd size, milk yield and level of specialization. The three latent managerial quality constructs BREED, FEED and LABOUR are included as latent causal variables as they are not directly observable and hence must be identified using various indicators. These indicator variables are included as a means of identifying the latent constructs. It is important to note that

despite the presence of several latent variables in the above model specification there is only one endogenous (dependent) latent variable, namely economic performance. Individual levels of TE and SE, estimated in Chapter 6, are incorporated into the MIMC model as observed indicators of latent economic performance.

The latent constructs BREED, FEED and LABOUR are incorporated as exogenous (independent) latent variables. These input quality variables are calculated from a set of observable variables found in typical farm accounting records, including total feed cost, ratio of concentrates to forage and a number of other indicators (figure 7.1). Variation in economic performance is explained through the structural equation which relates economic performance to the observable cause variables and latent constructs shown in figure 7.1.

## **7.2 Variables used in the analysis of economic performance**

### **7.2.1 Structural equation variables**

#### *(i) Herd size, indicated by the number of milking cows ( $Herd_{it}$ )*

Herd size, indicated by the number of milking cows, has commonly been used as a proxy for farm size (Bragg & Dalton, 2004; Tauer & Mishra, 2006; Abdulai & Tietje, 2007) and has the benefit of intrinsically accounting for differences in the quality of farm land (Gentner & Tanaka, 2002). Furthermore, by incorporating herd size into the production frontier, residual information not captured by the incorporated variables, which may be correlated with farm size, can be accounted for (Tauer & Mishra, 2006). In other words, efficiency related to farm size, not captured by the variables in the production function, is likely to be captured by the herd size variable. Considering the above, herd size appears to be the most appropriate measure of farm size for use in this study. Herd size is hypothesized to have a positive relationship with economic performance since increased herd size is expected to result in increased output, *ceteris paribus*.

#### *(ii) Average milk production per cow ( $Milk_{it}$ )*

Gloy *et al.* (2002) noted several studies which have reported a positive relationship between milk production per cow and various measures of farm financial success. Von Bailey *et al.* (1989), Huirne *et al.* (1997) and Gloy *et al.* (2002) all included average milk production per cow as a measure of productivity. Average milk production per cow captures latent characteristics such as a producer's knowledge and ability to apply efficient production, feeding and breeding practices

as well as the ability to benefit from new technologies (Gloy *et al.*, 2002). Tauer & Mishra (2006) suggest that milk production per cow is an indicator of poor or good management, capturing the effects of genetics, feeding, disease control and other managerial factors. Following Gloy *et al.* (2002), milk production per cow is hypothesized to have a positive relationship with economic performance, *ceteris paribus*.

(iii) *Level of specialization in dairy* (Spec<sub>it</sub>)

The level of specialization provides a measure of diversity on-farm. Bragg & Dalton (2004) measured the diversity of on-farm income using the Herfindahl index, which is calculated as the sum of the squared income shares. Gillespie *et al.* (2009) simply expressed the level of specialization as the percentage of farm income derived from milk, while Du Toit (2009) calculated the ratio of total milk income to gross farm income to represent the level of specialization in milk production. This study adopted the approach highlighted by Du Toit (2009), expressing specialization as a ratio of milk income to total farm income. The range is thus bound between 0 and 1, with values approaching unity indicating increased specialization in milk production.

Since all farms in the sample may be considered specialized, deriving more than 80% of total income from the dairy enterprise, the Spec variable is intended to capture differences between the most and least specialized farms in the sampled data set, thus revealing if a greater degree of economic performance can be derived from further specialization into dairy. Since relatively more specialized farms are more likely to dedicate a greater portion of their management efforts and farm resources towards dairy production, the level of specialization is hypothesized to have a positive relationship with economic performance, *ceteris paribus*.

(iv) *Trading income* (Trade<sub>it</sub>)

Trading income is included to determine whether income through the sale of dairy livestock (cull cows and calves, for example) is a potential means of improving farm performance. Trading income is calculated as follows, and is expressed as a ratio of trading income of total milk income.

$$\text{Trading income} = \text{livestock sales} + \text{closing value} - \text{livestock purchases} - \text{opening value} \quad (7.1)$$



Du Toit (2009) found trading income to have a positive effect on the competitiveness of East Griqualand milk producers. In line with this finding, additional income through the sale of dairy livestock is expected to improve economic performance. Trade is, therefore, hypothesized to have a positive relationship with economic performance, *ceteris paribus*.

(v) *Breeding management* (BREED)

Genetic improvement through breeding is an important source of technological change (Babcock & Foster, 1991, as cited by Atsbeha *et al.*, 2012). Dairy production involves a continuous transfer of genetic material, either naturally or by AI, and therefore managerial decisions such as choice of insemination method, selection of semen and breed of cows will determine the genetic performance of cows to some degree. This genetic variation, due to managerial influence, may result in productivity differences among farms, even if only in the short term (Atsbeha *et al.*, 2012).

Following Richards & Jeffrey (2000), breeding expense per cow and breeding expense per unit output were selected as indicators of the breeding management variable (BREED). Breeding expense was calculated as total rand value expenditure on artificial insemination (AI) divided by herd size and quantity of milk produced in litres, respectively. Farms using bulls, rather than AI, were assigned values of zero (0). To ensure identification, it is generally desirable to specify three indicators when constructing an index; however, due to data limitations this was not possible. Furthermore, it is important to note that a high degree of correlation may exist between breeding expense per cow and breeding expense per unit output since the denominators, herd size and milk output, are likely to exhibit a high degree of correlation. This should be borne in mind when interpreting the results. Since BREED is expected to capture the genetic progress due to managerial influence between farms, it is expected to exhibit a positive relationship with economic performance, *ceteris paribus*.

(vi) *Feeding management* (FEED)

Total expenditure on feed is generally one of the largest costs associated with milk production (Buza *et al.*, 2014) and is expected to be a significant determinant of economic performance. Total feed cost per unit output, cost of purchased feed per unit output and the ratio of purchased feed to home grown feed were all included as indicators of FEED. All costs are expressed in aggregate value terms, deflated by the CPI to account for inflationary effects. Total feed cost is represented

by the aggregation of total rand value expenditure on purchased feed, including supplementary feed, concentrates, and calf meal, as well as total expenditure on homegrown feeds. Expenditure on homegrown feeds is a function of several costs, including but not limited to, seed, fertilizer, planting, and harvesting costs. The ratio of purchased feed to homegrown feed is included in an attempt to assess a manager's ability to meet the nutrient requirements of the herd using pasture and home grown feeds. Since the ability to manage purchased and home grown feeds effectively is expected to improve economic performance, FEED is hypothesized to have a positive relationship with economic performance, *ceteris paribus*.

(vii) *Labour management (LABOUR)*.

A latent index of labour management was constructed in an effort to assess the ability of producers to effectively manage labour and implement labour saving technologies where possible. Following Richards & Jeffrey (2000), latent labour management indicators consist of labour per cow and labour per unit output. In this study, labour is expressed in terms of the aggregate wage bill in rand value and includes all labour of various quality. As mentioned for BREED, it is generally desirable to specify three indicators when constructing an index, however, due to data limitations this was not possible. Furthermore, a high degree of correlation may exist between labour cost per cow and labour cost per unit output since the denominators, herd size and milk output, are likely to exhibit a high degree of correlation. This should be borne in mind when interpreting the results for LABOUR. The results presented by Richards & Jeffery (2000) suggest that labour management (quality) is positively related to economic performance. Therefore, LABOUR is hypothesized to have a positive relationship with economic performance, *ceteris paribus*.

### 7.2.2 Measurement equation variables

1. Technical efficiency =  $\beta_1\text{PERF} + u_1$
2. Scale efficiency =  $\beta_2\text{PERF} + u_2$
3. Breeding expense per cow =  $\beta_5\text{BREED} + u_5$
4. Breeding expense per unit output =  $\beta_6\text{BREED} + u_6$
5. Concentrate/forage ratio =  $\beta_7\text{FEED} + u_7$
6. Feed cost per unit output =  $\beta_8\text{FEED} + u_8$

7. Concentrates per unit output =  $\beta_9\text{FEED} + u_9$
8. Labour cost per cow =  $\beta_{10}\text{LABOUR} + u_{10}$
9. Labour cost per unit output =  $\beta_{11}\text{LABOUR} + u_{11}$

### 7.3 MIMIC model specification

As mentioned above, the MIMIC model considers economic performance as a latent, unobservable variable for which many imperfect indicators exist. In order to describe the relationships between (1) indicator variables and latent variables; and (2) cause and latent variables, the MIMIC model consists of a set of structural equations and measurement equations. The structural equation specifies relationships among a series of latent variables ( $\eta$ ), their observable causes ( $z$ ), and a random error term ( $\zeta$ ) as follows:

$$\eta = \Phi\eta + \Gamma z + \zeta \quad (7.2)$$

where  $\Phi$  is a parameter vector showing the marginal effect of the latent variables on each other, and  $\Gamma$  is a parameter vector showing the marginal effect of the cause variables on the latent variables.

The measurement equations, specified below, relate each indicator variable ( $q$ ) to the latent variables ( $\eta$ ), and a vector of random measurement errors ( $\epsilon$ ):

$$q = \Lambda_q\eta + \epsilon \quad (7.3)$$

where the components of  $\Lambda_q$  are called factor loading coefficients. The error terms of equations (7.2) and (7.3) are uncorrelated with each other, have zero means and have covariances given by  $\Psi$  and  $\Theta$ , respectively. These covariance matrices provide information on the relationships between cause and indicator variables that are necessary to identify latent variable parameters (Richards & Jeffrey, 2000).

Following the general framework highlighted by Figure 7.1 in the opening section of this chapter, the MIMIC model attempts to relate unobserved dairy performance to a set of observable causes and a set of latent management indices, posited to affect latent economic performance. The latent managerial indices (BREED, FEED, and LABOUR) represent an attempt to investigate the effect of managerial quality on the breeding, feeding, and labour programme, since these are

hypothesized to be critical aspects of a farm's underlying ability to perform. Justification for the inclusion of these variables is provided in the previous subsection, outlining the variables included in the study. It is important to note that although latent in nature, these constructs remain explanatory (exogenous) in nature, and economic performance remains the sole endogenous latent variable. Since the model only consists of one endogenous latent variable, PERF, there is only one structural equation to be specified. The generic structural equation proposed may be expressed as follows:

$$PERF = Herd_{it} + MilkKL_{it} + Spec_{it} + Trade_{it} + BREED + FEED + LABOUR \quad (7.4)$$

Where the variables are defined as in the previous section. Latent managerial indices were included in an attempt to determine their effect on the latent economic performance of South African dairy farms as there has been limited empirical research into the critical success factors driving economic performance and farm financial success. Given the continuation of the consolidation trend in the domestic and international dairy industries, determining key success factors is considered to be of great importance.

Model identification remains one of the more challenging aspects of structural equation modelling, as failure to consider identification can lead to misleading results, particularly when dealing with models involving latent variables and higher degrees of complexity. Generally, an under-identified model means that a researcher cannot determine a unique value for at least one parameter in the model (Bollen & Davis, 2009). One of the generally accepted identification rules pertaining to measurement models states that a congeneric measurement model will be identified if at least three measures are associated with every latent construct. In the case that every latent construct is related with at least one other construct, the required number of measures is reduced to two.

It is important to note, prior to estimation, that there is some degree of concern regarding the identification of the latent managerial indices, particularly BREED and LABOUR. When constructing similar latent indices, researchers have typically specified three or more indicator variables, as specified above, to ensure identification (Ford & Shonkwiler, 1994; Kalaitzandonakes & Dunn, 1995; Richards & Jeffrey, 2000). However, due to compositional differences in the data from the two study regions, only two measures could be specified for each of the BREED and FEED indexes. Given that one of these must be normalized to unity for estimation purposes (Richards & Jeffrey, 2000), only one indicator retains explanatory power.

Furthermore, given that variables are expressed in aggregate value terms and the concern that the latent managerial constructs may not contain a sufficient degree of variability to be completely identified, it is considered prudent to specify several possible models and select the most appropriate model based on various measures of model fit. In an effort to remain comprehensive and ensure the best possible fit of the model to the data, six possible models have been specified, each with a different combination of structural and measurement variables.

The primary reason for a multi-model specification is to test the relevance of the latent managerial constructs (BREED, FEED, and LABOUR). Testing of these variables is important as data restrictions have resulted in BREED and LABOUR possessing only two indicator variables, of which one is standardized to unity for estimation purposes. Given the aggregate nature of the data, there is concern that there may not be sufficient variability in the indicators to full identify the latent constructs. Rather than overlook this potential caveat it is considered prudent to compare a number of different model specifications and select the model most suited to the dataset.

The six models are specified below:

Model 1:  $PERF = Herd + MilkKL + Spec + Trade + BREED + FEED + LABOUR$

Model 2:  $PERF = Herd + MilkKL + Spec + Trade + BREED + FEED$

Model 3:  $PERF = Herd + MilkKL + Spec + Trade + FEED + LABOUR$

Model 4:  $PERF = Herd + MilkKL + Spec + Trade + FEED$

Model 5:  $PERF = Herd + MilkKL + Spec + Trade$

Model 6:  $PERF = Herd + MilkKL + Spec + Trade + Lablitre + Allitre + feedratio$

Models one to five vary only in their inclusion/exclusion of the three latent management indices whereas model six has been specified to include one measure from each of these three management indices as structural variables. The final model is therefore not considered a MIMIC model but rather an application of conventional SEM.

Model estimation and fit analysis was conducted using the statistical software program R (R Core Team, 2015). The plm package (Croissant & Millo, 2008) was used to ensure the data were modelled with a panel data framework. The lavaan package (Rosseel, 2012) was used to model

the specified equations within a MIMIC model framework, with parameter estimation carried out using maximum likelihood methods. Relevant fit indices were also generated using the lavaan package (Rosseel, 2012).

#### **7.4 Empirical results and discussion of the MIMIC model**

The two foremost goals of structural equation modelling are the assessment of goodness of fit and the subsequent estimation of model parameters. Estimation of model parameters is subject to several possible estimation techniques, although in this instance maximum-likelihood estimation was adopted due to its prevalence in the literature, relative ease of application, and accessibility of modelling software utilising this technique. Assessing model fit has been identified as a prominent issue which plagues applications of structural equation modelling (Fan *et al.*, 1999). It is not a straightforward procedure as in traditional statistical approaches where variables are measured without error (Schermelleh-Engel *et al.*, 2003). Since there is no single test of statistical significance to identify the most appropriate model, it is necessary to evaluate model fit based on several criteria. The two most popular methods of evaluating model fit are based on (1) the  $\chi^2$  goodness-of-fit statistic; and (2) various descriptive measures of model fit to the sampled data, otherwise known as fit indexes (Hu & Bentler, 1999; MacCallum *et al.*, 1996).

The  $\chi^2$  goodness-of-fit statistic, traditionally used in model selection, assesses the discrepancy between the sample covariance matrix and the (fitted) covariance matrix produced by the specified models (Fan *et al.*, 1999). In an effort to supplement the  $\chi^2$  statistic, and avoid some of the associated sample size and distributional misspecification problems, a number of fit indices have been developed. These fit indices can be broadly categorized into absolute and incremental fit indexes (Hu & Bentler, 1999). Absolute fit indices assess how well a hypothesized model represents the sampled data by assessing the degree to which the fitted covariance matrix has accounted for the original sample covariance matrix. Incremental fit indices, on the other hand, quantify the proportionate improvement in model fit by comparing the hypothesized model with a more restrictive, nested, baseline model (Hu & Bentler, 1999; Fan *et al.*, 1999).

Identification of the most appropriate model is a topic of debate among the literature for several reasons. Firstly, determining the adequacy of fit indexes using different sampled data and under differing model conditions is a problem often encountered in applied research. Differing model conditions refer to the potential sensitivity of fit indices to sample size, model misspecification,

estimation technique, violation of normality and independence assumptions, and bias resulting from model complexity (Hu & Bentler, 1999). This potentially results in fit indices pointing to conflicting conclusions regarding the extent to which a model matches the observed data (Schermelleh-Engel *et al.*, 2003), which in turn generates uncertainty regarding model selection.

Secondly, there is a large selection of fit indices at a researcher's disposal, which raises the questions: which fit indices should be reported, and which indices should be considered most influential in model selection? These indices were developed under different theoretical rationales which makes comparison between different indices difficult and makes it almost impossible to select a single best index (Fan *et al.*, 1999). Finally, there is a great deal of debate concerning conventional cut-off criteria for the various fit indices. Although specific cut-off criteria have been proposed by several researchers for given fit indices, the adequacy and rationale for these criteria are often questioned. Since these indices may be affected by several study specific factors such as sample size, estimation methods, and distribution of data it could be argued that a universal specific cut-off criterion cannot be adopted (Sharma *et al.*, 2005).

Table 7.1 contains a summary of model fit parameters for the six model specifications highlighted in the previous section. Prior to selecting the most appropriate model it is useful to consider the conventional cut-off criteria traditionally referred to among the literature for each of the fit indices considered herein. Incremental indices will be dealt with first, followed by absolute fit indices and finally model comparison statistics. Firstly, the Tucker-Lewis Index (TLI), or Non-normed Fit Index, and the Comparative Fit Index (CFI) generally range from 1 to 0, with 1 indicating perfect fit. A rule of thumb is that a value of 0.97 or above is indicative of good fit, while a value of 0.95 is indicative of acceptable model fit (Schermelleh-Engel *et al.*, 2003). Caution should be exercised when interpreting TLI, particularly under small sample sizes, as the index can be anomalously small, implying poor model fit, while other indices suggest acceptable model fit (Anderson & Gerbing, 1984, as cited by Bentler, 1990).

Concerning absolute fit indices, the two measures of fit presented in Table 7.1 are the root mean square error of approximation (RMSEA) and the standardized root mean square residual (SRMR). Both descriptive measures provide an indication of overall model fit. Browne & Cudeck (1993), as cited by Schermelleh-Engel *et al.* (2003), and Sharma *et al.* (2005) suggest that RMSEA values less than or equal to 0.05 are an indication of good fit, values between 0.05 and 0.08 may be

considered acceptable fit, values between 0.08 and 0.1 as mediocre fit and values above 0.1 as unacceptable fit. Hu & Bentler (1999) suggest a cut-off value close to 0.06 for RMSEA, while Steiger (2007) considers 0.07 to be an acceptable cut-off criterion.

Table 7.1: Comparison of MIMIC model fit parameters

	Model 1	Model 2	Model 4	Model 5	Model 6
Minimum Function Test Statistic	1119.397	505.094	91.684	4.658	12.887
Degrees of freedom	53	35	20	3	6
P-value (Chi-square)	0	0	0	0.199	0.045
<b>Baseline model test</b>					
Minimum Function Test Statistic	2555.874	1795.296	1080.103	51.041	70.217
Degrees of freedom	72	49	30	9	15
P-value (Chi-square)	0	0	0	0	0
<b>Model vs. Baseline model</b>					
CFI	0.571	0.731	0.932	0.961	0.875
Tucker Lewis	0.417	0.623	0.898	0.882	0.688
<b>Log-likelihood and Information Criteria:</b>					
Log-likelihood user model (H0)	-2439.362	-1159.743	-478.971	-742.136	129.712
Log-likelihood unrestricted model (H1)	-1879.664	-907.196	-433.129	-739.806	136.155
<b>Number of free parameters</b>					
AIC	4934.725	2361.485	987.941	1500.271	-237.424
BIC	5028.176	2431.574	1038.004	1526.971	-200.711
Sample-size adjusted Bayesian (BIC)	4939.458	2365.035	990.477	1501.623	-235.564
<b>Root Mean Square Error of Approximation:</b>					
RMSEA	0.311	0.254	0.131	0.052	0.074
90% Confidence Interval (Lower)	0.295	0.235	0.105	0	0.011
90% Confidence Interval (Upper)	0.327	0.274	0.159	0.137	0.131
P-value RMSEA <= 0.05	0	0	0	0.392	0.200
<b>Standardized Root Mean Square Residual:</b>					
SRMR	0.432	0.162	0.142	0.028	0.038

AIC=Akaike information criterion, BIC=Bayesian information criterion, CFI=Confirmatory Fit Index

\*Model 3 failed to converge and therefore could not be reported

Concerning SRMR, Hu & Bentler (1999) indicated that a cut-off value close to 0.08 appeared to result in lower type II error rates. The authors went on to establish a series of combinational rules between various indices that were able to retain acceptable proportions of true population models and reject various types of misspecified models under most conditions. Furthermore, they suggested that for small sample sizes,  $n < 250$ , combinational rules based on CFI and SRMR are



preferable. For this combination rule, a CFI close to 0.95 and a value of 0.09 or lower for SRMR are recommended for practical applications.

Finally, concerning model comparison, the Akaike information criterion (AIC), Bayesian information criterion (BIC), and the sample-size adjusted BIC (SSABIC) are reported in this study. AIC adjusts  $\chi^2$  for the number of estimated parameters and is used to select the best fitting of several competing models (Schermelleh-Engel *et al.*, 2003). The AIC is non-normed and thus should not be interpreted in isolation but rather compared across competing models. Models with the lowest AIC are considered to be the best approximation of the sampled data. BIC and SSABIC are scaled in such a way that lower values, approaching zero, indicate improved model fit (Enders & Tofighi, 2008).

Analysing the results presented in Table 7.1, bearing in mind the suggested selection criteria outlined above, it is evident that Models 5 and 6 are the only models exhibiting any evidence of potentially acceptable fit. Model 3 failed to converge, therefore, no results could be reported. Models 1, 2, and 4 all exhibit significant  $\chi^2$  test statistics, indicating that the fitted model is not comparable to the population covariance matrix, resulting in a rejection of the null hypothesis of acceptable model fit. Furthermore, RMSEA and SRMR values are well above the conventional rules of thumb. Models 1 and 2 show CFI and TLI values well below the acceptable criteria and very high AIC and BIC values in relation to the other models. Model 4 shows the second highest CFI and TLI values, larger than model 6. Furthermore, the AIC and BIC values indicate that model 4 is preferable to model 5. This is an interesting result, considering the contrasting evidence provided by the various measures of fit.

For model 5, the p-value associated with the  $\chi^2$  test statistic is insignificant, indicating that the fitted model is comparable to the population covariance matrix, supporting the null hypothesis of acceptable model fit. For model 6, the p-value is significant at the 0.05 level indicating unacceptable model fit. This result should be interpreted with caution since there are several potential shortcomings associated with the  $\chi^2$  test statistic. Firstly, the assumptions of multivariate normal observed variables and sufficiently large sample size may not always be fulfilled. Secondly, model complexity is penalized in the sense that the value of  $\chi^2$  typically decreases as parameters are added to the model. Thirdly,  $\chi^2$  is sample size dependent. For increasing sample size and a constant number of degrees of freedom, the value of  $\chi^2$  increases. Therefore, as sample

size decreases, the value of  $\chi^2$  tends to decrease, which may result in the model pointing to an unacceptable fit, when in fact the model may be acceptable (Schermele-Engel *et al.*, 2003). It is therefore considered prudent to analyse several fit measures before drawing any conclusions as to the most acceptable model fit.

TLI and CFI values for model 5 were 0.898 and 0.961, respectively. The CFI value of 0.961 is above the suggested cut-off criteria proposed by Hu & Bentler (1999) but the TLI value of 0.898 is below the suggest cut-off criterion of 0.95 or higher. For model 6, TLI and CFI values were 0.875 and 0.688, respectively, well below the specified cut-off criteria. It is important to highlight that the TLI has been found to be erratic under small sample sizes (Bentler, 1990). RMSEA and SRMR values for model 5 are well below the suggested criteria, although the RMSEA value of 0.074 is marginally above the acceptable cut-off criteria proposed by Steiger (2007).

Rather than compare individual measures of fit, which can provide conflicting evidence, it is posited that the combination rules proposed by Hu & Bentler (1999) are likely to provide a better estimation of model fit, minimizing type I and type II errors. Due to the small sample size of this study, the combination rule involving CFI and SRMR is the most applicable. As mentioned, the CFI value exceeds the cut-off criteria of 0.96, and the reported SRMR value of 0.028 is well below the specified cut-off criteria of 0.09. The RMSEA value of 0.052 reported for model 5 is within the cut-off criteria of 0.06 and 0.07 proposed by Hu & Bentler (1999) and Steiger (2007), respectively. Furthermore, the confidence interval calculated for RMSEA appears to be broadly in line with suggested criteria, with a lower limit equal to zero and an upper limit of 0.137. Adopting these criteria, model 6 appears to be an unacceptable fit, despite exhibiting significantly lower AIC and BIC values.

Table 7.2 presents the maximum likelihood parameter estimates of the structural and measurement equations for models 5 and 6, although focus will remain on model 5, as this is considered the more acceptable model. Results indicate that technical efficiency is statistically significant, suggesting that efficiency is an important indicator of latent economic performance. The coefficient estimate of -0.882 is of expected size and is comparable, in absolute terms, to the value of 0.890 reported for economic efficiency by Richards & Jeffrey (2000). The negative directionality of this relationship is, however, not line with *a priori* expectations or the findings of Richards & Jeffrey (2000).

Table 7.2: MIMIC model parameter estimates

Model 5						
Measurement Equations	Estimate	Std. Err	Z-value	P(> z )	Std. lv	Std. all
PERF =~						
SE	1				0.023	0.391
TE	-0.882	0.247	-3.574	0	-0.02	-0.386
Structural Equations						
Herd	0	0	-0.936	0.349	0	-0.12
MilkKL	0.008	0.003	3.129	0.002	0.347	0.462
Spec	0.071	0.021	3.412	0.001	3.079	0.51
Trade	0.071	0.054	1.311	0.19	3.085	0.167
Variances						
SE	0.003	0	8.062	0	0.003	0.847
TE	0.002	0	8.166	0	0.002	0.851
PERF	0	0	0.734	0.463	0.309	0.309
Model 6						
Latent Variables	Estimate	Std.Err	Z-value	P(> z )	Std.lv	Std.all
PERF =~						
SE	1				0.025	0.431
TE	-0.727	0.188	-3.868	0	-0.018	-0.35
Regressions						
Herd	0	0	0.46	0.645	0	0.063
MilkKL	0.007	0.003	2.686	0.007	0.293	0.39
Spec	0.084	0.024	3.458	0.001	3.315	0.55
Trade	0.049	0.058	0.848	0.396	1.941	0.105
Ailitre	-0.063	0.148	-0.422	0.673	-2.478	-0.056
Lablitre	0.123	0.047	2.624	0.009	4.868	0.415
Feedratio	-0.054	0.02	-2.714	0.007	-2.154	-0.412
Variances						
SE	0.003	0	7.441	0	0.003	0.814
TE	0.002	0	8.845	0	0.002	0.877
PERF	0	0	0.422	0.673	0.17	0.17

One possible explanation may be found by examining the structure of the latent economic performance construct. Due to data limitations, efficiency analysis was limited to technical and scale efficiency leaving only two measures of economic performance to ensure identification. In a similar study by Richards & Jeffrey (2000), measures of technical, allocative and economic efficiency were included as indicators of latent economic performance. Furthermore, two of the three efficiency measures were normalized to zero to identify the economic performance construct. It is possible that using two measures of efficiency was not sufficient to fully identify latent economic performance. Another possibility is that the negative relationship observed between

technical efficiency and time was captured by the economic performance construct, resulting in a negative relationship between the two.

Unfortunately, per model selection criteria, all models incorporating BREED, FEED and LABOUR indices were not preferable to model 5, which represents an overly simplified version of the model originally proposed. Models incorporating latent managerial indices were most likely rejected due to the identification concerns highlighted prior to estimation, and due to limited variability in the measures used to identify the latent managerial constructs. Although no results were generated from these constructs, some important insights can be drawn from this result. Firstly, prior to estimation, future research should ensure that there are sufficient data, and variability in the data, to develop strong indicators of these latent constructs.

Regarding breeding management quality (BREED), the following improvements are proposed: (1) Since herd composition is an important indicator of managerial ability, at least one measure of herd composition should be incorporated as a measure of latent breeding quality. Calf-cow ratio, ratio of dry cows to cows in milk, and average time between calving are three possible measures for future consideration. (2) AI costs may not accurately proxy genetic progress, since farmers do not always accurately represent this expense in farm records, resulting in misleading results. Furthermore, farmers using bulls were naturally assigned AI costs of zero, implying no expenditure on genetic progress. AI is not the only means of improving on farm genetics. The use of carefully selected breeding bulls is also a viable means of improving herd genetics. Since the price of a bull essentially reflects its genetic potential, it should be incorporated as a measure of breeding quality, perhaps in conjunction with AI.

Concerning feed management (FEED), the variables included as indicators of latent feeding management are considered acceptable, although several possible improvements are suggested. Firstly, expressing variables in value terms is not advisable as price and quantity effects become conflated. Deflating variables by appropriate price indices is a common remedy, although these indices are not able to fully remove the effect of price. This means results may be influenced by some aspect of price underlying the data, potentially reducing the accuracy of the results and resulting in misleading interpretations. An important limitation of this study lies in the fact that each variable was not deflated by an appropriate price index; instead all variables were adjusted for inflation. Thus, price movements, outside of inflation may have influenced the results to some

extent. To counter this, it would be ideal to use a specific price index relevant to each variable considered in the analysis. For example, when considering purchased feed, it would have been more appropriate to have deflated prices by an actual feed price index created using historical prices of purchased dairy feeds. This would ensure that any changes in price over time would be correctly accounted for. One potential limitation with this approach would be sourcing the necessary data to facilitate the construction of such indices.

These difficulties can be overcome by using data expressed in quantities, if possible, although these data are not often available in South African agricultural research, as farmers do not typically keep such meticulous records. Secondly, a useful measure of latent feed management quality may be the quantity of concentrates, expressed in kilograms, fed per litre of milk. This is expected to give an indication of what proportion of a cow's nutrient requirement is met using pasture and homegrown feed.

Finally, regarding latent labour quality (LABOUR), several improvements are proposed. Firstly, where possible, data expressed in quantities rather than in value terms should be used, due to the reasons outlined above. In addition, knowledge of the employment structure of the farms would be beneficial, allowing labourers of differing skills to be differentiated from one another. This is not possible when using aggregate value data. Secondly, additional measures of labour should be considered to improve identification and explanatory power of the latent construct. One possible measure for future consideration is the capital to labour ratio used by Richards & Jeffrey (2000).

In addition to the three latent indices defined in this study, it may be beneficial, data permitting, to incorporate several financial measures into an index of financial management. Following Ford & Shonkwiler (1994), a financial management index may be constructed from several financial measures including the equity/asset ratio, interest expense as a portion of total cash expenses, debt per cow, and gross profit margin. This could be extended to include measures of liquidity and solvency such as the debt/asset ratio and leverage. Given the relatively high capital investment in modern dairying, an investigation into the effects of latent financial management ability could be highly beneficial and yield some interesting results. The primary limitation in this case is data availability.

Concerning the structural equation estimates presented in Table 7.2, coefficient estimates for milk production per cow, expressed in kilolitres (MilkKL) and level of specialization (Spec), were

statistically significant and exhibited positive signs. On the other hand, estimated coefficients for herd size (Herd) and trading income (Trade) were statistically insignificant. The significance of MilkKL and Spec is in line with expectations. The positive relationship between milk yield and economic performance is substantiated by the findings of Richards & Jeffrey (2000). The non-significance of the herd size parameter estimate is unexpected and does not correspond to the findings of Richards & Jeffrey (2000).

These results suggest that farmers may improve economic performance by improving milk yields per cow. Furthermore, income associated with the sale of dairy livestock, in the form of calves, heifers and cull cows, appears to be a viable means of improving economic performance for the sampled dairy farms. Post estimation model selection favoured the selection of the simplest model, meaning the effects of the three latent managerial indices on economic performance could not be investigated.

Although some of the findings of this study are not in accordance with prior expectations and previous research, this study represents a valuable attempt to model the economic performance of South African dairy farmers at a level of integration not yet seen in the South African literature. Several possible reasons for these results are presented below. Firstly, data have been deflated using a general price index rather than individual price indexes which would account for price changes specific to each variable. This lack of detail in deflating prices means that the effect of price may have confounded the results. Secondly, due to data limitations, latent BREED and LABOUR indices were constructed using only two indicators, in the hope that this would be sufficient for identification. It appears, therefore, that the data used in this analysis did not contain sufficient detail to support the calculation of the latent managerial indices, leading to poor identification. Finally, the use of technical and scale efficiencies as indicators of economic performance may not have been sufficient to completely identify latent economic performance as was hoped. In general, it appears that the data did not contain sufficient detail to facilitate the calculation of the MIMIC model originally proposed.

However, this study has provided valuable information regarding the investigation of farm performance on a more integrated level than traditionally considered and provides a good theoretical and statistical foundation upon which future research can improve. In assessing the limitation of this study, several suggestions have been made for future researchers to consider. It

remains the view of the author that the methodology outline in this study has the potential to provide valuable information on the aspects of dairy farming not investigated in traditional productivity analysis. These include feeding, breeding and labour management quality, and it is proposed that the inclusion of latent financial management quality would allow for a highly valuable study, with new insights into the factors affecting the true economic performance of South African dairy farms. If data with the required level of detail can be obtained, the methodology outlined in this study should provide some interesting results. In the face of continued industry consolidation, more integrated research is needed to determine what factors truly drive economic performance.

## CONCLUSION

This study used a two-stage approach to investigate the factors affecting the economic performance of a group of commercial milk producers from East Griqualand in southern KwaZulu-Natal and the northern parts of the Eastern Cape Province, and Alexandria in the Eastern Cape Province of South Africa. In the first stage, technical efficiency (TE) and scale efficiency (SE) were calculated through the specification of a production technology and subsequent estimation using parametric techniques. In the second stage, estimated TE and SE scores were incorporated into the analysis of economic performance, using structural equation modelling techniques. For the purposes of this study economic performance is defined as a latent, unobservable variable for which there exist many imperfect indicators, including various measures of efficiency.

Prior to estimation, several popular functional forms and distributional assumptions were modelled and subjected to likelihood ratio testing. Results suggest the translog production function with truncated normal distributional and time variant efficiency most accurately represented the underlying milk production technology. Stochastic frontier analysis was then used to estimate individual levels of TE for the sampled farms. The dataset used in the study was comprised of an unbalanced panel of financial and production data for 13 East Griqualand and 13 Alexandria milk producers, spanning a period of 8 years (2007-2014). Missing data analysis revealed that missing observations were missing completely at random (MCAR) and multiple imputation was implemented to deal with the missing data.

Estimated production frontier results suggest that dairy production exhibits increasing returns to scale and, of all input variables, total feed cost is most important in explaining the variability in dairy output, followed by herd size and capital expenditure. These findings are consistent with those of several international studies on the productivity of dairy farms. The smooth time trend included to capture the effects of technological progress did not have a statistically significant coefficient estimate, implying a lack of technological progress. This result should be interpreted with caution as the manner of its inclusion represents a crude approach to the measurement of technical change.

The mean level of TE in the East Griqualand and Alexandria samples was 86.5% and 88%, respectively, indicating that farms were producing between 13.5% and 12% below their potential due to inefficient means of production. These TE scores are well within the bounds highlighted by



the previous literature. While this may appear to suggest that South African commercial milk producers are at least as technically efficient as many of their international counterparts, this result should be interpreted with caution. Cross-study comparisons offer limited insight since they implicitly assume that the best practice farms, representing the estimated production frontier, are good estimates of the true production frontier, an assumption that may not be true in reality. These results suggest that, from a technical point of view, farms could expand milk production using the current levels of input and technology available. Farmers in East Griqualand and Alexandria can improve their productivity and technical efficiency simply by taking advantage of more efficient farming practices. Some examples may include; improved milking parlours, advanced herd management software, advanced pasture management systems, improved grass cultivars, and custom feed rations for each cow based on milk production potential.

Results indicate a reasonably high degree of homogeneity both among producers within the same region and between different regions. This result is not surprising considering all sampled farms are specialized milk producers, deriving more than 80% of total revenue from the dairy enterprise. Mean levels of TE have generally declined over the study period, indicating that farms on the best practice frontier are becoming more efficient through time, while the average farm has become less efficient in relation to the advancing frontier. Although the reasons as to why this is occurring cannot be answered through the results of this analysis, there are some possible explanations based on intuition and the previous literature. Essentially, the diffusion of technical advances from frontier farms appears to have slowed, increasing the delay between innovative farmers adopting new technologies and the average farmer adopting them. Further research is required to investigate this.

The mean level of scale efficiency over the study period was 95.2% implying that farms could have improved output by 4.8% had they operated at optimal scale. This confirms that most farms do not experience a substantial loss in output due to scale efficiency problems. Results suggest that very few farms, approximately 11%, operated at optimal scale. The majority of farms operated at suboptimal scale, indicating increasing returns to scale. Farms operating at suboptimal scale benefit from increased output, which brings them toward optimal scale. From a policy viewpoint, these results have important implications. If improved efficiency is desired then, given the observed trend towards larger dairy farms, it would be better to encourage farm expansion than to

discourage it. In practice, encouragement to expand is unlikely to stem from state intervention, government policies, or programmes, but rather from agricultural consultants promoting expansion based on the associated efficiency improvements.

It is worth noting that farms operating at supra-optimal scale, decreasing returns to scale exhibited higher levels of mean SE, closer to the values associated with optimal scale. In other words, the mean SE gap between supra-optimal and optimal farms was notably smaller than that between suboptimal and optimal farms. The degree of technical efficiency was found to be lower than that of scale efficiency, indicating a greater portion of overall inefficiency is due to operating below the efficient frontier, rather than due to operation at an inefficient scale.

For the second stage, several possible MIMIC models were specified due to concerns regarding the identification of the three managerial indices BREED, FEED, and LABOUR. Analysis of the resulting model fit identified the most simplistic model, including none of the proposed management indices as the best fitting. Empirical results pertaining to this model indicate that technical efficiency is a significant determinant of economic performance, although the negative coefficient estimate is not supported by the relevant literature. Of the structural variables, milk yield per cow and the level of specialization were identified as determinants of farm economic performance. This implies that farmers may improve their levels of economic performance by focusing resources and management efforts on improving milk yield per cow and by becoming more specialized in dairying.

This study addressed some gaps in previous local research on the productivity of milk producers by: (1) evaluating, prior to estimation, several functional forms, each with one of two popular distributional assumptions regarding the inefficiency term. Previous local research has generally not invested much time in the *ex-post* selection of functional forms and distributional assumptions, typically considering two functional forms at most; (2) estimating parametric scale efficiency from the translog production function, an approach which has not been applied in local research; and (3) investigating farm performance at an integrated level using a latent variable approach, incorporating estimated efficiencies in a second stage analysis.

The results of this study can be used by milk producers, policy makers, agricultural consultants, and other industry players to better understand milk production technology and the dynamics of technical and scale efficiency on South African dairy farms. The lack of research on the

productivity of the local dairy industry needs to be addressed as it is concerning that there is such a large body of literature on this topic pertaining to other important milk producing countries, yet very few studies employ these techniques at the domestic level. This would ensure that farmers and policy makers have access to relevant and reliable information, facilitating the decision making process and assisting them to make informed decisions.

Areas for further research include: (1) extending efficiency analysis to consider the effect of price, thereby facilitating the estimation of allocative and economic efficiency, in addition to technical efficiency. Including three measures of efficiency as indicators of latent economic performance is expected to improve identification in the estimation of the MIMIC model. (2) Specifying a minimum of three indicators for each of the latent managerial constructs to improve identification and explanatory power. For the breeding index, cow-calf ratio and the ratio of dry cows to cows in milk are two indicators of herd composition that may be valuable. Furthermore, the cost associated with natural breeding (cost of bulls) should be incorporated into breeding cost as this represents a viable means of genetic improvement. For the feed index, the quantity of dairy concentrates fed per cow or per unit output may be a valuable addition. (3) Constructing a latent index of financial management ability may add a great deal of value since aspects financial performance are seldom incorporated into farm level analysis. Factors such as the equity/asset ratio, debt/asset ratio, interest expense as a portion of total cash expenses, debt per cow, and gross profit margin could be valuable indicators of financial managerial ability; and (4) extending sample size to levels typically seen in the international literature may be beneficial, particularly when using SEM methods.

## SUMMARY

The South African dairy industry, and the dairy industries of many other important milk producing countries, has undergone significant structural change in recent years, with an observed consolidation trend towards fewer, larger milk producers. This is indicative of a more competitive milk market. In the face of increased competition, the economic efficiency of a milk producer's operation is likely to become an increasingly important determinant of farm financial success and survival in the industry. Furthermore, it is important that farmers understand the key drivers behind the success or failure, facilitating the decision to remain in business or exit the industry. Due to the imperfect nature of efficiency measures, farm performance was investigated at a more integrated level than traditionally considered. This involved specifying true farm performance as a latent variable, for which there exist many imperfect indicators, including traditional measures of efficiency.

For the purposes of this study, individual milk producer data were collected from the East Griqualand and Alexandria study groups for the period 2007 to 2014. Data collected comprised production and financial records for each of the sampled farms. Total sample size was 208 observations (26 farms x 8 years), although data omissions for some of the years resulted in an unbalanced panel. Missing data analysis confirmed data were missing completely at random (MCAR), supporting the use of multiple imputation using the Markov Chain Monte Carlo method to estimate the missing values. East Griqualand (EG) refers to the southern parts of KwaZulu-Natal, such as Kokstad, and northern parts of the Eastern Cape, such as Matatiele and Cedarville. The area is characterized mainly by natural sourveld grazing, relatively high rainfall (500-800mm per annum), and moderate temperatures (8.1-14.8°C mean annual temperature). This facilitates the growth of good natural and artificial pasture and may reduce the incidence of heat stress. Alexandria is a small farming town located close to the coast in the south-western corner of the Eastern Cape Province. The area is characterized by relatively high rainfall (500-700mm) but is notably warmer than the EG region (17.7-20.6°C mean annual temperature). Farms in both regions are predominantly pasture based, feeding purchased feed and concentrates to meet nutritional shortfalls.

The primary objective of this study is to determine the factors contributing to the economic performance of a panel of commercial milk producers from East Griqualand and Alexandria for

the period 2007-2014. This was to be achieved by addressing several specific objectives, including: determining the most appropriate functional form and distributional assumption, estimating technical and scale efficiencies, and determining if size economies are present on the sampled farms. Regarding economic performance, specific objectives included modelling economic performance in a latent variable framework, identifying the relative effects of the cause and indicator variables, including TE and SE, on economic performance, and subsequently identifying means of improving economic performance on the sampled dairy farms.

The first section of the study focused on the ex-post selection of the most appropriate milk production technology, and distribution assumption regarding the technical inefficiency term ( $u$ ). Cobb-Douglas, simplified translog, translog, Generalized Leontief, and normalized quadratic functional forms, each with either a half-normal or truncated normal distribution, were specified and subjected to likelihood ratio testing. Results showed that the translog model with truncated normal distribution was the best representation of the underlying milk production technology. Stochastic frontier analysis was used to estimate the individual levels of technical efficiency on the sampled farms over the study period. In the translog production function, aggregate dairy output, represented by the sum of total revenue from milk sales and livestock trading, was selected as the dependent variable, with herd size (H), total expenditure on purchased and home-grown feed (F), expenditure on veterinary products and services (V), total wage bill (L), the cost of capital (K), a regional dummy variable (D), and a smooth time trend variable (T) intended to capture technological progress, were included as independent variables.

Results showed that herd size, total feed expense, and the cost of capital positively influenced dairy output, while veterinary expense and labour did not influence dairy output for the sampled farms. Mean levels of technical efficiency indicate that milk producers in both regions are highly efficient, with most farms exhibiting TE scores between 90 and 100%. Furthermore, evidence suggests that a high degree of homogeneity between milk producers exists at both the inter and intra-regional level. Mean TE scores over the study period generally declined, indicating farms on the best practice frontier became more efficient through time, while the average farm has become less efficient in relation to the advancing frontier. Parametric scale efficiency was calculated from the parameters and scale elasticities estimated during the calculation of TE, using the methodology proposed by Ray (1998). Results of this analysis suggest that milk producers are highly scale

efficient in production and do not experience any substantial losses in output due to problems associated with non-optimal scale. Furthermore, it was observed that most of the sampled dairy farms operated with increasing returns to scale and would benefit from an increase in dairy output.

The second section of the study focused on modelling economic performance within a structural equation modelling framework. In this analysis, TE and SE estimated in the first stage of the study were included as indicators of a farm's latent economic performance. In addition, three latent indexes were constructed to represent the managerial quality of a producer's breeding, feeding and labour programme. These latent indices were included as explanatory variables in the structural equation along with herd size ( $Herd_{it}$ ), milk yield per cow ( $MilkKL_{it}$ ), trading income from the sale of livestock ( $Trade_{it}$ ), and the level of specialization in the dairy industry ( $Spec_{it}$ ).

Due to identification concerns regarding the latent constructs, several models were specified to test the inclusion of the latent managerial indices. A comprehensive assessment of model fit revealed the most simplistic model to be the most suitable. Results indicated that TE, level of specialization, and milk yield per cow influenced latent economic performance, while herd size and trading income did not. The use of too few measurement items in the construction of the latent managerial indices, in conjunction with lack of variability in these items, most likely led to poor identification and the subsequent exclusion of these indices from the final analysis. In future, the use of a greater number of more diverse indicators is suggested when constructing these latent indices. Furthermore, incorporating an index of financial managerial ability, indicated by several common measures of financial performance is an area for future research. Finally, future research would do well to investigate allocative and economic efficiencies, in addition to technical efficiency, as the effects of price should be considered in a holistic analysis of farm performance. Furthermore, including three measures of efficiency as indicators of latent performance is expected to improve identification and explanatory power in the secondary analysis.

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## APPENDIX

### APPENDIX 1: MISSING DATA ANALYSIS

#### Univariate Statistics

	N	Mean	Std. Deviation	Missing		No. of Extremes <sup>a</sup>	
				Count	Percent	Low	High
Y	205	11123119.742 27	6032294.1505 95	3	1.4	0	0
V	205	659437.45023 4	850987.19761 4	3	1.4	0	10
L	205	624022.59188 5	316425.43869 5	3	1.4	0	1
F	205	5491065.2445 8	3147075.0867 79	3	1.4	0	1
H	205	496.04455	242.624228	3	1.4	0	5
K	205	1746398.2054 5	1072480.1035 47	3	1.4	0	9
T	208	4.50000	2.296816	0	.0	0	0

a. Number of cases outside the range (Q1 - 1.5\*IQR, Q3 + 1.5\*IQR).

#### Missing Patterns (cases with missing values)

Case	# Missing	% Missing	Missing and Extreme Value Patterns <sup>a</sup>							Variable Values					
			T	V	L	F	H	K	Y	Y	V	L	F	H	K
35	6	85.7		S	S	S	S	S	S						
96	6	85.7		S	S	S	S	S	S	.	.	.	.	.	.
120	6	85.7		S	S	S	S	S	S	.	.	.	.	.	.

- indicates an extreme low value, while + indicates an extreme high value. The range used is (Q1 - 1.5\*IQR, Q3 + 1.5\*IQR).

a. Cases and variables are sorted on missing patterns.

**EM Correlations<sup>a</sup>**

	Y	V	L	F	H	K	T
Y	1						
V	.483	1					
L	.775	.494	1				
F	.918	.408	.638	1			
H	.898	.541	.789	.762	1		
K	.775	.618	.788	.589	.867	1	
T	.218	.358	.277	.191	.274	.308	1

a. Little's MCAR test: Chi-Square = 1.939, DF = 1, Sig. = .164



## 2.2: Condition index and variance decomposition for the Translog model

Condition Index	Variance Decomposition Proportions																													
	$\beta_0$	$\beta_V$	$\beta_L$	$\beta_F$	$\beta_H$	$\beta_K$	$\beta_{LL}$	$\beta_{VV}$	$\beta_{FF}$	$\beta_{HH}$	$\beta_{KK}$	$\beta_{HL}$	$\beta_{HV}$	$\beta_{HF}$	$\beta_{HK}$	$\beta_{LV}$	$\beta_{LF}$	$\beta_{LK}$	$\beta_{VF}$	$\beta_{VK}$	$\beta_{FK}$	$\zeta$	$\lambda$	$\beta_{HT}$	$\beta_{LT}$	$\beta_{VT}$	$\beta_{FT}$	$\beta_{KT}$	$\alpha$	
1.0	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
2.1	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
2.8	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
4.5	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
5.6	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
5.7	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
6.8	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
7.8	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
8.0	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
9.7	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
10.8	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
12.2	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
16.0	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.40
18.9	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
25.8	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
27.6	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
34.0	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
35.6	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
43.3	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.47	.	.	.	.	.	.	.	.	.	.	.	.	.	.
44.4	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
52.2	.	0.38	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
54.2	.	.	.	.	.	0.47	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
56.3	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.31	.	.	.	.	.	.	0.34	.	.	.	.
63.8	.	.	.	.	.	.	.	.	.	.	.	.	0.32	.	.	.	.	.	.	.	.	0.30	0.32	.	.	.	.	.	.	.
71.0	.	.	.	.	.	.	.	.	.	.	0.35	.	.	.	.	.	0.52	.	.	.	.	.	.	.	.	.	.	.	.	.
76.0	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.47	0.44	.	.	.	.	.	.	.	.	.	.	.	.
81.5	0.45	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.63	0.55	.	.	.	.	.	.	.
89.5	.	.	.	.	.	.	.	.	.	0.42	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
142.3	.	.	.	.	.	.	.	.	0.84	.	.	.	0.72	0.65	.	.	.	.	.	.	0.33	.	.	.	.	.	.	.	.	.

## 2.3: Condition index and variance decomposition for the Cobb-Douglas model

Condition Index	Variance decomposition proportions							
	$\beta_0$	$\beta_V$	$\beta_L$	$\beta_F$	$\beta_H$	$\beta_K$	$\zeta$	$\alpha$
1	.	.	.	.	.	.	.	.
3.987	.	.	.	.	.	.	.	.
6.557	.	.	.	.	.	.	0.88	.
42.845	.	.	.	.	.	.	.	.
83.421	.	0.86	.	.	.	.	.	.
132.819	.	.	0.60	.	.	.	.	.
211.077	.	.	0.38	.	.	0.91	.	.
224.593	0.50	.	.	0.96	0.45	.	.	0.56

### APPENDIX 3: WITHIN MODEL LIKELIHOOD RATIO TESTS

Cobb-Douglas LR tests

Model	# DF	LogLik	Df	Chisq	Pr>(Chisq)	Decision
OLS	9	176,84				
CDhn	10	198,44	1	43,209	2,46E-11 ***	CDhn
OLS	9	176,84				
CDtn	11	203,21	2	52,741	1,07E-12 ***	CDtn
OLS	9	176,84				
CDhnVAR	11	201,02	2	48,364	9,64E-12 ***	CDhnVAR
OLS	9	176,84				
CDtnVAR	12	205,1	3	56,524	1,09E-12 ***	CDtnVAR
CDhn	10	198,44				
CDtn	11	203,21	1	9,532	0,002019 **	CDtn
CDhn	10	198,44				
CDhnVAR	11	201,02	1	5,1549	0,02318 *	CDhnVAR
CDtn	11	203,21				
CDtnVAR	12	205,1	1	3,783	0,05178 .	CDtnVAR
CDhnVAR	11	201,02				
CDtnVAR	12	205,1	1	8,1601	0,004282 **	CDtnVAR

Most Suitable model: CDtnVAR

Simplified translog LR tests

Model	# DF	LogLik	Df	Chisq	Pr>(Chisq)	Decision
OLS	15	181,17				
STLhn	16	203,76	1	45,181	8,98E-12 ***	STLhn
OLS	15	181,17				
STLtn	17	209,13	2	55,933	2,16E-13 ***	STLtn
OLS	15	181,17				
STLhnVAR	17	205,84	2	49,352	5,87E-12 ***	STLhnVAR
OLS	15	181,17				
STLtnVAR	18	210,67	3	59,001	3,21E-13 ***	STLtnVAR
STLhn	16	203,76				
STLtn	17	209,13	1	10,752	0,001041 **	STLtn
STLhn	16	203,76				
STLhnVAR	17	205,84	1	4,1714	0,04111 *	STLhnVAR
STLtn	17	209,13				
STLtnVAR	18	210,67	1	3,0672	0,07989 .	STLtnVAR
STLhnVAR	17	205,84				
STLtnVAR	18	210,67	1	9,6483	0,001895 **	STLtnVAR

Most suitable model: STLtnVAR

Translog LR tests

Model	# DF	LogLik	Df	Chisq	Pr>(Chisq)	Decision
OLS	30	206,11				
TLhn	31	223,46	1	34,697	1,93E-09 ***	TLhn
OLS	30	206,11				
TLtn	32	226,78	2	41,343	3,27E-10 ***	TLtn
OLS	30	206,11				
TLhnVAR	32	224,42	2	36,622	3,51E-09 ***	TLhnVAR
OLS	30	206,11				
TLtnVAR	33	228,13	3	44,042	5,14E-10 ***	TLtnVAR
TLhn	31	223,46				
TLtn	32	226,78	1	6,6458	0,009939 **	TLtn
TLhn	31	223,46				
TLhnVAR	32	224,42	1	1,9253	0,1653	NSD
TLtn	32	226,78				
TLtnVAR	33	228,13	1	2,6992	0,1004	NSD
TLhnVAR	32	224,42				
TLtnVAR	33	228,13	1	7,4197	0,006451 **	STLtnVAR

Most Suitable model: TLtn or TLtnVAR

Generalized Leontief LR tests

Model	# DF	LogLik	Df	Chisq	Pr>(Chisq)	Decision
OLS	30	176,37				
GLhn	31	196,55	1	40,358	1,06E-10 ***	GLhn
OLS	30	176,37				
GLtn	32	199,63	2	46,533	2,42E-11 ***	GLtn
OLS	30	176,37				
GLhnVAR	32	197,19	2	41,649	2,81E-10 ***	GLhnVAR
OLS	30	176,37				
GLtnVAR	33	200,57	3	48,407	5,99E-11 ***	GLtnVAR
GLhn	31	196,55				
GLtn	32	199,63	1	6,1753	0,01295 *	GLtn
GLhn	31	196,55				
GLhnVAR	32	197,19	1	1,2914	0,2558	NSD
GLtn	32	199,63				
GLtnVAR	33	200,57	1	1,8739	0,171	NSD
GLhnVAR	32	197,19				
GLtnVAR	33	200,57	1	6,7578	0,009334 **	GLtnVAR

Most Suitable model: GLtn or GLtnVAR



Normalized Quadratic LR tests

Model	# DF	LogLik	Df	Chisq	Pr>(Chisq)	Decision
OLS	30	177,99				
NQhn	31	201,63	1	47,28	3,08E-12 ***	NQhn
OLS	30	177,99				
NQtn	32	204,99	2	54,006	5,69E-13 ***	NQtn
OLS	30	177,99				
NQhnVAR	32	202,7	2	49,413	5,69E-12 ***	NQhnVAR
OLS	30	177,99				
NQtnVAR	33	206,41	3	56,842	9,33E-13 ***	NQtnVAR
NQhn	31	201,63				
NQtn	32	204,99	1	6,7261	0,009501 **	NQtn
NQhn	31	201,63				
NQhnVAR	32	202,7	1	2,1337	0,1441	NSD
NQtn	32	204,99				
NQtnVAR	33	206,41	1	2,8365	0,09215 .	NQtnVAR
NQhnVAR	32	202,7				
NQtnVAR	33	206,41	1	7,4289	0,006418 **	NQtnVAR

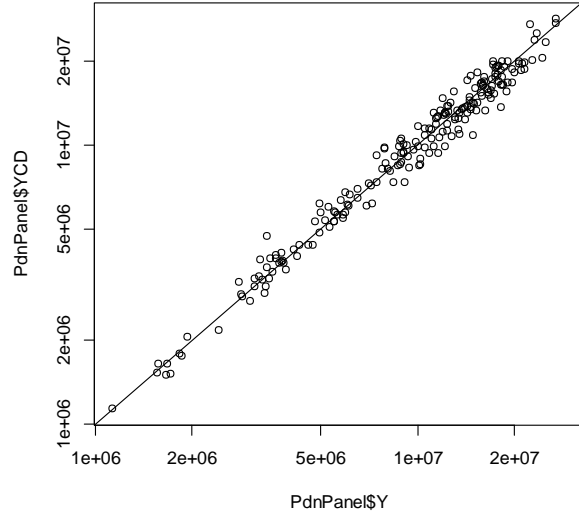
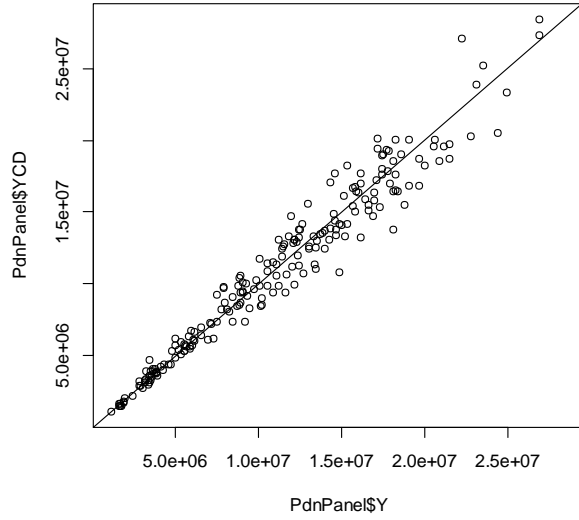
Most suitable model: NQtnVAR

Significance codes

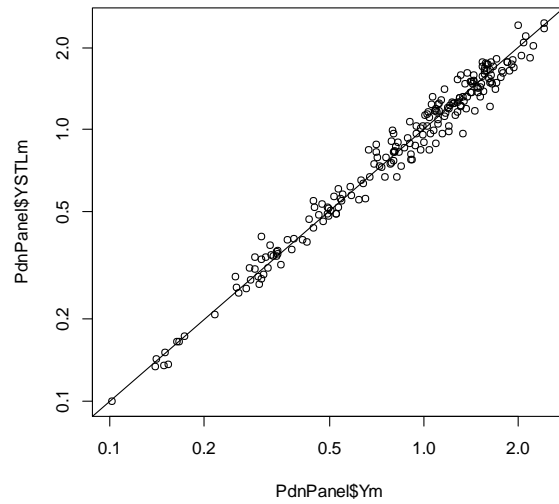
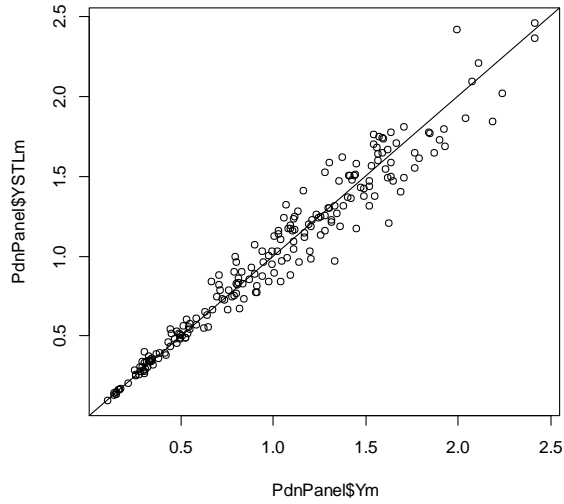
Code	Value	Confidence level
***	0,001	99,9%
**	0,01	99%
*	0,05	95%
.	0,1	90%

## APPENDIX 4: RESIDUAL PLOTS DEMONSTRATING GOODNESS OF FIT

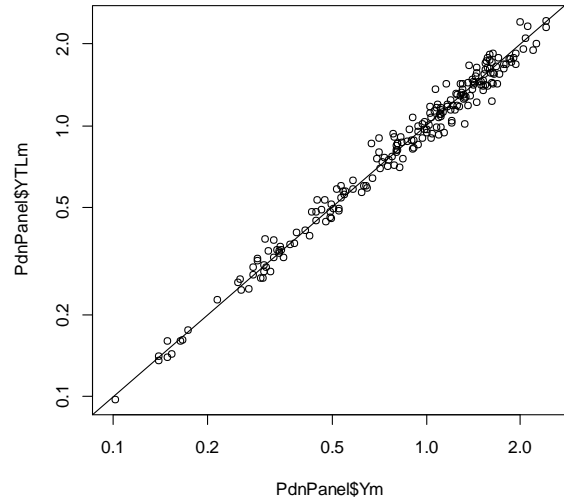
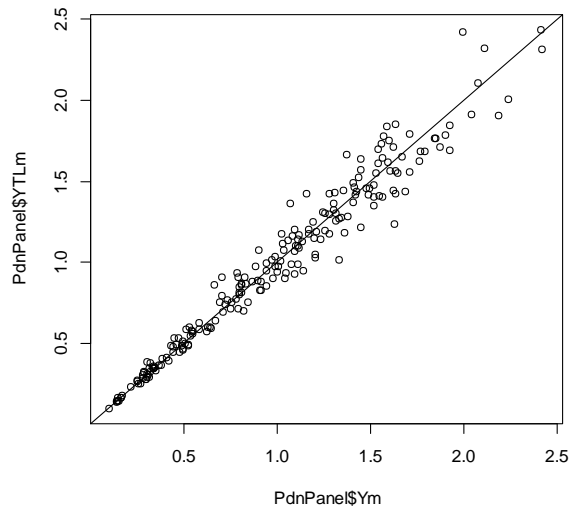
### 4.1: Cobb-Douglas functional form



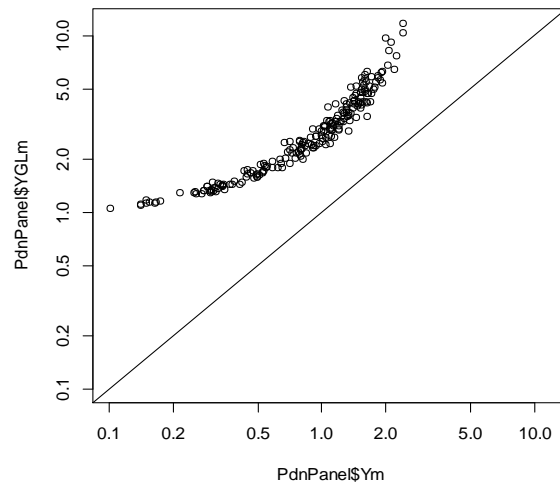
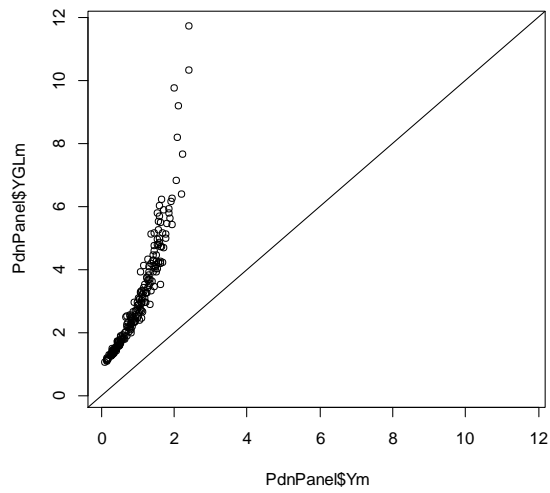
### 4.2: Simplified translog functional form



### 4.3: Translog functional form



### 4.4: Generalized Leontief functional form



## 4.5: Normalized Quadratic functional form

