

**STOCHASTIC NON-PARAMETRIC
FRONTIER ANALYSIS IN
MEASURING TECHNICAL EFFICIENCY**

**A CASE STUDY OF THE NORTH AMERICAN
DAIRY INDUSTRY**

A Thesis Submitted to the College of
Graduate Studies and Research
In Partial Fulfillment of the Requirements
For the Degree of Ph.D. in the
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ABSTRACT

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Regulatory institutions governing many industries in Canada are similar to those of the United States. Some differences in regulations and institutions can be found in those industries for which the two countries compete in export markets, and many agricultural products fall into the latter category. With respect to the production and export of dairy products, Canada has recently implemented policies that are substantially different from those found in the U.S.

Differences in dairy policy have been the source of several recent trade disputes between the two countries. Despite efforts to the contrary by participants in the major policy agreements governing agricultural trade (i.e., CUSTA; NAFTA, and WTOA), the regulated structure of the Canadian dairy industry has been maintained. The U.S. and New Zealand have challenged the marketing practices of the supply managed by Canadian dairy sector. These policies have a direct impact on the productive efficiency of dairy farms. In this regard, the dairy industry in Canada and the U.S. provides a natural context for an experiment allowing us to compare the relative performance of otherwise almost identical producers under different agricultural policies.

The objective of this thesis is to estimate and compare the technical efficiency of a large set of dairy producers in Canada (Ontario and Quebec), with their counterparts in the U.S. (New York and Wisconsin) by using a stochastic nonparametric frontier regression analysis. Our motivation for using stochastic nonparametric frontier estimates comes from the fact that there are problems inherent in the structure of stochastic parametric frontier models. Specifically in the latter models, the literature has shown that the efficiency scores are sensitive to the

choice of both functional forms and the distribution assumptions made about the one-sided random component of the composed error term.

To solve this econometric model, an iterative procedure called a smoothing process is used to estimate the mean response function and its parameters constructed in a generalized additive model. Using the method of locally scoring smoothing, the parameters of the regression function are estimated by employing two separate nonparametric techniques: locally weighted scatterplot smoothing (LOWESS), and spline smoothing. After estimating the response function and its parameters, the technical efficiency scores are computed. These efficiency indices are also compared with the one obtained from conducting a stochastic parametric (translog) frontier function.

The results show that the overall mean technical efficiency obtained from translog function for all regions is higher than that of the corresponding values obtained from the nonparametric approaches. Both parametric and nonparametric methodologies indicated evidence of differences between the mean technical efficiency of dairy farms in all regions. This means various policies implemented in the two countries significantly impacted the performance of dairy producers. The direction of these differences was in the favor of U.S. dairy farmers, who produced milk more efficiently than their Canadian counterparts. This implies that the regulated dairy industry in Canada has led to lower technical efficiency of Canadian dairy farmers. Canadian farmers surely benefited financially from the implementation of supply management over the duration of this study, but from an efficiency perspective, policymakers might realize that the current support policy is only sustainable at a cost. Furthermore, Canada's commitments to international agreements such as the WTO may no longer readily allow the federal government and the provinces to pursue some elements of the current supply management policy.

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TABLE OF CONTENTS

PERMISSION TO USE	i
ABSTRACT	ii
ACKNOWLEDGMENTS	iv
TABLE OF CONTENTS	vi
LIST OF TABLES	ix
LIST OF FIGURES	ix
I. INTRODUCTION	1
1.1 Background	1
1.2 Problem Statement	3
1.3 Objectives of the Study	4
1.4 Scope of the Study.....	5
1.5 Organization of the Study.....	6
II. LITERATURE REVIEW	7
2.1 Introduction.....	7
2.2 Frontier Function Estimation Methods	9
2.3 Frontier Function Studies in the Dairy Sector.....	22
2.3.1 Deterministic Frontier Functions	22
2.3.1.1 Parametric Frontiers	22
2.3.1.2 Nonparametric Frontiers	24
2.3.2 Stochastic Frontier Functions.....	27
2.3.2.1 Parametric Frontiers	27
2.3.2.2 Nonparametric Frontiers	32
2.4 Sensitivity of Efficiency Scores	33
2.4.1 Choice of Functional Form	33
2.4.2 Choice of Functional Form and Distribution Assumption....	34

III. METHODOLOGY	40
3.1 Introduction.....	40
3.2 Multiple Regression and Linear Models.....	41
3.3 Additive Models.....	43
3.4 Generalized Additive Models	46
3.4.1 Locally weighted Scatterplot Smoothing (LOWESS).....	48
3.4.2 Spline Smoothing	49
3.5 The Construction of the General Model.....	54
3.5.1 The Model Specification	55
3.5.2 Estimation of the Mean Response Function.....	59
3.6 Measuring Efficiency	63
3.7 Statistical Inference.....	65
IV. DAIRY INDUSTRY IN NORTH AMERICA	
(CANADA and The United States).....	69
4.1 Introduction.....	69
4.2 The Canadian Dairy Sector	70
4.2.1 Background	70
4.2.2 Structural Change in the Canadian Dairy Sector	
(Producer Viewpoint).....	72
4.2.3 The Canadian Dairy Policy	74
4.2.3.1 Farm Milk Price Policy	75
4.2.3.2 Farm milk Quota Policy	77
4.3 The U.S. Dairy Sector	78
4.3.1 Background	78
4.3.2 Structural Change in the U.S. Dairy Sector	
(Producer Viewpoint)	80
4.3.3 United States Dairy Policy	82
4.3.3.1 Dairy Price Support Program	83
4.3.3.2 Pooled price Discrimination Program.....	84
4.3.3.3 Import Barriers Policy.....	84
4.3.3.4 Export Subsidies Program.....	85

4.3.3.5 Federal Milk Marketing Order Program	85
V. EMPIRICAL APPLICATIONS	87
5.1 Introduction	87
5.2 Source of Data.....	88
5.3 Variable Descriptions.....	90
5.3.1 Data Descriptive Analysis	91
5.3.1.1 Milk Output.....	91
5.3.1.2 Land.....	91
5.3.1.3 Labor	92
5.3.1.4 Total Feed Costs.....	92
5.3.1.5 Number of Milk Cows	93
5.4 Results.....	94
5.4.1 Within-Region Results	96
5.4.2 Between-Region Results	103
5.5 Testing Process.....	116
6. SUMMARY AND CONCLUSIONS	118
6.1 Motivation and Method	118
6.2 Major Policy Findings.....	123
6.3 Areas for Further Research	124
REFERENCES.....	127

LIST OF TABLES

4.1 Number of Canadian Dairy Farms, Cows on Farms and Cows per Farm..	73
4.2 Number of U.S. Dairy Farms, Cows on Farms and Cows per Farms	82
5.1 Descriptive Characteristics of the Data Set.....	90
5.2 Statistical Description of the Variables per Cows.....	94
5.3 Technical Efficiency of Dairy Producers (Within-Regions: LOWESS)	100
5.4 Technical Efficiency of Dairy Producers (Within-Regions: Spline Smoothing)	101
5.5 Technical Efficiency of Dairy Producers (Within-Regions: Translog)	102
5.6 Equivalent Number of Sample Dairy Farms (Between-Regions).....	103
5.7 Technical Efficiency of Dairy Producers (Between-Regions: LOWESS).....	105
5.8 Technical Efficiency of Dairy Producers (Between-Regions: Spline Smoothing).....	106
5.9 Technical Efficiency of Dairy Producers (Between-Regions: Translog)	107
5.10 Sample Correlation Coefficient of the Estimated Mean Technical Efficiency	110
5.11 Technical Efficiency of Dairy Producers (Battese-Coelli Model).....	111
5.12 Summary of the Estimated Technical Efficiency of Dairy Producers (Between-Regions).....	113
5.13 Summary of the Independent Test between Efficiency Class Intervals and Time Trend	116

LIST OF FIGURES

2.1 Technical and Allocative Efficiencies	10
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CHAPTER I

INTRODUCTION

1.1 Background

The historical discussion concerning the measurement of productivity and efficiency in the economic literature dates back at least fifty years with papers by Debreu (1951) and Koopmans (1951). Farrell (1957) was the first to extend the work of Debreu and Koopmans so as to operationalize the measurement of productivity and efficiency. The productivity of an economic agent can be measured simply as a scalar ratio of outputs to inputs that the agent uses in its production process. And an agent's productivity may vary based on differences in production technology, in the efficiency of the production process, in the environment in which production occurs, and finally in the quality of inputs used by the agent. On the other hand, efficiency is measured by comparing observed and optimal values of the agent's outputs and inputs. This comparison can take different forms. The first is the ratio of observed to maximum potential output obtainable from a given level of input. The second is defined by considering a given level of input, and is the ratio of minimum potential to observed input required to produce a given output. Lastly, some combination of these two approaches is also possible.

Before Farrell's (1957) work, a number of economic studies were concerned with the measurement of efficiency. Although these studies produced careful measurements of some, or all, of the inputs and outputs used in the production process of a decision-making unit, they failed to combine these measurements into any satisfactory estimate of efficiency. This failure occurred because these studies ignored critical theoretical issues. The negligence in addressing the theoretical side of measuring efficiency has been removed by continuing research into the problem.

Initially, economists tried to measure efficiency by interpreting the average productivity of inputs. In the 1950s, economists found that this method of measuring efficiency was unsatisfactory as it ignored all other inputs used in the process of production except the input in question. To circumvent this, several researchers introduced different methods to measure efficiency, including the computation of *index numbers*. However, attempts to construct “*indices of efficiency*”, in which a weighted average of inputs is compared with outputs, were subject to the usual index number problems. These included data aggregating; the a priori assumption that all firms produce efficiently; random noise is not accounted for; and a lack of knowledge about the functional form of production and the values of the parameters of the underlying technology.

Economists eventually developed a better-founded theoretical method for measuring efficiency, the so-called *efficiency frontiers*, which have been widely used in applied studies. Much of this work has tried to better define the frontier along with the contributions these functions make in measuring the efficiency of an economic unit. Recently, Coelli (1995) has described frontiers as *bounding functions*. In general, this definition is useful since one can find many examples of bounding functions in the microeconomic literature. Some examples include a production function which represents the maximum output attainable from a given set of inputs; or a cost function that represents minimum cost, given input prices and output; and a profit function which represents maximum profit, given output and input prices.

In estimating the efficiency of an economic unit, economists are interested in frontier functions because they would like to know the maximum (minimum) distribution of outputs (costs), rather than the mean. From production theory, this is equivalent to a production (cost) frontier, with the term frontier emphasizing the concept of an individual agent’s objective maximization (minimization). In this study, a special example of frontier estimation known as *stochastic nonparametric frontier analysis* is developed. Using this, we will compute the *technical efficiency* of Canadian dairy producers in the provinces Ontario and Quebec, and compare and

contrast their efficiency with U.S. dairy producers in the states of New York and Wisconsin. In addition, a flexible stochastic parametric frontier function is estimated for comparison to the two-fold econometric approach developed here.

1.2 Problem Statement

The problem to be examined in this thesis can be broken down into two major parts: theoretical issues and applied work. The problem to be examined in the theoretical part of the study deals with a property inherent to the *stochastic parametric frontier* methodology. Evidence shows that stochastic parametric frontier estimates are sensitive to both the choice of functional form and distributional assumptions about technical inefficiency. Thus, efficiency scores obtained from different stochastic parametric frontier function could vary based on these sources, and not on real changes in efficiency. This study argues that the proposed nonparametric frontier estimation methodology alleviates these problems to a large extent.

The applied part of the study will focus on examining the impact of the different policies in the dairy industry, as they are currently implemented in Canada and the United States. Agricultural policy in the Canadian dairy sector has been characterized by regulations on the supply side (i.e., supply management) enacted by federal and provincial governments through the Canadian Dairy Commission (CDC) and provincial dairy marketing boards. In the United States, the dairy industry is very similar to its Canadian counterpart in terms of availability of inputs, technology, and physical production conditions. However, because the industry was not subject to supply controls, during the time period of this study, U.S. dairy farms could operate on a larger scale, and, were not under the same degree of regulatory constraints as the quota values serve as a capital barrier to entry.

Our methods and data set will allow us to examine whether or not government intervention in the Canadian dairy industry has led to inefficiencies in

production and a possible misallocation of resources. If this is the case, removal of producer protection through new dairy policies would induce major changes for primary dairy producers in Canada. For instance, trade liberalization would expose Canadian dairy producers to lower and more uncertain prices. As a result, the individual and industry level of production will need to adapt. The ability of Canadian dairy producers to compete in liberalized markets depends on the type of technology used and the level of technical efficiency compared to their U.S. counterparts. A comparison of overall technical efficiency between Canadian and American dairy producers will help quantify these differences and suggest ways in which to adjust Canadian dairy policy in the near future.

1.3 Objectives of the Study

The problem of measuring the technical efficiency of an economic unit is important to both economists and policy makers. If the theoretical arguments as to the relative efficiency of different economic systems are to be subjected to empirical testing, it is essential to be able to make measurements of efficiency. On the other hand, if economic policy and planning is to concern itself with the performance of a particular economic unit, it is important to know to what level a given industry can be expected to increase its output by simply increasing its efficiency, without absorbing further resources. Corresponding to the previous section, the objectives of this study are divided into two different parts.

The theoretical part of the study has two objectives. First, a stochastic non-parametric frontier analysis is developed and expanded in order to measure the technical efficiency of economic dairy units. This methodology is more robust when compared to conventional stochastic parametric frontier estimates with respect to their imposed functional forms and predetermined distribution assumptions of technical inefficiency. Second, a statistical test is developed to draw inferences about the assumption of separable predictors, a weak assumption that is contained in the nonparametric approach to stochastic frontier estimation.

In the applied part of the study, the main objective is to estimate the technical efficiency of dairy producers in all four regions of the study. To achieve this, two different estimation methods are pursued; 1) Estimate the technical efficiency of dairy producers in homogeneous geographical areas by building a so-called *within-regions* model, and 2) Build another model to measure technical efficiency of dairy producers in geographically distinct areas by constructing a so-called *between-regions* model. The former model does not permit a cross-border efficiency comparison, unlike the latter model, which is appropriate to test for differences in technical efficiency between the two countries.

The primary purpose of this study is to develop a novel econometric estimation methodology in order to alleviate some of the major pitfalls that currently exist with stochastic parametric frontier analysis. The secondary purpose of the study is to generate results from both parametric and nonparametric frontier estimation approaches so as to better compare the two methods. Finally, efficiency results obtained for the highly regulated Canadian dairy system will be compared to results about the less regulated dairy industry in the U.S. This analysis will help identify the type of policy environment that promotes better performance in the dairy industry.

1.4 Scope of the Study

The first goal of this study is to review the literature concerned with building techniques of efficiency estimation. This will facilitate an understanding of both the theoretical and application part of the issue. The second goal of this study is to highlight the pitfalls of previous models and methodologies. This will help us develop an econometric estimator to help alleviate those shortcomings. The third and most important goal or contribution of this study is to suggest a new method to estimate all types of efficiency (technical, allocative, and economic efficiency), one that avoids the problems inherent in the other methods.

1.5 Organization of the Study

The remaining chapters are organized as follows. Chapter 2 presents a comprehensive review of both theoretical and applied research in both estimating frontiers and computing technical efficiency in the dairy industry. Chapter 3 explains the conceptual framework, and describes the proposed stochastic nonparametric methodology used in the empirical portion of this study. A short review of non-parametric econometric theory is offered prior to developing the new non-parametric frontier estimator. Chapter 3 also reviews the nonparametric approaches used in estimating the parameters of the model. The history of the dairy industry in North America and a brief review on dairy policy implemented in the regions of the study is presented in Chapter 4. Chapter 5 discusses the results obtained by applying the new methodology developed in Chapter 3, as well as a flexible parametric functional form, to the dairy industry data. Results are given separately for both the *within-region* and *between-region* models. Chapter 6 summarizes the study with some concluding remarks and presents ideas for further research.

CHAPTER II

LITERATURE REVIEW

2.1 Introduction

Agriculture plays an important role in improving the standard and quality of life in every country, especially in developing countries. This is not a new insight as development economists have argued this point for a long time. Hayami and Ruttan (1985) presented an analysis of the role of agriculture in enhancing the economic condition of a country.

One strategy to improving farm output and farmers' income is the adoption of new technologies. The adoption of new technologies, as a means of accelerating economic development, has been the focus of a number of economists and policy-makers. Schultz (1964), Kuznets (1966), Nishimizu and Page (1982), and Hayami and Ruttan (1985) focused particularly on the role of new technologies in fostering economic development. But technological progress is not the only parameter that determines output growth. Enhancement in efficiency (technical, allocative, and overall) can also affect growth in output.

The earliest study of efficiency at the farm level dates back to the mid-1960s when Chennareddy (1967) and Sahota (1968) tried to measure the allocative or price efficiency of peasant farmers using data from India. Later Lau and Yotopoulos (1971) developed a dual profit function model to measure both allocative and technical efficiency. Several researchers have applied this profit function model including, Sidhu (1974), Trostler (1978), Khan and Maki (1979), and Junankar (1980). Toda (1976, 1977) also developed an extension of the Lau-Yotopoulos model.

As mentioned previously, perhaps the most important work in the efficiency measurement literature is that of Farrell (1957) who drew upon the work of Debreu (1951) and Koopmans (1951). This research laid the foundation for the development of a number of related models, known collectively as *frontier* models (see section 1.1 for a definition of frontier in this context).

There are two main benefits that result from estimating frontier functions, as compared to estimating average functions using *ordinary least squares* (OLS) approach. First, when a frontier function is estimated, the result is strongly influenced by the best performing firm, and therefore the frontier reflects the technology set that the most efficient firm employs. Compare this to the estimation of an average function, which only reflects the technology set employed by an average firm. Second, frontier functions provide a useful performance benchmark. These functions normally represent best practice technology, against which the efficiency of other firms within the industry can be measured. It is for this reason that frontier estimation continues to attract attention in the empirical economics literature.

Frontier models provide a number of advantages over non-frontier models like the one proposed by Lau and Yotopoulos (1971). A non-frontier model yields efficiency measures for groups of firms, whereas a frontier model can provide firm specific efficiency measures to the researcher. Another advantage of the frontier methodology is that the word ‘frontier’ is consistent with the theoretical definition of a production, cost, and profit function, i.e., a solution to a maximum and minimum problem. This alone makes the frontier methodology popular in applied economic research (see, e.g., Forsund et al., 1980 and Bravo-Ureta and Pinherio, 1993).

The purpose of the following sections is to explore how economists have applied frontier models to analyze the agricultural sector, particularly the dairy industry. First, we present a summary of the frontier methodology to provide a frame of reference. Second, we review efficiency measures obtained from employing various estimation models. Third, we discuss some key methodological issues that

arise in the empirical analysis of efficiency using frontiers. Finally, we address several drawbacks contained in the previous models used for measuring efficiency and we offer a new approach to estimating an efficiency frontier function.

2.2 Frontier Function Estimation Methods

In order to measure the efficiency of firms, the researcher can estimate a frontier cost or production function, and this can be done using various models. But if measuring efficiency is the objective, why don't analysts use econometric or linear programming approaches to estimate frontiers? Why can't a partial measure of efficiency, such as tons of wheat per hectare or litre of milk per cow be used as an indication of firm efficiency? In fact, interpreting these measures as overall firm efficiency creates bias because these types of measures only consider particular inputs, i.e., land and labor, and ignore other ones, i.e., capital, machinery, fuel, fertilizer, pesticides, and feed. Coelli (1995) states that the identification of particular inputs in the formulation of management and policy advice is likely to result in excessive use of those inputs that are not included in the efficiency measure and could result in underutilization of those inputs identified in the management and policy advice. To correct for this potential problem, efficiency measures can be constructed to account for more than one factor of production. These types of measures will be presented in the following sections.

It is necessary to create a standard or benchmark for the measurement of efficiency. For example, to say that a firm, given its level of input usage, produces only 90 percent of potential output requires that we need to know what the optimal level of output actually is. Defining the standard against which to measure efficiency is at the core of every study related to measuring the efficiency of firms. Farrell (1957) focussed this discussion by defining a simple or partial measure of firm efficiency that could be readily extended to multiple inputs.

The frontier function model proposed by Farrell used the efficient unit isoquant as a standard to measure all types of efficiencies. Farrell also suggested that

the efficiency of a firm consists of two main components. The first component, *technical efficiency* (TE), reflects the ability of firms to obtain the maximum output from a given set of inputs. The second component, *allocative efficiency* (AE) or *price efficiency* (PE) refers to the ability of firms to use inputs in optimal proportions, given their respective input prices. Multiplying these two measures together yields *total (overall) economic efficiency* (EE) or simply *economic efficiency*. Note that it is important to distinguish technical efficiency from technological change. An upward shift of the production function or a downward shift of the unit isoquant represents technological change. Figure 2.1 shows how to obtain the technical, allocative, and economic efficiency. In this Figure, SS' represents an isoquant drawn in an input-input space and adjusted by the unit of output. Assuming point P as the quantity of inputs that a firm uses to produce a unit of output, the firm's technical efficiency is obtained by the ratio of OQ/OP . Given the information on input prices, shown by the isocost line AA' , the allocative efficiency or price efficiency can be computed by the ratio of OR/OQ . Thus, the ratio of OR/OP yields the economic efficiency of the firm.

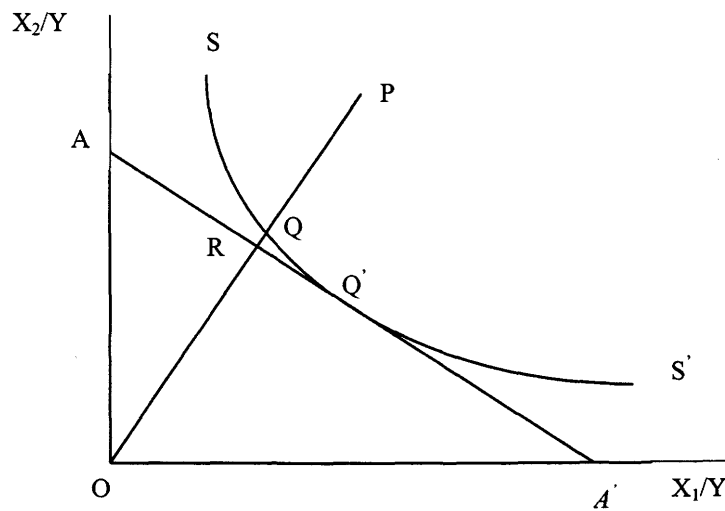


Figure 2.1 Technical and Allocative Efficiencies

No matter what type of methodologies is chosen; the estimation of technical efficiency is obtained in terms of inputs and outputs. When we examine efficiency in

isoquant space, i.e., using *input-oriented* measures, we address the following question: can input use be decreased proportionally without changing the output quantity produced? Alternatively, we may want to know how we could expand the quantity of output produced without changing the quantity of input used. In this case, our focus is within an output-output space, or an *output-oriented* measure. We do not obtain the same result if we estimate technical efficiency using either input or output oriented measures except when the production technology exhibits *constant returns to scale* (Fare and Lovell, 1978).

The original work of Farrell has been subsequently extended by a large number of researchers. These studies can be classified into three basic types: *parametric*, *non-parametric*, and *semi-parametric*. Parametric frontier models are particular analytical functions with an *a priori* fixed number of parameters. Non-parametric frontier models are those which are robust with respect to the particular functional form and to the distribution assumptions. Semi-parametric frontier models are the combination of both parametric and non-parametric frontier models. More details on frontier function estimation methods can be found in Forsund et al. (1980), Schmidt (1985-86), Bauer (1990), Seiford and Thrall (1990), Battese (1992), and Coelli (1995).

We can also classify frontier functions by how we interpret the deviation of a group of firms from the best performing firm in the sample. In this sense, frontier functions are either *deterministic* or *stochastic* frontiers. In a deterministic production frontier model, output is assumed to be bounded from above by a deterministic (non-stochastic) production function. However, the possible influence of measurement errors and other statistical noise upon the shape and positioning of the estimated frontier is not accounted for. In other words, deterministic models assume that any deviation from the frontier is solely due to inefficiency. On the contrary, in a stochastic frontier model, output is assumed to be bounded from above by a stochastic production function. Therefore, the error term in stochastic frontier models has two parts: one representing randomness or statistical noise, and the other representing technical inefficiency.

Measurements of inefficiency in industry were first constructed by estimating deterministic frontiers and subsequently by using stochastic frontiers. Aigner and Chu (1968) were the first researchers to estimate a deterministic frontier using Cobb-Douglas production function through linear and quadratic programming techniques. They argued that for a given industry firms might differ from each other in their production processes. The distinguishing features among firms could be represented by:

- attained values for certain technical parameters in an industry production function,
- differences in scales of operation, and
- various structures in their organization

Timmer (1971) extended the Aigner-Chu model by introducing a *probabilistic frontier* model. He estimated a series of frontier production functions by dropping the extreme observations at each stage. This process continues until the rates of change of the parameter estimates stabilize. Timmer's (1971) approach has two critical shortcomings that have caused his methodology to be used less widely. First, the percentage of omitted observations is determined arbitrarily. Second, his methodology, like all deterministic programming approaches, yields estimators with undefined statistical properties.

Another class of deterministic parametric models, the statistical production frontier, was proposed by Afriat (1972). In this model, technical efficiency could be measured by introducing a one-sided disturbance term. To illustrate Afriat's model, we use the following specification:

$$Y \leq f(x_1, x_2, \dots, x_k, \theta) \quad (2.1)$$

where Y is output, the X_i s are inputs, f is the production function dependent on the inputs chosen and some parameters, θ . We can rewrite equation [2.1] as

$$Y = f(x_1, x_2, \dots, x_k, \theta) - u \quad u \geq 0 \quad (2.2)$$

where u is a non-negative variable intended to capture inefficiency in production and the remained variables are identical to those in equation [2.1]. The unknown functional form in both equations [2.1] and [2.2], i.e., $f(x_1, x_2, \dots, x_k)$, is non-stochastic. Thus, a deterministic frontier model like equation [2.2] can be converted into a statistical model by making statistical assumptions about u . Specifically, if we replace the unknown function f by a Cobb-Douglas production technology, then equation [2.2] changes to

$$Y_i = A + \sum_{j=1}^k \beta_j X_{ij} - u_i \quad (2.3)$$

where Y and X 's are written in logarithms. A statistical model can be generated by the assumption that the u_i 's are independently and identically distributed (*i.i.d.*) with mean μ , finite variance, and the u_i 's are uncorrelated with the inputs. Then clearly the transformation;

$$Y_i = (A - \mu) + \sum_{j=1}^k \beta_j X_{ij} - (u_i - \mu) \quad (2.4)$$

has error term with zero mean and satisfies conditions (consistency) necessary to estimate ordinary least squares (OLS). This consistency encompasses the terms $A - \mu$ and β , but it does not contain the intercept. Richmond (1974) noticed the inconsistency of the intercept and proposed that the estimated intercept can be corrected by shifting it upward until no residuals are positive and one residual is zero. Subsequently, Gabrielson (1975) and Greene (1980a; 1980b) showed that Richmond's procedure creates a consistent estimator for the intercept. The solution for removing the inconsistency of the intercept estimated by OLS has become known as *corrected ordinary least squares* (COLS). The ordinary least squares method provides an unbiased estimator of the slope parameter in a corrected ordinary least squares model, yet the downward bias of the OLS method on the intercept parameter must be adjusted up by the sample moments of the error

distribution (Coelli, 1995). The shortcoming of the COLS procedure is that the asymptotic distribution of the corrected intercept is unknown and this property rules out making inference about the inefficiency measures.

In an early attempt to give a statistical foundation to the mathematical programming methods of frontier estimation, Schmidt (1976) explicitly added a one-sided disturbance term to the following model;

$$Y_i = f(X_i; \beta), \quad (2.5)$$

that yields

$$Y_i = f(X_i; \beta) + \varepsilon_i \quad i = 1, \dots, N \quad (2.6)$$

where $\varepsilon_i \leq 0$. If we assume a particular distribution for the disturbance term, we can estimate equation [2.6] using maximum likelihood (ML) techniques. For instance, if we assume that $-\varepsilon_i$ has an exponential distribution, then we can employ linear programming to estimate the parameters. However, if one assumes a half-normal distribution for $-\varepsilon_i$ then a quadratic programming technique can be used to estimate the parameters of equation [2.6]. Thus, we can express Aigner-Chu's estimates as maximum likelihood estimates (MLE) under a particular error specification.

From equations [2.5] and [2.6], it is clear that the distribution of the one-sided error term is critical to the efficiency estimates. For example, if we assume a specific distribution such as gamma or exponential for the u_i , then the associated likelihood function can be derived and maximum likelihood estimators (MLEs) can be calculated. In fact, this is exactly what Afriat (1972) suggested. He specified a model similar to equation [2.1] except that the u_i 's were assumed to have a gamma distribution and the parameters of the model were estimated using the maximum likelihood (ML) method. To summarize, the key points here are:

- When we introduce explicit assumptions about the distribution of the disturbance term, we can estimate frontier functions by maximum likelihood method.
- If we do not introduce any assumptions about the distribution of the disturbance term, then we can use the corrected ordinary least squares (COLS). This entails parallel shifting the frontier upwards until no positive error term remains.

Many economists have criticized the reliability of these methods. The critiques can be classified into four types. First, while it has been argued that the model can be estimated by ML techniques under appropriate assumptions, this information is of little value. Aigner et al. (1977) made this statement since the usual regularity conditions for the application of maximum likelihood are violated. In particular, because by definition $Y_i \leq f(X_i; \beta)$, the range of the random variable Y is dependent on the parameters that must be estimated. In this case, the usual theorems cannot be invoked to determine the asymptotic distributions of the parameter estimates. Under these circumstances it is not clear how much we know about the frontier after it is estimated. The second problem with these approaches is that they all are extremely sensitive to data outliers. The third problem is that there still exists a lack of explicit economic or statistical justification with the probabilistic frontier approach. The fourth problem arises from the need to reconcile observations above the estimated frontier with the concept of the frontier as the maximum (or minimum) possible value. This problem can be alleviated by appealing to the measurement error in the extreme observations. However, it seems preferable to incorporate the possibility of measurement error and of other unobservable disturbances in a less arbitrary fashion. Unfortunately, the mathematical programming techniques do not lead to estimates with known statistical properties.

Regarding the statistical noise issue, Aigner et al. (1976) constructed a more reasonable error structure than a purely one-sided disturbance term. Specifically, it was assumed that;

$$\begin{aligned}
\varepsilon_i &= \left[\varepsilon_i^* / \sqrt{(1-\theta)} \right] & \text{if } \varepsilon_i^* \geq 0 & \quad i = 1, \dots, N \quad \text{or} \\
\varepsilon_i &= \left[\varepsilon_i^* / \sqrt{\theta} \right] & \text{if } \varepsilon_i^* < 0 &
\end{aligned}
\tag{2.7}$$

where the errors ε_i are independent normally distributed random variables with zero means and constant variance, σ^2 , for $0 < \theta < 1$. In the two extreme cases, i.e., $\theta = 1$ or $\theta = 0$, ε_i^* has either a negative or positive truncated normal distribution, respectively. Aigner et al. (1977) justified the above error specification because firms presumably behave differently in their production process of Y for a given set of input values. There are differences due to random variation in;

- the ability of a firm to utilize best practice technology, a source of error that is one-sided, $\varepsilon_i \leq 0$, and/or
- an input quantity or measurement error in Y , a symmetric error.

Aigner et al. (1977) interpreted θ as the measure of relative variability in these two error sources. For instance, its values could encompass the full frontier function provided that $\theta = 1$, or the average function if $\theta = 1/2$, along with intermediate cases of some interest. They showed that as $\theta \rightarrow 1$, the positive error component has a large variance, hence a small effect in the likelihood function, and the negative error dominants. A similar interpretation follows for the case of $\theta \rightarrow 0$, although a behavioral explanation for this situation is lacking. When $\theta = 1/2$, the likelihood function has the form of a mixture of two half-normal, each with equal influence. This error structure allows the fitted function to be estimated along with the usual parameters of interest through the parameter θ . Thus, those who criticized the use of average functions instead of frontiers (e.g., Aigner and Chu, 1968) and those who criticized estimating just a frontier or envelope function as the appropriate industry function (e.g., Timmer, 1971) were muted by this accommodating specification.

The shortcomings of deterministic frontier analysis led two groups of researchers, i.e., Aigner et al. (1977) and Meeuseen and Van den Broeck (1977), to

simultaneously propose the concept of stochastic parametric frontier models. In these models, where output is bounded from above by a stochastic functional form, a composite error term is incorporated. This error contains a two-sided symmetric term that captures random effects outside the control of the firm, including measurement errors and other statistical noise typical of empirical analysis, along with a one-sided component that captures inefficiency. Since the establishment of this method, other researchers have used stochastic parametric frontier functions in a variety of applications.

Let us illustrate how to construct a stochastic frontier function. Using a Cobb- Douglas production function, consider equation [2.8]

$$Y_i \leq A + \sum_{j=1}^k \beta_j X_{ij} + v_i \quad (2.8)$$

where noise is accounted for by the term v_i , a symmetric random error term. By adding v_i to a non-negative error term, u_i , in equation [2.3], we obtain

$$Y_i = A + \sum_{j=1}^k \beta_j X_{ij} + v_i - u_i \quad i = 1, \dots, N \quad (2.9)$$

therefore, the error term, $v_i - u_i$ has two components: one representing randomness or statistical noise, v_i , and the other representing technical inefficiency, u_i . Aigner et al. (1977) now argued that to properly characterize differences in outputs among firms with identical input vectors, or to explain how a given firm's output lies below the frontier, a disturbance term is a necessity. They constructed their error structure in equation [2.6] as $\varepsilon_i = v_i + u_i$, for $i=1,2,\dots,N$, where the error component v_i represents the symmetric disturbance, and is assumed to be independently and identically distributed (*i.i.d.*) as $N(0, \sigma^2)$. As well, the error component u_i s are assumed to be distributed independently from v_i s, as well as satisfying $u_i \leq 0$.

Aigner et al. (1977) considered two other interesting cases:

- u_i is derived from a $N(0, \sigma_u^2)$ distribution truncated from above at zero, and
- $-u_i$ has an exponential distribution.

In equation [2.9], if $\sigma_v^2 = 0$ then the model collapses to a deterministic frontier. It also collapses to the Zellner et al. (1966) stochastic production function model when $\sigma_u^2 = 0$. In the latter case, $Y_i \leq f(X_i; \beta) + v_i$, implying that the frontier itself is now stochastic.

The econometric logic behind this specification is that the production process is subject to two identifiable random disturbances with different characteristics. There are many studies, which measure and interpret these two error components. For instance, Marschack and Andrews (1944) suggested that the summation $v_i + u_i$ reflects technical efficiency and what they called the “*will, effort and luck*” of a producer. Zellner et al. (1966) believed that with respect to agricultural production, the error component v_i reflects factors such as weather, unpredictable variations in machine or labor performance, etc. From a practical point of view, such a distinction facilitates the estimation and interpretation of a frontier. The non-positive disturbance u_i reflects the fact that each firm’s output must lie on or below its frontier, i.e., $f(X_i; \beta) + v_i$. Any such deviation is the result of factors under the firm’s control, such as technical and economic inefficiency, or perhaps the will and effort of the manager and his/her employees. But the frontier itself can vary randomly across firms, or even over time for the same firm. In this case, the frontier is stochastic, with random disturbance, $v_i (<, =, >) 0$ being the result of favorable as well as unfavorable random extreme events such as luck, climate, topography and machine performance. Errors of observation and measurement on Y constitute another source of $v_i (<, =, >) 0$.

In summary, stochastic frontier functions are estimated in two ways. First, if the researcher does not assume an explicit distribution for the efficiency component prior to estimation, then frontier functions can be estimated using a stochastic version of corrected ordinary least squares (COLS) approach. Second, if the researcher chooses to assume an explicit distribution for this term, such as exponential, half-normal, truncated-normal (Stevenson, 1980), or the two-parameter gamma (Greene, 1990), then we can estimate the stochastic frontier using well-established maximum likelihood (ML) methods. In fact, Greene (1980a) proved that the MLE is more efficient than the COLS. Two years after Greene's (1980a) finding, Jondrow et al. (1982) proposed an extension that allowed stochastic frontier models to compute individual firm-specific efficiency measures. This was a major step forward for empirical research.

In spite of the enhancements pertaining to the theory of stochastic frontier functions, these models still suffer from three inherent serious difficulties. First, the technical inefficiency of a particular firm (or observation) can be estimated but not consistently. We may consistently estimate the whole error term for a given observation, but remember the whole term contains statistical noise as well as technical inefficiency. Jondrow et al. (1982) argued that the variance of the distribution of technical (in)efficiency, conditional on the whole error term, does not vanish when the sample sizes increases. Second, the estimation of the model and the separation of technical inefficiency from statistical noise require specific assumptions about the distribution of technical inefficiency. Schmidt and Sickles (1984) showed that it is not clear how robust stochastic frontier results are to the error term assumptions. They suggested that one way to get around this point is to note that evidence of strong technical inefficiency is substantial skewness of the production-function error distribution. However, not all agree that skewness should be regarded as evidence of inefficiency. Third, it may be incorrect to assume that inefficiency is statistically independent of the regressors; for example, if a firm were aware of its level of technical inefficiency, this would likely affect its input choices.

More recent extensions of the stochastic frontier approach take advantage of panel data structures. Panel data have some advantages over cross-sectional data in the estimation of stochastic frontier models in the sense that most of the problems described above are potentially avoidable if one has panel data available. First, the technical inefficiency of a particular firm can be estimated consistently as T (time) approaches infinity, that is $T \rightarrow \infty$. In other words, adding more observations from the same firm yields information that is not available by adding more firms to the sample. Second, with a panel model, strong distribution assumptions are not necessary as they are with a single cross section. Schmidt and Sickles (1984) suggested that essentially, evidence of inefficiency can be found in constancy over time as well as in skewness. Finally, with panel data, the parameters of the function as well as the firm's inefficiency levels can be estimated without the need to assume that technical inefficiency is uncorrelated with the regressors.

The researchers may choose from a variety of different efficiency estimators, depending on what they are willing to assume about the distribution of technical inefficiency and its potential correlation with regressors. Another advantage of working with panel data is that such data generally implies that there are a large number of degrees of freedom for parameter estimation. The use of panel data also permits simultaneous investigation of both technical changes and efficiency changes over time. This is possible so long as technical change is defined by an appropriate parametric model and the (in)efficiency effects in the stochastic frontier model are stochastic and have a pre-specified distribution (see, e.g., Coelli et al., 1998).

Pitt and Lee (1981) were the first to specify a panel-data version of the Aigner et al. (1977) model with a half-normal error term. The Pitt and Lee (1981) model was also used by Schmidt and Sickles (1984) who analyzed the technical efficiency of a sample of 12 U.S. airlines observed for 35 quarters. The advantages of working with panel data encouraged researchers to extend the stochastic frontier methodology. Among numerous studies exploiting the properties of panel data, we refer the reader to Battese and Coelli (1988); Battese et al. (1989); Kalirajan and

Shand (1989); Cornwell et al. (1990); Kumbhakar (1990); Kalirajan (1991); Battese and Coelli (1992); Battese and Tessema (1993); Battese et al. (1993); Lee and Schmidt (1993); Tran et al. (1993); Battese and Coelli (1995); and Giannakas et al. (2003a).

A number of alternative functional forms of production/cost in addition to restrictive forms (i.e., Cobb-Douglas) have been used in the frontier literature. The two most popular alternative forms are the transcendental logarithmic (Greene, 1980b), and the Zellner-Revankar (1970) generalized production function (see, e.g., Forsund and Hjalmarsson, 1979, and Kumbhakar et al., 1991). The Zellner-Revankar model removes the returns-to-scale restriction on production. The translog form also imposes no restrictions upon returns to scale or substitution possibilities among inputs, but has the drawback of being susceptible to multicollinearity and degrees of freedom problems. These problems can be avoided by using multi-equation (system) models, but these are more complicated to compute in conjunction with the stochastic frontier framework. Nevertheless, there have been several attempts to estimate the parameters of stochastic frontier functions in multi-equation (system) models based on production function (e.g., Kumbhakar et al., 1989, and Kumbhakar et al., 1991), cost (e.g., Bauer, 1990; Greene, 1993; and Kumbhakar, 1997), and profit functions (e.g., Kumbhakar et al., 1991, and Kumbhakar, 1994).

There is also a line of research that investigates the determinants of technical inefficiencies among firms by regressing the predicted inefficiency effects upon a vector of firm-specific factors (e.g., age, education, firm size). These studies began with independent research by Kalirajan (1981) and Pitt and Lee (1981) who proposed a two-stage analysis to interpret the differences between the mean efficiencies among firms. In practice, this two-stage analysis of mean efficiencies, however, possessed major methodological drawbacks (Coelli et al., 1998, p.207). Later, Kumbhakar et al. (1991) and Reifschneider and Stevenson (1991) simultaneously proposed a single-stage model to investigate the determinants of technical inefficiencies among firms, which avoided the drawbacks of the two-stage model. Finally, Huang and Liu (1994) and Battese and Coelli (1995) developed a

single-stage model for this process that is currently widely used by applied researchers.

2.3 Frontier Function Studies in the Dairy Sector

A small number of studies have investigated the technical, allocative, and overall efficiency of dairy producers using both deterministic and stochastic frontier analysis. For expository purposes, a review of these studies in chronological order is presented. The studies can be divided into two major groups, according to the type of methodology used, deterministic frontier vs. stochastic frontier. In turn, each of the studies can be further subdivided into (a) parametric and (b) non-parametric frontiers. In addition, they can also be classified based on the type of data in the sense of (a) cross-sectional, (b) panel data and (c) dual frontiers.

In addition to focusing on some methodological aspects and on the reported efficiency levels, we also summarize the findings concerning the relationship between efficiency and various socioeconomic variables wherever applicable. Basically, two approaches are commonly used to examine these relationships. One approach is to compute correlation coefficients or to conduct simple non-parametric analyses. The other method, referred to as a second step analysis, first measures farm level efficiency and then uses a regression model so that efficiency can be expressed as a function of exogenous socioeconomic attributes.

2.3.1 Deterministic Frontier Functions

2.3.1.1 Parametric Frontiers

Bravo-Ureta (1986) measured the technical efficiency of New England dairy producers based on a probabilistic frontier production function (PFPF) model of the Cobb-Douglas type. He analyzed cross-sectional data on 222 dairy farms in 1980, and estimated efficiency parameters using two methods, linear programming and ordinary least squares. Bravo-Ureta's model was derived from an earlier study by Forste and Frick (1979), who concluded that high U.S. dairy support prices (relative

to cost of production) during the late 1970s and early 1980s created an environment where inefficient producers survived when perhaps they should not have survived. Bravo-Ureta used annual milk production per farm measured in hundredweight as the dependent variable. The independent variables were the number of dairy cows, annual consumption of purchased concentrate-feed in tons, annual labor input including hired, operator, and family labor measured in full-time worker equivalents, and annual machinery capital services measured in 1980 dollars. A dummy variable was also used to identify the impacts of breeding on dairy production. Estimates of technical efficiency among the farms ranged between 57.69 and 100.00 percent with a mean of 82.17 percent. This means the same volume of milk could have been achieved with approximately 18 percent fewer inputs, if all farms operated at 100 percent efficiency. The sum of production elasticities was 1.058, which was significantly different than unity at a 0.01 level of significance. These results were consistent with those reported by Hoch (1976) and Grisley and Gitu (1984), who estimated production and cost models for California and Pennsylvania dairy farms respectively. Bravo-Ureta concluded that although economies of scale were slightly greater than one, farm size and technical efficiency were statistically independent variables. His results also indicated that the estimated technical efficiency scores approximately followed a normal distribution.

Tauer and Belbase (1987) measured the technical efficiency of New York dairy producers by estimating a deterministic Cobb-Douglas production frontier function using a corrected ordinary linear squares approach with a cross-sectional data from 1984 collected from 432 farms. They chose the value of milk, livestock, and crops as a dependent variable. The authors also used hired and family labor, feed purchases, machinery and crop expenses, livestock expenses, real state expenses, and miscellaneous expenses as independent variables. Their results indicated that the average technical efficiency of the group was 0.693, implying that these farmers only obtained 69 percent of potential output from their inputs. Compare this result to an average of 72 percent technical efficiency for British dairy farms (Russell and Young, 1983) and 80 percent for large Pennsylvania dairy farms (Grisley and

Mascarenhas, 1985). In order to find the causes of inefficiency, Tauer and Belbase (1987) constructed a regression of the estimated technical efficiency scores against 15 farm characteristics as independent variables. They found that favorable location and large farm size led to greater efficiency as opposed to participation in a dairy cooperative (the Dairy Herd Improvement Cooperative) and the use of mail-in computerized records, both of which were correlated with a decrease in efficiency scores.

Romain and Lambert (1995) measured the level of technical efficiency in milk production and analyzed the relationship between production costs, the level of technical efficiency, and farm size in two Canadian provinces (Quebec and Ontario) using a deterministic transcendental production function. They chose annual milk production per cow (measured in hectolitre) as the dependent variable. They chose annual quantity of fodder per cow (measured in tons), annual quantity of grain and concentrated nutrients per cow (measured in kilograms), labor per cow (measured as the number of workers), and capital stocks such as buildings, machinery, and dairy equipment per cow (all measured in dollars) as their independent variables. Moreover, they identified socioeconomic variables found to characterize the most cost efficient dairy farmers. The results indicated that in Quebec, technical efficiency increased slightly with herd size. Conversely, in Ontario, herd size was not significant in explaining variations in technical efficiency. The farmer's level of education, participation in a milk recording program, expenditure per cow for veterinarian care and artificial insemination, the quality of hay, and the number of years as member of a management club were all variables found to characterize technically efficient farms.

2.3.1.2 Nonparametric Frontiers

Weersink et al. (1990) measured the technical efficiency of Ontario dairy farms using a non-parametric programming approach and decomposed the estimated technical efficiency into purely technical, congestion and scale efficiency. They extended the deterministic non-parametric approach of Fare et al. (1985) and built

their model using a cross section of Ontario dairy farms in 1987. The authors also investigated the factors causing variations in technical efficiencies among sample farms by using a censored regression. The dependent variable in their study was milk output measured in hectolitres of 3.6 percent fat content milk. The independent variables were livestock, feed, machinery, buildings, capital, other, and labor measured in dollar terms, except for the last input, which was measured in the number of equivalent worker units. Weersink et al. (1990) reported that approximately 42 percent of the farms in the sample were technically efficient and that pure technical allocation and non-optimal scale of production were found to be as the major source of inefficiency. The estimated efficiency scores in this study varied from 64.7 percent to 100 percent with a mean of 91.8 percent. In addition, herd size, milk yield, and butterfat content of milk had positive effects on efficiency, whereas negative effects came from overcapitalization and the proportion of total feed purchased.

Cloutier and Rowley (1993) used a non-parametric deterministic multiple-output multiple-input efficiency estimation technique known as data envelopment analysis (DEA) to estimate the technical efficiency of Quebec dairy farmers using information on 187 dairy farms in 1988-1989. The authors chose the annual total quantity of milk (litres) produced, revenues from the sale of milk, and other revenue accruing to individual farms as measures of output. They used herd size, labor (hired and family, measured in annual worker-equivalents), cultivated land (rented and owned, measured in hectares), amount of animal feed, and a composite measure of other inputs as their independent variables. Since they found the individual scores generated by DEA procedure to be sensible, the authors performed two sensitivity checks. First, they explored the stability of the results by comparing individual efficiency scores for 1988 and 1989. Secondly, they split the sample for 1989 into two parts according to the size of the farms, and compared their results. The mean efficiency score for 1989 (0.913) was higher than 1988 (0.883). Moreover, they found the efficiency of the best farm was 50 percent higher than the worst farm, and that the best farm was only 10-12 percent more efficient than the average levels of

performance. In addition, they reported that large farms were much more likely to be ranked as technically efficient than small ones, both in their subsample and in the comprehensive sample.

Mbaga et al. (2000) measured the technical efficiency of two groups of dairy farms in Quebec. While the actual production technology was unknown, they checked three commonly used functional forms (Cobb-Douglas, translog, and generalized Leontief) along with three alternative potential inefficiency distributions (half-normal, truncated-normal, and exponential). To gain information about the robustness of the obtained technical efficiency, they also estimated a production frontier using data envelopment analysis (DEA) as an alternative methodology. The authors obtained cross-sectional data on 1143 farms that specialized in dairy production in 1996. They divided these farms into two groups (non-maize and maize regions) as proxies for differences in climate and soil quality. The researchers considered yield of milk per cow measured in hectolitres as the dependent variable. As inputs, they used the quantity of feed concentrate and forage consumed in kilograms; labor measured in annual total units of full-time dairy farm workers; capital measured as the total value of assets in dollars, and finally the average weight of dairy cows as a proxy for the genetic quality of the herd (all measures were computed on a per cow basis). To save space, the results obtained from the DEA analysis are not reported here and interested readers may consult the cited reference for more details.

Their results indicated that all the correlation coefficients, as well as the rank correlation coefficients between the DEA scores and those of the parametric models, were relatively low. The average efficiency scores obtained from the DEA approach were 0.9215 for the non-maize region and 0.95 for the maize region, well within the mean efficiency scores reported by Cloutier and Rowley (1993). For the maize region, the average DEA score was similar to those generated by the generalized Leontief (GL) function, but scores were somewhat lower for the non-maize region. The DEA model showed that about 66 percent of the farms were classified as being

over 90 percent efficient, while more than 93 percent of the farms fell in this category with the GL function, irrespective of the efficiency distribution. These results appear to confirm that fact that there is some discrepancy between the efficiency scores obtained using non-parametric DEA and the efficiency scores obtained from parametric stochastic frontier analyses. Hjalmarsson et al. (1996) and Singh et al. (2000) offer evidence to support this statement.

Readers interested in further details on data envelopment analysis should look at articles by Norman and Stoker (1991), Ali and Seiford (1993), Charnes et al. (1994), Coelli et al. (1998), and Cooper et al. (2000).

2.3.2 Stochastic Frontier Functions

2.3.2.1 Parametric Frontiers

Battese and Coelli (1988) estimated a generalized stochastic frontier production function to compare the mean technical efficiencies of dairy producers in two states of Australia (New South Wales and Victoria) in addition to predicting individual technical efficiencies of dairy farms by using panel data. They found data for three financial years (1979-81) for 69 farms from Victoria and 43 from New South Wales. Battese and Coelli used total gross farm (crop and livestock) returns as the dependent variable. They also chose the value of total farm labor (in workweeks), the total costs of fodder, seed and fertilizer and the value of the capital as independent variables. Given that the non-negative firm effects were time-invariant and had a general truncated normal distribution, they obtained the best predictor for the firm-effect random variable and the appropriate technical efficiency of an individual firm, given the values of the disturbances in their model. Estimates of the mean technical efficiencies indicated that dairy farms in New South Wales were about 77 percent technically efficient, whereas those in Victoria had scores averaging about 63 percent. An asymptotic test rejected any similarity in the estimated coefficients. Using the estimated parameter values, the predicted individual technical efficiencies of dairy farms indicated that in New South Wales, the technical efficiencies ranged from 0.548 to 0.927. By comparison, the predicted

technical efficiencies of dairy farms in Victoria ranged from 0.296 to 0.934. The Battese-Coelli model indicated that the traditional (average) Cobb-Douglas production function was not a suitable model to estimate efficiency. Their basic conclusion concurs with the findings of Stevenson (1980) in an application involving cross-sectional data only for the U.S. primary metals industry. A major conclusion of the Battese-Coelli model is that the more general model for describing firm effects in frontier estimation best accounts for the situation in which there is a high probability of firms not being fully technical efficient. However, this is not the case for the half-normal and exponential distributions.

Kumbhakar et al. (1989) studied technical, allocative, and scale efficiency of owner-operators of dairy farms in Utah using a stochastic production frontier function in a simultaneous equation profit maximization framework. They considered two endogenous inputs (capital and labor), and four exogenous variables (land, education, off-farm income, and farm-grouped size) as the independent variables to explain the variation in the total milk produced as their dependent variable. They obtained primary cross-sectional data by contacting 116 families from a population of 510 in the Utah counties by interviewing each owner-operator with the 66.7 percent response rate. The researchers separated the observations, and constructed models by size (small, medium, and large), based on dollar sales during 1985. The results indicated positive correlation between farmer education and productive efficiency because education improves managerial ability and enhances the productivity of labor and capital. Their empirical findings also showed that productivity was negatively related to off-farm income because the larger off-farm income the less time the farm-operator spends managing farm operations. Kumbhakar et al. (1989) found that large farms (having more than 100 milking cows) were technically more efficient than small farms (having less than 50 milking cows). Output for these farms, on average, was 11.53 percent higher compared to the small farms. However, the output of large farms, on average, would have increased by 20.16 percent had these farms been operating on the production frontier. The corresponding figure for medium-sized farms was 11.46 percent. Due to allocative

inefficiency, costs of small farms, on average, were increased by 5.91 percent whereas the figures were 3.74 and 33.58 percent for medium- and large-sized farms, respectively. They also found that most of the farmers in all size categories were scale inefficient. Loss of profit due to scale inefficiency ranged from 5.59 percent for large farms to 13.73 percent for small farms. Kumbhakar et al. (1989) concluded that it was happened because milk prices had been decreased during the past three years prior to their study period and the farms might not have fully adjusted their outputs to the change in prices.

Bravo-Ureta and Rieger (1991) extended a stochastic efficiency decomposition model to analyze technical, allocative, and economic efficiency based on Kopp and Diewert's (1982) deterministic methodology, initially proposed in 1982. They used cross-sectional data for a sample of 511 New England dairy farms to estimate a Cobb-Douglas stochastic production frontier, which is the basis for deriving a stochastic cost frontier and related efficiency measures. Bravo-Ureta and Rieger (1991) chose milk production per farm measured in hundredweight as dependent variable and annual consumption of purchased dairy concentrate, and forage feed both in tons per farm, annual labor used per farm measured in full time worker-equivalents, and dummies (technology and location) as independent variables. The results showed that mean economic efficiency for the farmers in the sample was 70.2 percent, and that, on average, there was little difference between technical (80.3 percent) and allocative (84.6 percent) efficiency. Analyses of the relationship between the obtained efficiencies and four socioeconomic variables, i.e., farm size, education, extension, and experience revealed that the socioeconomic variables did not affect on the efficiency levels.

Kumbhakar et al. (1991) investigated the determinants of farm-level efficiency of the United States dairy farmers by estimating their technical and allocative efficiency obtained from a system-of-equations approach consisting of the stochastic production function (SPF) and the first-order conditions of profit maximization. One advantage of their model, unlike the preceding studies, which assumed the mean of technical inefficiency to be invariant across observations, was

that they allowed the mean to be a function of exogenous variables and therefore it was made farm-specific. The functional form of their production technology was general enough to allow returns to scale (RTS) to vary across observations. The objective of their study was to examine profitability of the U.S. dairy farms in relation to RTS and relative economic efficiency. Using the equation $\Pi = PY(1 - RTS)$ in which Π is profit, P is output price, Y is output, and RTS is returns to scale, the authors stated that “if efficiency and RTS vary across farms, those with lower RTS and relatively more efficient will be more profitable.” The underlying assumption of such expression is that farms allocate their inputs and output efficiently, which is a robust assumption. Kumbhakar et al. (1991) analyzed cross-sectional data on 519 dairy farms collected from 28 states of the U.S. in 1985. They chose milk production per farm measured in hundredweight as dependent variable. The independent variables were the number of dairy cows, annual labor input including hired, operator, and family labor measured in man-hour equivalent, and annual capital stock measured in actual number of dairy machinery hours. The results showed that (a) farmers’ level of education was a factor to determine their technical inefficiency, (b) large farms were relatively more efficient both technically and allocatively, (c) returns to scale of the large-sized farms were lower than those of small and medium-sized farms, (d) given the output price, large farms were more efficient relative to small and medium-sized farms, and (e) both technical and allocative inefficiency were to decrease significantly with increase in the level of education of the farmer.

Kumbhakar and Heshmati (1995) estimated technical efficiency of Swedish dairy producers and examined whether inefficiency was distributed randomly across farms (as assumed in cross-sectional studies) or if there was a persistent component of inefficiency, which varied across farms but was invariant over time. They used a stochastic translog production frontier technique in a rotating panel data context by utilizing a data set from 1976 to 1988, which contained 4890 observations collected from 1425 farms. They decomposed technical efficiencies into a persistent farm-specific (time-invariant) component and a farm-and-time-specific residual

component. The researchers used a multi-step procedure to estimate all parameters of the model except the intercept and the variance components. No distribution assumptions were made regarding the error components and the maximum likelihood method was used to estimate the variance components and residual component of technical efficiency. Thus, the estimates of the production function parameters are robust to the distribution assumptions on the error components. Kumbhakar and Heshmati (1995) used an aggregate measure of total income from production of milk, beef, pork, lamb, wool, poultry, and other dairy products as the dependent variable. They chose five inputs (fodder, material, land, labor, and capital) and two characteristic factors (farmers' age and time) as independent variables. The empirical results showed that the mean persistent technical inefficiency was 10.27 percent (with a variation of zero to 39.11 percent) while the mean residual inefficiency was 3.90 percent (varied from 1.2 to 17.05 percent). The authors concluded that a decline and/or withdrawal of a specific support policy, like a price support, might change the structure of the dairy industry. For instance, farms with relatively high levels of persistent technical inefficiency are likely to go out of business if, per say, support payments are reduced or stopped.

Ahmad and Bravo-Ureta (1995) used an unbalanced panel data to decompose dairy output growth into technological progress, technical efficiency, and input-growth for a sample of 1072 observations collected from 96 dairy farms in Vermont during the period of 1971 to 1984. They used a single equation stochastic production function model in which the dependent variable was total annual milk produced, measured in hundredweight. They also chose the number of dairy cows, total labor input including hired and family measured in worker equivalents, purchased dairy concentrate feed measured in tons, animal, crop and miscellaneous expenses as independent variables. The results showed that the average technical efficiency was approximately 77 percent and the size effect (56 percent) played a greater role than productivity growth (44 percent) in increasing milk production.

Reinhard et al. (1999) estimated technical and environmental efficiencies of Dutch dairy farms using unbalanced panel data, which contained 1545 sample

observations collected from 613 specialized dairy farms during 1991 to 1994. Nitrogen surplus, arising from the application of excessive amounts of manure and chemical fertilizer, was used as an environmentally detrimental input. They specified a stochastic translog production frontier to estimate the output-oriented technical efficiency in addition of specifying an input-oriented technical efficiency of a single input, i.e., nitrogen surplus, to estimate the environmental efficiency. The results showed that the mean output-oriented technical efficiency was 0.894 while the mean input-oriented environmental efficiency was only 0.441. Furthermore, intensive dairy farms were both technically and environmentally more efficient than extensive farms.

2.3.2.2 Nonparametric Frontiers

To our knowledge, no one has attempted to estimate the technical efficiency of farms for any agricultural activity with the use of *stochastic non-parametric frontiers*. Relevant to this thesis is the fact that Kneip and Simar (1996) developed a general framework for frontier estimation using panel data by constructing a new stochastic non-parametric frontier estimator. The methodology that we develop in this thesis builds upon the work of Kneip and Simar by using a statistical approach known as a *generalized additive model* (GAM) to estimate a stochastic non-parametric frontier function for panel data from the North American dairy sector.

Before we introduce the Kneip-Simar methodology and the extension suggested in this research, it is useful to discuss the reasons for using the generalized additive model approach. Why are the efficiency scores obtained from estimating parametric frontiers sensitive to the choice of functional form? How do the efficiency results differ if we consider different distribution assumptions for the one-sided error term representing factors that are under the control of decision-making units? In the next section we focus on problems that are endemic to stochastic parametric frontier estimation.

2.4 Sensitivity of Efficiency Scores

In general, the literature has shown that efficiency scores are sensitive to the choice of both functional forms and the distribution assumptions made about the one-sided random component of the composed error term in parametric frontier estimations. Despite the research contributions that have been made, all of the previously suggested methods suffer from either the choice of functional form or the distribution assumption, and up to now very little has been done about the need for a pre-specified functional form and distribution assumptions. Nevertheless, many papers have been published by implementing these tools. Many publications ignore the fact that there are serious drawbacks with stochastic parametric frontier estimation methods. Let us now examine some research that takes these factors into better consideration.

2.4.1 Choice of Functional Form

One tool for choosing a correct functional form is economic theory. Economic theory can help researchers specify the structure of their model by determining important variables that should be taken into account, identify methodologies being used for solving the specified model, and accounting for restrictions and other requirements to solve an optimization model. Moreover, since the validity of statistical tests and inference are conditional on model specification, the functional form chosen should be appropriate for the specific research use or hypothesis to be tested. In this way, it captures applicable theoretical concerns and allows data to “speak.” In this regard, Berndt and Khaled (1979), Chalfant (1984), Swamy and Binswanger (1983), and Shumway and Lim (1993) have shown how misspecification of functional form could cause serious problems if a policy is implemented based on the biased results obtained from an incorrect functional form.

Anderson et al. (1996) evaluated the ease of application and empirical performance of a non-nested testing procedure relative to a traditional nested

procedure, in order to rank the performance of alternative functional forms. The authors conducted tests to examine the choice of functional form using four aggregate agricultural production data sets in the United States across three major agricultural states (i.e., California, Florida, and Iowa) and two models. Their motivation in developing the empirical model was to find a common policy objective that measured the aggregate responsiveness of output supplies and input demands to changes in expected prices. The researchers chose three widely used flexible functional forms- translog (TL); generalized Leontief (GL); and normalized quadratic (NQ). These functions, which are all derived from second-order Taylor-series expansions, are also referred to as *locally flexible*. They employed statistical procedures to rank these functional forms: (a) a *likelihood ratio* (LR) test for restrictions on two parameters of a Box-Cox transformation identifying the TL, GL, and NQ as special cases; and (b) the *likelihood dominance criterion* (LDC), proposed by Pollak and Wales (1991), which uses these functional forms as non-nested alternative. The authors concluded that it is important to examine alternative functional forms in policy analysis because the preferred functional form appears to be inherently data and model specific. They also concluded that empirical tests for choice of functional form should be considered as a part of standard pretests for model specification in production analysis. This is the same conclusion that Mbagwa et al. (2000) presented in their study.

2.4.2 Choice of Functional Form and Distribution Assumption

Bravo-Ureta and Rieger (1990) estimated the technical efficiency of 404 U.S. dairy farms located within six northeastern states, with data collected between 1982 and 1983. They used a Cobb-Douglas functional form and estimated four alternative production frontier models: simple linear programming, a statistical production frontier using corrected ordinary linear squares, a statistical production frontier using maximum likelihood, and a stochastic frontier assuming a half-normal distribution for the efficiency component of the error term. They evaluated the sensitivity of the results obtained from the choice of a frontier estimator. They used milk production

per farm, measured in hundredweight and adjusted for 3.5 percent butterfat basis, as the dependent variable. In addition, they chose four inputs to production: labor including operators, hired, and family (measured in full-time worker equivalents per farm), consumption of purchased dairy concentrates (measured in tons per farm), veterinary and breeding fees along with other animal expenses, and other feed and machinery expenses included fertilizer, lime, seed, spray plus machinery repairs, gas and oil. A general conclusion arising from their research was that these frontier production function estimators were upward-scaled versions of the ordinary least squares. The researchers also found that different models yielded different efficiency levels across farms. The authors observed that the correlation between the indices from the various methods was high, which implied that the ordinal ranking of firms by their measured level of technical efficiency appeared to be independent of the method used, for a given year. Furthermore, the correlation between efficiency indices for the same method across time, although positive, was much lower than correlation between the indices. In addition, their analysis revealed a weak but positive connection between efficiency and farm size, while efficiency and returns over variable costs exhibited a strong positive relation that was robust across time and model selection.

Giannakas et al. (2003a) examined the effects of different functional forms on the estimation of efficiency using a panel data set of 125 olive farms in Greece during the period 1987- 1993. They used a generalized quadratic Box-Cox (GQBC) functional form for estimation, which nests the generalized Leontief (GL), the generalized quadratic (GQ), translog (TL), the constant elasticity of substitution (CES), and the Cobb-Douglas (CD) as special cases. They wanted to examine the sensitivity of efficiency scores to the various functional forms. Annual olive production (measured in kilograms) was used as the dependent variable, and the aggregate inputs to production were: (a) total labor, comprising hired, family and contract labor (measured in working hours); (b) fertilizers (measured in kilograms); (c) other cost expenses (measured in drachmas, constant 1990 prices); and (d) land, including just the area where the olive-tree was planted (measured in stremmas). The

authors estimated the parameters of the functional forms by using classic panel data estimators: the least squares dummy variable (LSDV) approach and the random effect approach. They also examined pooled least squares compared to the LSDV (fixed effect) and the random effect models using an F-test and a Lagrange multiplier test. The overall mean values of efficiency scores obtained for the entire period were dispersed between 53.4 to 72.3 percent. The GQBC and CES functions yielded the highest mean values, at 72.3 and 70.1 percent respectively, while GL yielded the lowest average efficiency at 53.4 percent. The other models fell in between these values. Highest efficiency scores were between 93 and 94 percent in all the models, but minimum efficiency differed significantly between functions, ranging between 32 and 45 percent for GL and GOBC, respectively. On average, all the functions generated a decreasing trend in mean efficiency scores until 1990, after which they followed a slightly increasing trend.

In sum, Giannakas et al. (2003a) obtained different efficiency results from each functional form, implying that the choice of a particular parametric specification may not be a matter of indifference for the researchers, unless individual efficiency measures are more important. The major conclusion to be drawn from this study is that when the researchers intend to estimate the efficiency of a firm, they should proceed with a general-to-specific modeling strategy to determine the appropriate functional form. An inappropriate choice of functional form could result in significantly biased efficiency estimates and provide misleading policy recommendations regarding potential efficiency improvements.

The last study we review in this section is that of Giannakas et al. (2003b) predicting efficiency using stochastic frontier production models in the presence of misspecification of functional form and distribution assumptions about the random efficiency component. The purpose of the study was to provide some theoretical explanation for the sensitivity of technical efficiency measures to the choice of functional form. They assumed inappropriate functional specifications could be considered to be misspecification in the conditional mean of the stochastic frontier

regression model. Their study used the same data sets, variables, and functional forms as their other in 2003 (see, Giannakas et al., 2003a). In their conclusions, they showed that under misspecification, the estimates of technical efficiency, confidence intervals and production elasticities were biased, even asymptotically. Furthermore, they implemented a series of Monte Carlo simulations and revealed the severity of the bias was dependent on functional specification, along with the percentage contribution of the variance of technical inefficiency to the total variance of the composed errors. They advised that a routine diagnostic check should be performed regarding the specification of functional forms in stochastic frontier studies.

As we mentioned earlier, Kneip and Simar (1996) were the first to attempt to fix the inherent pitfalls of using stochastic parametric frontier analysis for measuring efficiency. In the process, they developed a general framework for estimating production frontier models with panel data. In their methodology, they assumed a sample of firms $i = 1, \dots, N$ on several time periods $t = 1, \dots, T$, and analyzed the performance of stochastic non-parametric frontier models. Because their methodology covered all types of frontier models in the context of panel data, they assumed the conventional parametric formulations in the literature were particular cases. They also investigated the convergence rate of the estimated parameters in their approach. We will see later that in any stochastic nonparametric frontier model, the number of firms, N , and the time periods, T , play an important role on the speed of convergence of the estimators. In fact, both factors must be large enough to yield reliable estimates of the individual production function and estimates of the frontier function.

Kneip and Simar (1996) used a simple non-parametric smoothing technique known as the *Nadaraya-Watson kernel estimator* in order to solve for the underlying production function. Nadaraya (1964) and Watson (1964) first introduced this family of estimators, based upon the work of Tukey (1961). But Rosenblatt (1956) was the first statistician to propose the technique of kernel estimation, and this has since been widely employed in the field of non-parametric regression analysis. A kernel

estimator is a complicated version of a simple nonparametric method of estimating a regression function, known as the *local averaging approach*. What the local averaging method does is to estimate the value of a function $v(x)$ within a closed interval of $x \in [0,1]$, which can be summarized as follows. First, given the fact that v is continuous, any function values at x_i 's in the vicinity of x should be approximately close to $v(x)$. Second, by averaging the values of the regression function Y_i 's in relation to x_i 's in the neighboring of x , one can obtain an unbiased estimator of $v(x)$, approximately. One advantage of the local averaging approach is to reduce the variation arising from the random shocks.

In a kernel function, the simple procedure of averaging in the previous method is replaced by a function contains the weighted sum. These weights define a neighborhood of points around the point of estimation x , known as the *grid point*. In this approach, more weight is given to the observation Y_i 's whose x_i 's is near the grid point. Since the weights are continuously given to the pair of observations, as a result, make kernel estimators smooth and sensitive to local property of the function. In addition, flexibility in form and mathematical tractability are other advantages to kernel estimation. Despite such advantages as compared to the local averaging method, kernel functions have some major drawbacks. Some of the potential difficulties for kernel estimators include boundary bias, lack of local adaptivity, an inclination to flatten out peaks and valleys, sensitivity to the form of the chosen kernel function (e.g., uniform, triangle, Epanechnikov, quadratic, triweight, Gaussian, and Cosinus) which determines the shape of smoothing, and an over-reliance upon a smoothing parameter, called the *bandwidth*, which regulates the degree of smoothness for kernel estimates. Interested readers can read more about the kernel estimation in Hardle (1990); Simonoff (1996); Hart (1997); Fomby (2000); and Sarda and Vieu (2000).

Nevertheless, these issues are not the reasons that we turn away from the Kneip-Simar methodology in favor of what is proposed here. The rate (or speed) of

convergence of the estimators to the true parameters, in a multivariate density estimation, is the key reason why we avoid using any kernel functions in this study. Kernel estimators are extremely sensitive to the number of dependent and independent variables selected in the model, a situation known as the *curse of dimensionality*. Specifically, when the dimension of the variables increases, the estimation of the multivariate density function becomes more difficult due to the following reasons. First, these types of density functions are more complicated than of a univariate density function. This occurs because with a multivariate density function, there will be more possibilities among which variable must be chosen for the implementation process as well as more choices of smoothers parameters available to be set. Second, the graphical visualization of a multivariate density function is difficult as its dimension increases that force one to follow the slicing procedure. This phenomenon becomes rigorous when one uses more than three independent variables. Third, from a practical point of view, it does not make sense to use a nonparametric kernel estimator if the number of dimensions representing the number of variables in the model is large, which makes the need for progressively large sample sizes in higher dimensions in order to obtain an accurate estimation of the density function. As Simonoff (1996, p.101) states “in high dimensions, local neighborhoods are almost surely empty, and neighborhoods that are not empty are almost surely not local.” Interested readers can read more about the curse of dimensionality in Hardle (1990) and Silverman (1986).

Interestingly, Kneip and Simar (1996) suggested that other types of nonparametric approaches could be developed to overcome the curse of dimensionality issue. Therefore, in this thesis we propose to extend the stochastic non-parametric frontier estimation methodology so as to mitigate the effect of the curse of dimensionality. The extension we propose involve the use of *generalized additive models (GAMs)* as developed by Hastie and Tibshirani (1990). This class of statistical models is defined in the next chapter.

CHAPTER III

METHODOLOGY

3.1 Introduction

In the previous chapter we stated that the methodology we propose in this thesis is indirectly tied with what Kneip and Simar studied in 1996. We noted that the authors used a specific nonparametric frontier analysis in measuring the technical efficiency of the European railway industry by using the Nadaraya-Watson index, which is a simple ratio of two kernel functions. Then, we highlighted the pitfalls of their method, particularly the curse of dimensionality problem.

Following a suggestion presented by Kneip and Simar (1996), we introduce another method of nonparametric frontier analysis that alleviates the inherent problem of limitation in predictors existing in any kernel estimators. To do this, we propose a new stochastic nonparametric frontier methodology to remove the curse of dimensionality problem by using *generalized additive models (GAMs)*, introduced by Hastie and Tibshirani (1986; 1990).

In this chapter, we present our methodology and show how it can remove the curse of dimensionality problem. Before we directly get into the model, there are two points worth mentioning. First, the core of our methodology is the concept of *smoothing*. Applications of *smoothing techniques* in regression analysis have been rapidly spread among researchers and experts. These techniques are increasingly used in the biosciences, environmental sciences, medical research, and intensively in the field of engineering and nonparametric econometrics. For instance, in nonparametric econometrics, smoothers can be thought of as nonparametric estimates of the regression model. Second, since we shall see that our methodology has a close relationship with a generalization of the linear regression model, it would be more appropriate to review the problem involving the estimation of multiple

regression and linear models prior to proposing the methodology. Afterwards, we shall briefly introduce the theory of *additive models* and its extension, i.e.; the theory of generalized additive models. We will also explain two nonparametric *based-smoothing* approaches used in this study to estimate the parameters of the frontier function.

The organization of this chapter is as follows. First, we explain the general problem of estimating multiple regression and linear models. Both additive models and generalized additive models are derived by generalizing the conventional linear regression models, so it is useful to outline the limitations in estimation of the linear and generalized linear models. Second, we introduce the theory of *additive models* followed by describing the extension of such models; the so-called generalized additive models. Third, we briefly describe both nonparametric approaches used for estimation of the parameters of the frontier production function used in this study. These two techniques are *locally weighted scatterplot smoothing* (LOWESS), also known as *locally regression model* (LOESS), proposed by Cleveland (1979), and *spline smoothing*, also known as *cubic smoothing spline*, proposed by Whittaker (1923) and developed by Wahba (1990). Finally, using the preceding sections, we propose our methodology in detail. In chapter five we shall apply the methodology to the sample data set.

3.2 Multiple Regression and Linear Models

Consider a standard multiple regression model as [3.1];

$$Y = \alpha + X_1\beta_1 + X_2\beta_2 + \dots + X_p\beta_p + \varepsilon \quad (3.1)$$

Where $E(\varepsilon) = 0$, and $\text{var}(\varepsilon) = \sigma^2$. In this equation, we may have n observations on a vector of dependent variable Y , denoted by $y = (y_1, \dots, y_n)^T$ explained either at p separate vectors of $x^i = (x_{i1}, \dots, x_{ip})$, or designed into a matrix of $X = (x_1^i, \dots, x_p^i)$,

where in both cases $i = 1, \dots, n$. We may also assume that the covariates x are either predetermined, or random variables, and/or a combination of both. The main goal of equation [3.1] is to model the dependence of Y on X . There are several reasons why we are interested in analyzing such relationship. Three of the most important reasons are as follows:

- *Description*: we want a model to describe the dependence of the response on the predictors so that we can learn more about the process that produces Y ,
- *Inference*: we want to assess the relative contributions of each of the predictors in explaining Y , and
- *Prediction*: we wish to predict Y for some set of values X .

In equation [3.1] we indirectly undertake a strong assumption about the dependence of $E(Y)$ on each covariates of the matrix X : the dependence is linear in each of the predictors. This assumption is one of the principal hypotheses of the classical linear regression models. In fact, if the assumption in question holds, then the linear regression models are extremely useful because (i) they provide a simple description of the data, (ii) they show how each of the predictors contributes with a single coefficient, and (iii) they establish a simple method for predicting new observations.

The linear regression models can be extended in different ways. One way of such generalization is to use the *surface smoothers*, which as we mentioned can be thought of as nonparametric estimates of the regression model defined as equation [3.2];

$$Y = f(x_1, \dots, x_p) + \varepsilon \quad (3.2)$$

Using surface smoothers does not mean that we can generalize linear functions flawlessly. One problem of using surface smoothers is to choose the shape of the smoother functions, so-called *kernel functions*, which can be thought of as neighborhood that define local in p dimensions. In addition to the difficulty of arbitrarily choosing the type of kernel functions, we will face the *curse of*

dimensionality problem, which exists in high dimensions, i.e., $p > 2$ if we use kernel functions as the surface smoothers (Bellman, 1961).

Due to the *localness* problem of kernel functions for estimation of the mean response function in nonparametric regression analysis, several multivariate nonparametric regression techniques have been proposed to alleviate the curse of dimensionality problem. Among them, we can refer to the *recursive-partitioning* regression, or the *projection-pursuit* regression, which directly addresses the dimensionality issue. Given sufficient data, both models have good predictor power and under suitable conditions they are all consistent for the true regression surface. However, they all suffer from being difficult to interpret, specifically in examining the effect of any particular variables once a complicated surface is fitted. For low dimensional surfaces we can look at slices defined by conditioning all but one of the variables, but this task becomes impossible in higher dimensions (see, Hastie and Tibshirani, 1990, and Schimek, 2000 for further discussion).

Such problems in estimating the mean response function restrict one to focus on additive models and generalized additive models (GAMs). In particular we shall special pay attention to GAMs in this study, where the curse of dimensionality problem does not exist. In fact, we build our methodology based on the theory of the generalized additive models, which we will briefly review alongside additive models in the following sections.

3.3 Additive Models

Consider any multiple variable regression model such as equation [3.1], in which the conditional mean relationship between the mean response, i.e., $E(Y)$ and each of the predictors x_i is assumed to be linear and additive. Equation [3.1] can also be written as

$$E(Y) = m(X) + \varepsilon \quad (3.3)$$

where the assumptions of zero mean and constant variance for the residual side of the equation still hold. In equation [3.3], we can define the structural relationship between the response variable Y and the vector of p covariates $X = (x_1, \dots, x_p)^T$ through

$$m(x) = E(Y | X = x) \quad (3.4)$$

where $x = (x_1, \dots, x_p)^T$ and $m(x) = m(x_1, \dots, x_p)$. Based on the assumption of linearity and additivity of the conditional mean relationship between the response and the predictors, from equation [3.4], we realize that $m(x)$ is linear and additive with respect to the predictors. If we relax the linearity assumption, but maintain the additivity postulate in equation [3.4], then a class of models, known as additive models, is obtained. With additive models, an individual functional form connects each of the explanatory variables to the dependent variable.

Given equation [3.3], consider equation [3.5], in which the dependent variable is approximated by the additive model

$$m(X) \cong f(X) = Y = \alpha + \sum_{j=1}^p f_j(X_j) \quad (3.5)$$

where α is a constant and the f_j s are arbitrary univariate smooth functions, one for each predictor. To avoid having free constants in each of the functions f_j , it is necessary that $E[f_j(X_j)] = 0$. This requirement, which is set in the range of $1 \leq j \leq p$, implies $E[f(X)] = \alpha$ and is necessary for the purpose of identification. If the additivity assumption defined in equation [3.5] is correct, then we have

$$E\left[f(X) - \alpha - \sum_{j \neq q} f_j(X_j) \mid X_q\right] = f_q(X_q) \quad (3.6)$$

for $q = 1, \dots, p$. One way to estimate each of the univariate functions f_1, \dots, f_q , corresponding to the explanatory variables, is to follow an iterative process. For

example, by assuming a known constant for α and given functions $f_j, j \neq q$, the right hand side of equation [3.6] can be estimated by a univariate regression fit based on each pair of observations $(X_{iq}, f_i(X))$ for $i = 1, \dots, n$. Therefore,

$$\hat{f}_j^* = \hat{f}_j - n^{-1} \sum_{i=1}^n \hat{f}_j(X_{ij}) \quad (3.7)$$

where \hat{f}_j^* is estimated each time using an iterative procedure replacing \hat{f}_j , the process continues until the convergence occurs. The described approach, which is discussed in section [3.5], is known as the *backfitting algorithm*, introduced and analyzed by Friedman and Stuetzle (1981) and Breiman and Friedman (1985). For further information on how the backfitting algorithm applies to additive models, see Schimek and Turlach (2000).

The additive model has an *a priori* motivation as a data analytic tool. Since each variable is represented separately in equation [3.5], the model maintains an important interpretive feature of the linear model. This interpretation comes from the fact that the variation of the fitted response surface, holding all but one predictor fixed, does not depend on the values of the other predictors. In practice it means that once the additive model is fitted to data, we can plot the p coordinate functions separately to examine the roles of the predictors in modeling the response (or dependent variable). However, we should not forget that the additive model is an approximation to the true regression surface. This expression, to some extent, is similar to the situation when we fit a linear regression model. In such cases, we generally do not know if the model is correct; instead, we are just hoping that it will be a good first order approximation to the true response surface.

So far, we have briefly reviewed the theory of additive models in which the mean of the response is modeled as an additive sum of the predictors. As we mentioned, these models extend standard linear regression models. In the following

section we will explain another useful class of linear models, known as generalized additive models (GAMs). Hastie and Tibshirani (1986; 1987a; 1987b) and Stone (1986) proposed the theory of generalized additive models in a series of works, which were gathered in Hastie and Tibshirani's (1990) monograph.

3.4 Generalized Additive Models

Generalized additive models (GAMs) are an extension of what Nelder and Wedderburn (1972) and McCullagh and Nelder (1989) proposed as *generalized linear models* (GLMs). Generalized linear models are themselves an extension of classical linear models. In a generalized linear model, the unknown regression function, such as $m(X)$ in equation [3.3], is modeled linearly through a known *link function* G in a parametric manner. In such a generalization, we can get more benefit by relaxing the linearity assumption while maintaining the additivity assumption by replacing the former function with some smooth function in a nonparametric way as we did for the additive models. This gives us more flexibility for comparison to the additive models.

Generalized additive models allow the conditional mean of a response variable to be dependent on a sum of individual univariate functions where each of them contains one component of the covariate matrix, known as predictors. By relaxation of the linearity assumption in a generalized additive model, the predictor effects in equation [3.5] might be nonlinear, because the functions f_j are now arbitrary.

To see how we can derive a generalized additive model from an additive model, consider a general form of an additive model like equation [3.5], where it becomes

$$E[Y|X = x] = G \left[\alpha + \sum_{j=1}^p f_j(x_j) \right] \quad (3.8)$$

in which $G(\cdot)$ is a fixed link function and the distribution of Y follows an exponential family similar to the generalized linear models. Like the described additive model, we assume that $E\left[f_j(X_j)\right] = 0$ so that $E(Y) = \alpha$ for identification purposes. The estimation of a generalized additive model contains two steps. In the first step, we estimate the additive predictors while in the second step the estimated additive predictors are linked to the function $G(\cdot)$ through an iterative process. The former part can be done by solving a system of normal equations and the linkage part is applied by another iterative procedure, the so-called *local-scoring* algorithm (see Schimek and Turlach, 2000, p.280-297). It is called “local scoring” because a local averaging process is used to generalize the *Fisher scoring* procedure. This procedure is applied to estimate the parameters in a generalized linear model. In practice, the local-scoring algorithm is similar to the Fisher scoring procedure. However, in the latter models, the least squares step, which is used to update the estimate $\hat{\beta}$ for the linear predictor $X'\beta$, is replaced by the solution obtained from solving the normal equations part of the model, which in turn is applied by the backfitting algorithm to update the estimates for α and f_j s. The local scoring algorithm is described in Hastie and Tibshirani (1990, p.141). Later, particularly when we present our model, we discuss more about the theory of generalized additive models and how to estimate them.

In this study, we use two nonparametric approaches to estimate the mean response variable and its parameters in the generalized additive model, as described in equation [3.8]. As mentioned in the introduction part of this chapter, these two techniques are *locally weighted scatterplot smoothing* (LOWESS), also known as the *locally regression model* (LOESS), proposed by Cleveland (1979), and *spline smoothing*, also known as *cubic smoothing spline*, proposed by Whittaker (1923) and developed by Wahba (1990). In the following sections, we shortly explain these two techniques.

3.4.1 Locally Weighted Scatterplot Smoothing (LOWESS)

The locally weighted scatterplot smoothing, or the locally regression model, is introduced by Cleveland (1979) and developed by Fan (1992; 1993) and Hastie and Loader (1993). The basic idea of using the LOWESS approach is to find a point in the space of the predictors and then search the neighborhood points that are smoothed using surface smoothers to estimate the mean response function. For instance, we may consider any point x , a so-called local observation, in the space of the predictors. Estimating a local regression model can be specified through different approaches. In a local regression we attempt to find a neighborhood containing the initial point x in which the regression surface is well approximated by a function from a specific parametric point of view. Therefore, our specification from the local regression model leads to methods of fitting the response function. The method consists of smoothing the response as a function of the predictors.

We outline the procedures of fitting a local regression model in a series of steps. In these procedures, our goal is to smooth $s(x_0)$, in which $s(\cdot)$ depicts the scatterplot smoother functions, using k nearest neighborhoods. First, we identify the k nearest neighbors of x_0 which are denoted by $\Omega(x_0)$. In the second step, we determine the furthest near-neighbor observation from x_0 and compute the distance between these two points. That is, we calculate $\Delta(x_0) = \max_{\Omega(x_0)} |x_0 - x_i|$. Next, using the *tri-cube* weight function (Cleveland et al., 1993, p.314), we assign weights ξ_i to each point in $\Omega(x_0)$ as

$$\xi \left(\frac{|x_0 - x_i|}{\Delta(x_0)} \right) \quad (3.9)$$

where

$$\xi(u) = (1 - u^3), \text{ for } 0 \leq u \leq 1 \quad (3.10)$$

In the last step, and by using the weights computed in the third step, we obtain the scatterplot smoother $s(x_0)$ value at the initial point x_0 by applying the *weighted least-squares* (WLS) of response variable y to predictors x in the domain of $\Omega(x_0)$.

Locally weighted scatterplot smoothers are popular among statisticians and econometricians for at least two reasons. First, these methods are able to produce robust results in respect to the outliers. For example, Cleveland (1979) discussed the use of a robust regression within each neighborhood to provide appropriate estimation against outliers. In practice, Cleveland's results mean that we should repeat smoothing the data and simultaneously scale the points by down-weighting them with large residuals. Second, with the scatterplot smoothers, we are able to easily find the neighborhoods for the target point x_0 . There are many methods of finding neighborhoods available to this, however two of them, i.e., *nearest neighborhood* and the *asymmetric nearest neighborhood*, are the most popular. Econometricians prefer using the former method since it is less biased, as compared to the latter method. The nearest neighborhood is less biased because, given a fixed number of points, the average distance of the points to the main point (or target point) in the nearest neighborhood is less than the asymmetric nearest neighborhood (Hastie and Tibshirani, 1990, p.30-31).

3.4.2 Spline Smoothing

The second nonparametric approach used in this study to estimate the mean response function modeled in the GAMs theory is spline smoothing, also known as a cubic smoothing spline. The proposition of spline-smoothing concept dates back to Whittaker (1923) who worked on methods of graduating data and derived the smoothing spline estimator. This work was continued by Schoenberg (1964). At first, the smoothing spline was regarded as a numerical analysis tool. However, like other numerical methods, it suffers from lack of statistical inference. Wahba (1990) proposed and developed the modern concept of smoothing spline, which thereafter

has been considered as a method of nonparametric regression analysis. Spline smoothing, which provides a flexible methodology for fitting data in a nonparametric manner, has gained popularity among econometricians and is applied in a wide variety of sciences such as analysis of growth data, medicine, remote sensing experiment, and economics (see, e.g., Wegman and Wright, 1983, and Eubank, 1984).

To illustrate spline smoothing, consider another version of equation [3.3], a general functional form

$$y_i = m(x_i) + \varepsilon_i, \quad i = 1, \dots, n. \quad (3.11)$$

where $m(\cdot)$ is an unknown regression function and $\varepsilon_1, \dots, \varepsilon_n$ are assumed to be uncorrelated random errors with zero mean. Suppose our concern is to estimate m from the observed data in equation [3.11]. Based on the theory of classical linear regression, one way to estimate m is the simple linear regression method. The classical linear regression approach uses the least squares method to estimate $\hat{m}(x) = \hat{\alpha} + \hat{\beta}x$, where $\hat{\alpha}$ and $\hat{\beta}$ are, respectively, the intercept and slope estimators obtained by minimizing the residual sum of squares

$$RSS(m) = \sum_{i=1}^n [y_i - m(x_i)]^2 \quad (3.12)$$

over all observations in relation to the assumed functional form of $m(x) = \alpha + \beta X$. The problem with using the OLS approach is that there may not be a linear relationship between the regressand and the regressors. One way to find the source of such failure in describing precisely the relationship between the dependent and independent variables is to use a Taylor-expansion series as

$$m(x) = m(x_0) + m'(x_0)(x - x_0) + o(|x - x_0|^2) \quad (3.13)$$

which assumes m is at least twice differentiable and that there is a point x close to some fixed point x_0 . Equation [3.13] states that for x close to x_0 , m follows a linear model whose intercept and slope are, $m(x_0) - m'(x_0)x_0$ and $m'(x_0)$, respectively. This may occur in two extreme cases. The first one happens when the unknown function m is assumed to be linear, which only happens if the slope of the regression function $m'(x_0)$ remains constant and the residual term $o|x - x_0|^2$ is small. The invariant assumption of the slope is a heavy condition to impose on the functional form because in many applications this may not be the case. This pitfall means that one might consider the other extreme case, which is to alter the entire estimation process by considering the minimization of $RSS(m)$ over functions m with variant slope instead of minimizing the residual sum of squares, shown in equation [3.12]. This means at each point X we will have different slopes, which connect every two responses by lines associated with their own individual slopes.

These two extreme cases can be compared in terms of the information they provide. The first extreme case, i.e., linear regression fit, which assumes inflexible slope uses too little of the information in the data, provides a useful summary of the data in addition of presenting a satisfactory description of the features in the data. In contrast, the second extreme case, which assumes flexible slopes, uses too much information. Moreover, it does not provide a useful summary of the data and fails to show a satisfactory description of basic trends in the data. This failure may occur due to the regression function in equation [3.11] rather than to the random-noise component of the model.

The problem that exists in each of the two extreme cases motivates one to find a way to avoid the issue such that neither of the fits with constant slopes nor the fits with variant slopes applies. To do this, we can consider penalizing functions whose slopes are changed very quickly. First, we assume the rate of change in the slope of a function m is given by m'' . Since this slope varies from one point to the

another, by taking the integral from the entire changes in slope of the fitted function we wind up

$$\Phi(m) = \int_{x_1}^x m''(x)^2 dx \quad (3.14)$$

With this view, a new approach that takes into account for the quick variation in slopes of the fitted function is obtained as

$$RSS(m) + \tau \Phi(m), \quad \tau \geq 0, \quad (3.15)$$

which can be minimized over all functions provided that they are capable of being twice differentiated. In equation [3.15], τ is called the *smoothing parameter* (or *span degree*) that indicates the level of importance we place on the structure of the function, given that to some extent the slope of the fitted function is flexible. For example, as τ approaches infinity, we have less concern about the variant slope and move towards the conventional linear regression with fixed slope. On the contrary, if τ is close to zero, the result will be a regression with a completely flexible slope.

Eubank (2000) showed that if n in equation [3.14] is greater than or equal to two, then there is a unique, computable minimizer \mathcal{G}_τ for equation [3.15] called a *cubic smoothing spline*. The cubic smoothing spline estimators are linear in the sense that one can find constants like $g_i(x)$, $i = 1, \dots, n$ for each estimation point x such that

$$\mathcal{G}_\tau(x) = \sum_{i=1}^n g_i(x) y_i \quad (3.16)$$

By introducing the cubic smoothing spline estimator to some extent we can solve the problem of fitting regression with variant slopes. However, we create a new problem, which is the determination of appropriate smoothing degree, or *spanning degree* for a given set of data. This problem arises because of the lack of theory as well as the lack of an appropriate algorithm. The cubic smoothing spline estimators are sensitive to the degree of smoothing, which means we will not have the same

span degree for every data set. In light of smoothing spline approach, the best choice of the smoothing degree τ is a value that minimizes the *squared-error loss*, as indicated in equation [3.17];

$$L(\tau) = n^{-1} \sum_{i=1}^n \left[m(x_i) - \mathcal{G}_\tau(x_i) \right]^2 \quad (3.17)$$

From equation [3.17], we may notice that an appropriate choice of the smoothing degree depends upon two factors: (i) the unknown true regression curve, and (ii) the inherent variability of the estimator. There are several solutions suggested to reduce the severity problem of choosing appropriate smoothing degree. Among them, *cross-validation* (CV) introduced by Stone (1974,1977) and Allen (1974); *generalized cross-validation* (GCV) proposed by Craven and Wahba (1979); and *plug-in methods* proposed by Gasser et al. (1991) are widely used. In this study, we chose the cross validation method as the base choice for the smoothing parameter τ to estimate the unknown $L(\tau)$ in equation [3.17]. We shall explain the cross validation method in the following sections. Interested readers can find more about the spline smoothing in Eubank (1984; 1988; and 2000) and Wahba (1990).

In summary, we will use generalized additive models to estimate the mean response variable in equation [3.3] by using two nonparametric approaches to alleviate the curse of dimensionality problem, as described in Kneip and Simar (1996). So far, we have briefly explained the theories of GAMs, LOWESS, and spline smoothing. The remainder of this chapter will introduce the structure of the model, the estimation process, and the suggested method to compute technical efficiency. The empirical application of the model will be presented in chapter five of the study. Before moving forward, one point is worth mentioning. In order to avoid conflicting notation of the proposed model with what we have seen in the theoretical part of this chapter, we have decided not to follow the same notation and view the rest of the chapter as autonomous material. However, we number the equations continuously and refer to the equation's number as it appears through this chapter, wherever applicable.

3.5 The Construction of the General Model

In this section, we introduce the methodology that is used to measure technical efficiencies of Canadian (Ontario and Quebec) and U.S. (New York and Wisconsin) dairy producers. The information related to the farm input and output prices are not available in the sample data otherwise we would have estimated allocative and overall (economic) efficiencies. Nevertheless, this lack of information does not affect the credibility of the model. As we mentioned, we compute technical efficiency by analyzing a *stochastic nonparametric production frontier model*. We will also use the results obtained from a conventional flexible parametric functional form, i.e., the *transcendental logarithmic function*, also known as *translog function*, proposed by Christensen et al. (1971; 1972; and 1973), to compare with the results from the nonparametric approaches. The estimated technical efficiency in the parametric case is obtained using the COLS method of Richmond (1974) and the frontier model of Battese and Coelli (1992). The translog function is a second order Taylor-series expansion in logarithm format of a true but unknown technology around a point of approximation. We will also emphasize two characteristics of every panel data set: the number of farms, $i = 1, 2, \dots, N$, which is changed every year, and the sequence of time periods, $t = 1, 2, \dots, T$. These two components are important in stochastic nonparametric frontier analysis because they facilitate the convergence of the estimators to the true parameters at a reasonable *speed of convergence rate*.

The remaining material is organized as follows. First, we set up a general model, which contains no prespecified functional form and does not assume any predetermined assumptions on the inefficiency components. As Kneip and Simar (1996) stressed, one may estimate the parameters of the general model with a nonparametric approach, provided that the number of farms and the sequence of time periods are both large. This condition must be met in all nonparametric methods to project the model with more reliable estimators. It also helps us to estimate the true parameters of any function (production, cost, and profit) as well as the best performance of the current technology, i.e., *frontier functions*. Second, we

consider a more narrow model that distinguishes between the farms, whose technological functional forms are similar to each other, but their differences can be distinguished by a parameter called the *location effect*, α_i . Finally, we will introduce a method to measure technical efficiencies based on the preceding material.

3.5.1 The Model Specification

When we do regression analysis, we look forward to finding a relationship between a dependent variable (regressand) $\{Y_{it}\}_{i=1,\dots,N_i}^{t=1,\dots,T}$ and independent variables (regressors, predictors) $\{X_{it}\}_{i=1,\dots,N_i}^{t=1,\dots,T}$. For example, if we have N independent pairs of observations¹ $\{(X_{it}, Y_{it})\}_{i=1,\dots,N_i}^{t=1,\dots,T}$, we can write the general regression model as

$$Y_{it} = f_i(X_{it}) + \varepsilon_{it}, \quad i = 1, 2, \dots, N, \quad \text{and} \quad t = 1, 2, \dots, T. \quad (3.18)$$

where Y_{it} is the output, f_i is the unknown functional form of the regression, X_{it} is a multidimensional series of inputs with real values, i.e., $X_{it} \in \mathfrak{R}^d$. Furthermore, ε_{it} is the random shock term assumed to be distributed identically and independently among the farms with zero mean and same distribution \mathfrak{I} . It also possesses compact support, denoting how much variability Y_{it} has around the mean response function, which means

$$E[Y|X = x].$$

We are usually able to guess about the relationship between dependent and independent variables by either drawing a scatter diagram or doing some residual analysis. The former method also presents a guide for the structural framework of the model. The credibility of a graphical approach decreases as the number of predictors is increased. Therefore, we need other methodologies to discover the

relationship between variables in the model. Sometimes, that relationship might have been formed in a special manner. Among all particular relationships between the mean response and the regressors in the model, Hardle (1990, p.3) highlighted three characteristics. These are *monotonicity or unimodality; location of zeros and the size of extrema*.

In equation [3.18], f_i can be estimated by either parametric or nonparametric methods. A parametric approach considers the relationship between dependent and independent variables in a prespecified functional form. Conversely, a nonparametric method refers to a type of regression analysis used to obtain robust estimators that allow the data to determine the shape of the functional form with no constraints dictated by the theory. Nonparametric regression analysis is indeed different from what statisticians usually mean by *nonparametric statistics*, counted as a *free-distribution* method. In light of the former definition, neither the distribution of the error terms nor the functional form of the regression function is prespecified.

There are four reasons to justify using nonparametric regression analysis in applied studies. First, there is wide potential for the use of nonparametric methods in demonstrating the relationship between dependent and independent variables in a model. Second, these methods allow users to predict the mean response function without imposing any framework to the structure of the function. The third purpose introduces the nonparametric approach as a tool to recognize the outliers in a series of observations. Finally, it deals with replacing data instead of missing information as well as finding new observations in the vicinity of x 's by interpolating.

By estimating the conditional mean response function f_i in equation [3.18] over a vector of regressors, we often search to analyze the average dependency of a regressand on the predictors, given a certain value of the regressors. This means that

¹ There are some parametric and nonparametric statistical tests indicating the independence

the f_i can be obtained by integrating the response function which is multiplied by the simple ratio of the joint density function of (x, y) over the marginal density function of x (Hardle 1991, p.124). The special case of such derivation occurs when the numerator of the described ratio follows a normal distribution with zero mean, which turns the regression out to be a simple (multiple) linear regression model. This is not the case when a nonparametric approach is used where no assumptions regarding the distribution of the error terms and functional form are made. In other words, the nonparametric approach “*let the data speak for themselves.*”

Before we explain the structure of the model, we need to review a few conditions that apply to the model to maintain the stochastic aspect of the issue. Kneip and Simar (1996) have thoroughly described these conditions, providing related theorems and their proofs. In this part of the study, we only present the results of these conditions and offer references for interested readers who want more details. Moreover, as explained previously, the focus of this study is on the production function. This emphasis on the production side will not affect the credibility of the model and by adjusting some proper descriptions, we would be able to apply the model to the other two types of the economic behavior: cost and profit functions. A short description of the conditions is as follows:

- (a) In equation [3.18], we assume the mean response function f_i , the error term ε_{it} , and the vector contains a series of the regressors X_{it} , are independent from each other.
- (b) The information related to each farm i , $i = 1, 2, \dots, N$ is observed through a sequence of time periods t , $t = 1, 2, \dots, T$ which leads us to consider an individual production function averaged over all farms by an unknown mean response function f_i . We also assume that the function f_i is smooth enough to be at least twice differentiable.

of observations. See Madansky (1988), and Seigel and Castellán (1988) for more details.

- (c) Each farm must be independently drawn from a population using an appropriate randomized sampling method. It means all farms in the sample data are identically independently distributed (*i.i.d.*).
- (d) We also suppose that each regressor in the model x initially belongs to the domain set of the independent variables, i.e., $x \in \mathfrak{R}_D$. Although the distribution type of the independent variables is not prespecified, it is assumed that the real value of the mean response function f_i is obtained by using the values of the regressors in equation [3.18]. In this case, given the underlying technology, we can write the best practice of an individual farm in the sample size, known as the *frontier*, as follows

$$\wp(x) = \sup \left\{ y \in \mathfrak{R} \mid \mathfrak{F}_x > 0 \right\} \quad (3.19)$$

Where $\wp(x)$ is the frontier farm, and \mathfrak{F}_x is a maximal non-prespecified density function for the mean response function that is set to produce the maximum yield corresponding to the frontier farm. The term *sup* in equation [3.19] stands for *supremum*, a known terminology in the *input distance function* (IDF) theory (Fare and Primont 1995, p.19). If our analysis contains cost (or any input) function, the word *supremum* in equation [3.19] is replaced by *inf* stands for *infimum* in the *output distance function* (ODF) theory (Fare and Primont 1995, p.9). Economists usually use the term *supremum* and *infimum* in the *multi-output production theory* because sometimes the conditions of obtaining maximum (minimum) from the underlying production or profit (cost) functions may not be met.

- (e) In equation [3.18], we defined ε_{it} as random shock terms to denote the variability of Y_{it} around $f_i(x)$. Random shock terms are stochastic and, hence, allow for random noise. Thus, there is a compound error term, defined for any individual production function, which means any deviation from the frontier

function $\varphi(x)$ is imputed to the technical inefficiency and the conventional random error terms.

- (f) Finally, we assume the vector of the regressors in the model does not have a prespecified density distribution, which means any arbitrary chosen positive real valued number would be less than the unknown density distribution for each real values of the regressors that fall in the domain of the independent variables.

3.5.2 Estimation of the Mean Response Function

In this section, we show the estimation procedure of the unknown mean response function f_i . To do this, we suppose each farm in the sample has a unique production function. Prior to assuming such hypothesis, we should know that the criteria of having a large number of observations in both the number of farms and the sequence of time periods, even few years, are met. Given these two assumptions there are few nonparametric approaches used to obtain the estimation of the mean response function $\hat{f}_i(x)$. For instance, Kneip and Simar (1996) used the *Nadaraya-Watson kernel estimators*, proposed simultaneously by Nadaraya (1964) and Watson (1964), which is the simple ratio of two kernel estimators. In this study, we use the *generalized additive models* (GAMs), introduced by Hastie and Tibshirani (1986; 1990), described in section [3.4]. Pagan and Ullah (1999, p.157-59) listed a series of applied research, which studied nonparametric regression analysis to obtain estimators with various methods in different areas such as economics, finance, marketing, and forecasting. The GAMs approach has not been used in any study related to measuring efficiency, and in particular, in the dairy industry. Therefore, it gives an advantage to this study to make a considerable contribution to the economic literature.

To start presenting our model, assume the observations related to each farm in the sequence of time periods is fixed, then we can expand the general regression model, defined in equation [3.18] as

$$f_i(X_{it}) = c + \sum_{j=1}^d f_{ji}(X_{jit}) + \varepsilon_{it} \quad (3.20)$$

where the definition of the variables remains the same. We also assume that f is the unknown mean regression curve that must be estimated via a series of common d regressors used by each farm, i , in the sample size that is drawn independently from a population. Moreover, for the described identification problem, we impose that the value of f_{ji} for each farm to be equal to zero, which means $E\left[f_{ji}(X_{jit})\right] = 0$ (see, section 3.3). By considering d regressors in the estimation process, we indirectly remove the problem of *curse of dimensionality* existing inherently in the nonparametric models that use any type of the kernel functions. In light of estimation process in a nonparametric manner, Hastie and Tibshirani (1986; 1990) used generalized additive models, while Newey (1994), Tjøstheim and Auested (1994), Linton and Nielsen (1995), and Chen et al. (1996) suggested other techniques.

Given the definition of frontier in equation [3.19], suppose that it takes the general functional form as

$$\varphi_i(X_{it}) = c + \sum_{j=1}^d \varphi_{jt}(x_{jit}) \quad (3.21)$$

then equation [3.18] can be written as

$$Y_{it} = f_i(X_{it}) + \varepsilon_{it} = c + \sum_{j=1}^d \varphi_{jt}(x_{jit}) + \varepsilon_{it} \quad (3.22)$$

which φ_{jt} represents the functions of single input variables and the identification problem holds (see, section 3.3). We chose the backfitting algorithm to estimate φ_{jt} as the iterative smoothing process. Here, we explain the algorithm for only two predictors, but the idea can be extended in a straightforward manner. Suppose the model is

$$E\left[Y \mid x_1, x_2\right] = f\left(x_1, x_2\right) = c + f_1\left(x_1\right) + f_2\left(x_2\right) \quad (3.23)$$

Furthermore, we may notice that

$$f_1\left(x_1\right) = \int f\left(x_1, x_2\right) g\left(x_2\right) dx_2 = E\left[f\left(x_1, X_2\right)\right] \quad (3.24)$$

By considering the assumption $E\left[f_2\left(x_2\right)\right] = 0$, we can obtain the following result,

$$\int f_2\left(x_2\right) g\left(x_2\right) dx_2 = 0 \quad (3.25)$$

Thus, $f_1\left(x_1\right)$ is estimated by $\hat{f}_1\left(x_1\right) = T^{-1} \sum_{i=1}^T \hat{f}\left(x_1, x_{i2}\right)$ where $\hat{f}\left(x_1, x_{i2}\right)$ is some nonparametric estimator of $f\left(x_1, x_2\right)$ (see Chen et al., 1996 for detailed discussion).

Given the assumption that the unknown means response function f is a twice-differentiable smooth function, we can now obtain the reliable nonparametric estimators using the backfitting algorithm. This algorithm, first, estimates $\hat{f}_1\left(x_1\right)$ in the simple generalized additive model, introduced in equation [3.23]. Then, while fixing the estimate $\hat{f}_1\left(x_1\right)$, it tries to project the mean regression function on x_2 by smoothing the residual $Y - c - \hat{f}_1\left(x_1\right)$, which leads to the estimation of $\hat{f}_2\left(x_2\right)$. Since the backfitting algorithm is an iterative process, the next step is to improve the estimation of $\hat{f}_1\left(x_1\right)$ by smoothing the residual $Y - c - \hat{f}_2\left(x_2\right)$ on x_1 , which, in turn, leads to enhance the estimators that are used to smooth the residual $Y - c - \hat{f}_1\left(x_1\right)$ on x_2 in the second step. This procedure continues until the reliable and efficient estimators are achieved. It is important to know that the explained algorithm needs the initial estimation of $\hat{f}_1\left(x_1\right)$ and hence, the estimate of $\hat{f}\left(x_1, x_{i2}\right)$. In this study, we use the locally weighted scatterplot smoothing and

spline smoothing approaches (see, sections 3.4.1 and 3.4.2) to obtain the initial estimate of $f_1(x_1)$ in the iterative smoothing process.

The innermost part of generalized additive models theory is based on the iterative process called *smoothing process*. The smoothing process generates smoothing estimators that are widely used in nonparametric regression analysis. It takes the average locally in the neighborhood of any fixed points of the predictors in the multidimensional vector of the regressors in the model so that the mean $f_i(x)$ becomes the mean of Y_i for all x in the procedure. This task cannot be done by using any conventional kernel functions, or by generalizing the familiar univariate smoothing techniques (Schimek 2000, p.278). Bellman (1961) gave an explanation for the poor property of kernel functions: “it is necessary to define neighborhoods in the d -dimensional space, but under the curse of dimensionality neighborhoods with a fixed number of points becomes less local as the dimension increases.”

It is important to note that using the smoothing process is not free. We have already discussed the problem of choosing the degree of smoothing (see, section 3.4.2). We stated that the problem of determining an optimal choice of smoothing degree arises because of the lack of theory or the proper algorithm. The cost of using smoothing process is that the obtained estimators are sensitive to the choice of smoothing degree and are not consistent. In section (3.4.2), we also mentioned that the cross validation (CV) and the generalized cross validation (GCV) are two popular procedures that have been suggested for removing the problem of choosing optimal degree of smoothing. In this study, we use the CV method, which provides optimal smoothing parameter that leads to have consistent estimators. Given equations [3.24] to [3.25] and the described procedure of backfitting algorithm, what the cross validation approach does is to minimize

$$\sum_{i,-t} \left[Y_{it} - c - \hat{f}_{i,-t}(x_{it}) \right]^2 \quad (3.26)$$

in which the estimation process of $\hat{f}_{i,t}$ is as follows. In the first step, for a fixed farm i , $i = 1, 2, \dots, N$ and in every sequence of time period t , $t = 1, 2, \dots, T$ we put aside the i -th and t -th observations and estimate the mean response function f_i defined in equation [3.18] based on the $n - 1$ remaining observations in the sample size. In the second step, we repeat the algorithm and continue obtaining the estimated f_i until convergence. This method in the nonparametric literature, as Kneip and Simar (1996, p.192) mentioned, is known as the *leaving out the observation* (y_{it}, x_{it}) .

Finally, the general model specified in equation [3.18] can also be estimated in a parametric fashion way by taking into account a prespecified functional form. In this case, equation [3.18] can be written as

$$f_i(x) = \beta_{0i} + x'\beta \quad (3.27)$$

where $\beta_{0i} \in \mathbb{R}$ and $\beta \in \mathbb{R}^d$. Applying the *least squares* method to equation [3.27] provides the unbiased estimation of the parameters. While the *easy-to-use* properties of the OLS approach have made it so popular in frontier literature, one issue should not be forgotten: the efficiency scores obtained from analyzing any parametric functional form of frontier are sensitive to the choice of both functional forms and distribution assumptions of the technical inefficiency effects (see, section 2.4). Nevertheless, in the empirical application part of this study, we use a flexible production functional form, i.e., *translog function*, to compare its results with the ones obtained by analyzing the nonparametric approaches.

3.6 Measuring Efficiency

Sometimes in applied microeconomic studies, particularly in agriculture, the performance of an individual farm is of interest. For example, the ability of farm A

to compete with the other farms depends on its managerial abilities to combine inputs to produce a given level of output with an underlying technology. Since the interest of this study is to measure the technical efficiency of dairy producers, herein, we derive a method of estimating technical efficiency from the proposed model. Suppose the model specified in equation [3.28] can incorporate the efficiency component as

$$f_i(X_{it}) = f(X_{it}) + \alpha_{it} \quad (3.28)$$

where the efficiency term are modeled by the additive $\alpha_{it} \in \mathfrak{R}$, for $i = 1, 2, \dots, N$, and $t = 1, 2, \dots, T$. Equation [3.28] indirectly assumes that each farm shares the same production frontier and the differences among them are captured by the efficiency term α_{it} . Thus, we can consider

$$\alpha_{it} = f_i(X_{it}) - f(X_{it}) \quad (3.29)$$

where $f(\circ)$ is the average production frontier with respect to the unknown density \mathcal{F}

$$f(x) = E[f_i(x)] \quad (3.30)$$

For each observed situation (i, t) , the quantity α_{it} represents the distance between the average production level of the farm i and the average production level of all the technologies being used (Kneip and Simar, 1996, pp.195). By averaging the α_{it} in equation (3.29) over time produces

$$\alpha_i = \frac{1}{T} \sum_{t=1}^T \alpha_{it} = \frac{1}{T} \sum_{t=1}^T f_i(X_{it}) - \frac{1}{T} \sum_{t=1}^T f(X_{it}) \quad (3.31)$$

and replacing f_i and f by their estimates, the estimates of the α 's can be shown to have superior statistical properties (Kneip and Simar, 1996).

As a result, given the estimates of f and the α 's, the individual functions f_i , for $i=1,2,\dots,N$, can be obtained as follows:

$$\hat{f}_i = \hat{f}(X_{it}) + \hat{\alpha}_i \quad (3.32)$$

in this case, the frontier function can be redefined as

$$\hat{\phi}(X_{it}) = \max_{i=1,2,\dots,N} [\hat{f}_i(X_{it})] = \hat{f}(X_{it}) + \max_{i=1,2,\dots,N} \hat{\alpha}_i \quad (3.33)$$

3.7 Statistical Inference

In this part of the study we introduce various methods to analyze the statistical inference used to support the model structure. Up to this point, we have proposed a novel methodology in nonparametric econometrics to estimate the technical efficiency. As mentioned earlier, we built this model based on the statistical theory of generalized additive models. Like other parametric and nonparametric statistical methods, which have certain advantages and disadvantages, there are some shortcomings in the generalized additive models approach. The main pitfall of this method is its inherent assumption of the additive separability of the variables. As Kneip and Simar (1996, p.209) expressed, “the additive separability of the predictors could be a wrong approximation of the real function.” Therefore, to verify applicability of the results obtained from the nonparametric approaches, we need to construct a statistical test to examine whether the additive separability assumption of the predictors in the nonparametric models holds.

There are a few studies that have statistically tested the additive structure of generalized additive models, though the estimation process of the nonparametric functions in these studies is different. For example, Linton and Nielsen (1995) proposed a method to discriminate between the additive and multiplicative specifications of a mean response function, $f(X)$. Specifically, they defined a simple kernel estimation procedure based on the *marginal integration method* that estimates a univariate predictor in both additive and multiplicative nonparametric

regression. Similarly, Linton and Gozalo (1996) developed a statistical test to examine additivity in a nonparametric regression model. The authors defined a direct predictor by using the marginal integration approach, thereby avoiding an iteration process in their methodology. Finally, Chen et al. (1996) proposed a method to test the additive separability assumption in a generalized additive model featuring a Cobb-Douglas production function using five inputs. Their technique has an advantage over the Linton-Nielsen technique in the sense that the dimension of X , i.e., the number of explanatory variables, is not restricted to $d = 2$. They applied the additive kernel estimator to a Wisconsin livestock farm data set and concluded that all their predictors were additively separable except the hired labor variable.

In this study we use the *residual deviance* obtained from the GAMs method, which is aggregated in a table called *the analysis of deviance* table, to test the additive separability of the predictors. As stated in Hastie and Tibshirani (1990), the value of the deviance is, in fact, the logarithm of the likelihood ratio. Analysis of deviance is useful for inference in generalized additive models (see, Bowman and Azzalini, 1997, and Schimek and Turlach, 2000). We can perform statistical inference by comparing the value of deviance with the standard likelihood ratio (LR) test with a chi-squared distribution. The residual deviance is equivalent to the well-known residual sum of squares in parametric econometrics if the generalized additive model uses only one predictor.

We could find the value of deviance (or the LR statistic) for a fitted model by representing $\hat{\psi}$, which is defined as:

$$D(m; \hat{\psi}) = 2 \left\{ l(\psi_{\max}; m) - l(\hat{\psi}; m) \right\}$$

Where ψ_{\max} is the parameter value that maximizes the log likelihood $l(\psi; m)$ (or restricted model) over all ψ , as compared to the unrestricted model, also called the *saturated model*. For the generalized additive models, using simulation Hastie and Tibshirani (1990, p.282) showed that $D(m; \hat{\psi})$ has asymptotic degrees of freedom

equal to the difference in the dimensions between the two restricted and unrestricted models being compared. Thus, a chi-square distribution is still a useful asymptotic approximation for screening the applicability of generalized additive models. However, the finite distribution theory is still very much undeveloped.

As a conclusion, the methodology to estimate the technical efficiency of dairy producers can be summarized in three following steps:

(i) First, the mean response function of the production function is estimated by using the theory of generalized additive models. The estimation process is performed by using the two nonparametric techniques (LOWESS and spline smoothing) as well as the parametric translog function.

(ii) Second, the additive separability assumption of the selected predictors in the model is statistically examined by using the residual deviance analysis.

(iii) Finally, the estimated residual values obtained from the first step are used to compute the technical efficiency of individual dairy farmers. The estimated technical efficiency scores are then classified into the group mean, known as efficiency class interval.

The empirical application of this chapter along with the results will be presented in the following chapters. Before applying the sample data to the model, it would be useful to review the dairy industry in North America. Knowing the characteristics of the regions of the study will help readers understand why we have chosen dairy sector for the applied side of our study. The next chapter explains how the dairy industry functions in Canada and America. Once again, we emphasize that we do not examine at the dairy industry in both countries from a policy perspective, and neither do we derive strong policy implications for the study. Our main interest is to show what differences exist in the technical efficiency of dairy producers in

both countries as a result of different policies, which implicitly assesses the results of policy intervention.

CHAPTER IV

THE DAIRY INDUSTRY IN NORTH AMERICA (Canada and The United States)

4.1 Introduction

Strong economic and social linkages have characterized the relationship between Canada and the United States of America for the past four decades. In most industries, work practices and institutions within the Canadian economy are similar to those found in the United States, but in agriculture, and particularly in the production of dairy products, Canada implements policies that are often different than those in the U.S.

Differences in dairy policy have caused several trade disputes. Despite the three major trade agreements, i.e., the Canadian-U.S. Free Trade Agreement (CUSTA); the North American Free Trade Agreement (NAFTA); and the Uruguay Round Agreement on Agriculture (URAA), trade in dairy products is still an argumentative issue. The debate has brought European countries and New Zealand to the discussion table. The European Union (EU) established supply management for the dairy sector in 1984 and intends to maintain it until 2007-08 as part of their Agenda 2000 Common Agricultural Policy (CAP) reform signed in March 1999 (Benjamin et al., 1999).

As previously mentioned, the main goal of this thesis is to compare technical efficiency of dairy farmers in selected provinces and states in Canada (Ontario, Quebec) and the U.S. (New York, Wisconsin). In this chapter, the focus is on current dairy policies implemented in both countries. This will give readers a better idea about the impact of particular regulatory conditions that have been applied to the dairy industry. A review of the dairy industry in both countries facilitates a comparison of the estimated technical efficiencies of dairy producers. Indeed, one

can hypothesize that producers' performance is affected by the distinct policies operating in each country.

This chapter begins with a review of the Canadian dairy industry. Next, various policies that have been implemented in the Canadian dairy sector are explained. In this case, two major policies, i.e., *farm milk price policy*, and a *farm milk quota* policy along with overall trade policy affect the dairy industry. Finally, the regulatory history of the U.S. dairy industry is reviewed followed by describing the set of U.S. dairy policies, including *dairy price support*, *pooled price discrimination*, *import barriers*, *exports subsidies*, and *federal milk marketing order*.

4.2 The Canadian Dairy Sector

4.2.1 Background

The dairy industry is one of the Canada's largest agricultural sectors. It operates under a supply management system that protects the industry from world dairy markets. In fact, several other Canadian agricultural sectors (e.g. chicken, eggs and turkey) also operate under a supply management regime. The history of dairy supply management in the Canadian dairy industry dates back to mid-1960s with the introduction of the Canadian Dairy Commission (CDC) Act.

In a competitive market, supply management reduces output and thus can lead to a net welfare loss to society due to the income transfer from consumers to producers. Empirical studies have sought to measure the impacts of supply management on the Canadian economy (see, e.g., Veeman, 1982). But there are advantages as well as disadvantages to any supply management regime.

First, supply management removes producer income uncertainty that occur due to price instability resulting from fluctuations in the quantity of milk produced. Second, supply management ensures that domestic demand is met and there are no costly surpluses. Third, supply management offers domestic consumers stable, albeit

artificially high and still not as compared to U.S., prices for market dairy products ignoring shift in supply due to decrease risk. Fourth, a supply management regime ensures that dairy farmers always obtain a reasonable return, which enables them to plan and invest in input suppliers, bank, and processors. This investment circulates back into the economy at large. Fifth, supply management facilitates the implementation of strict quality controls. Strict quality controls on a supply managed system, in part, explain why Canadian dairy products rank high in terms of quality on an international level. Finally, the establishment of quota policy in milk production serves as a tool to control excess supply over domestic consumption.

Conversely, there are several disadvantages to supply management systems. The first problem is that, theoretically, it might remove any incentive for dairy processors to explore new varieties of dairy products. Domestic consumers observe less variety in the market than U.S. (Statistics Canada, 2001). Second, market entry under this type of policy is very difficult. In Canada, entrants have to pay *quota value* for producing milk, and the price of quota is an extra production cost that decreases their expected net gains. These gains might capture in land values so land prices usually become higher in dairy farming regions though quota can be traded independently within each of the provinces. Third, there are direct costs, such as monitoring, implementing, and enforcing costs in performing a supply management system. Finally, once a supply management regime is established, it can be very difficult to remove it. Nevertheless, supply management policy has brought stability to the Canadian dairy sector, in terms of price of milk products, quantity of products available, and producer income (Statistics Canada, 2001).

The Canadian Dairy Commission (CDC) also controls imported dairy products in a way that does not impede the dairy domestic market. For instance, prior to 1995, the CDC used *import quota policy* to limit the volume of imported dairy products, the majority of which came from the United States. After the Uruguay Round Agreement on Agriculture (URAA) in 1994, the CDC was required to change its policy from an import quota to an *import tariff* as a way to add stability to the supply of milk products in the domestic market.

The ultimate outcome from the implementation of a supply management system is to induce a different domestic farm price that is usually higher than the world price for similar products. In turn, the higher domestic price gives foreign countries an incentive to ship comparable products to the domestic market. However, strong import control tools enacted by the federal government limit the amount of dairy imports to Canada. For example, the tariff on dairy products was set about 299 percent for butter, 246 percent for cheese, and 246 percent for milk in 2001 (Schmitz et al., 1996, p.39). On the other hand, under supply management, dairy products exported from Canada must be priced near the world price in order to be competitive internationally. And since Canada is a member of World Trade Organization (WTO), it may face challenges and penalties it fails to abide by the conditions imposed by this institution. For example, the URAA forced member nations to *i*) reduce subsidies for agricultural export products and *ii*) decrease the quantity of subsidized export agricultural products by the year 2000.

The minimum access commitments (MAC) policy is another effect of the WTO trade agreements, which specifies country-members to decrease their level of dairy industry protections. Based on this policy, country-members must allow a portion of their domestic consumption to be provided by imports. It is also required that the minimum access commitments be slightly increased over time (Schmitz et al., 2002, p.276).

4.2.2 Structural Change in the Canadian Dairy Sector (Producer Viewpoint)

Dairy farms operate in all provinces of Canada. According to the CDC report, Canadian dairy farms produced 78.1 millions of hectolitre milk in 2000-2001 dairy year. This amount is obtained from 19,363 dairy farms with the convention rate of 3.6 kilograms of butterfat per hectolitre (Canadian Dairy Commission). The historical dairy farm data shows that the number of farms has steadily decreased from 56,370 in 1979-80 dairy year to 19,363 in 2000-2001 dairy year; an average reduction of 4.74 per cent per year.

In this study, a structural change in Canadian dairy industry is reviewed historically. In particular, this section focuses on the number of dairy farms and the herd size (number of cows per farm) and how they have changed during the last decade. Table 4.1 shows the number of Canadian dairy farms, dairy cows and cows per farm from 1991 to 2001.

Table 4.1 Number of Canadian Dairy Farms, Cows on Farms and Cows per Farm

Year	No. of Dairy Farms	No. of Cows (million)	Cows per Farm
1991-1992	31,200	1.38	44.2
1992-1993	29,358	1.26	42.9
1993-1994	26,199	1.27	48.5
1994-1995	25,700	1.27	49.4
1995-1996	24,615	1.24	50.4
1996-1997	23,818	1.24	52.1
1997-1998	22,643	1.20	54.8
1998-1999	21,576	1.18	54.9
1999-2000	20,576	1.14	55.4
2001-2001	19,363	1.16	59.9

Source: Canadian Dairy Commission. various issues.

As Table 4.1 shows the number of Canadian dairy farms has declined by 37.9 percent in the 1990s from 31,200 in the 1991-1992 dairy year to 19,363 in the 2000-2001 dairy year. Unlike the reduction in the number of dairy farms, the Canadian dairy industry has experienced a rise in the average number of dairy cows per farm during 1991-2001 dairy year. From Table 4.1 one can see that individual farming units have grown in size over the last ten years. In 1991-1992 dairy year, each dairy farm had, on average, 44.2 dairy cows, while this figure in 2000-2001 dairy year was about 59.9 dairy cows per farm; an increase of 3.086 per cent per year.

Table 4.1 also indicates that the number of milk cows in Canada has decreased in the 1990s. In the beginning of the 1990s, there were 1.38 million milk cows on

Canadian dairy farms. These dairy cows produced 75.3 million hectolitres milk. After ten years, the number of milk cows were declined to 1.16 million cows while the total volume of milk production increased to 78.1 million hectolitres (Canadian Dairy Commission). This means that Canadian dairy industry has experienced an increase in the production per cow from 5,456 kilograms in 1991-92 dairy year to 6,732 kilograms in 2000-2001 dairy year.

Finally, there are seven varieties of cow breeds in Canada. These cow breeds are Holsteins, Ayrshires, Jerseys, Guernseys, Brown Swiss, Canadienne, and Milking Shorthorns.

4.2.3 The Canadian Dairy Policy

For more than three decades, the Canadian dairy industry has been largely closed to international trade. Milk imports have been subject to tariff and non-tariff barriers that have allowed less than 10 percent of domestic consumption to be imported. Imports come mainly from the United States. Exports by individual farmers and processors have also been restricted to relatively small amounts of surplus disposal.

Following the URAA, Canadian dairy industry has moved towards a liberalized sector. This is evidenced by the introduction of so-called *tariff-rate quotas* (TRQs), which have permitted a small increase in imports of dairy products. A tariff-rate quota (TRQ) is a combination of an import quota and an import tariff. A TRQ allows a fixed quantity or value of imports at a preferential tariff (sometimes zero), whereas all imports over that quota are subject to a higher tariff. A higher tariff always is so prohibitive that imports above the quota are zero (Reed, 2001). Generally, this policy should present an opportunity for exporting countries to gain access to markets of importing countries. But the domestic price in importing countries can still be maintained above the world price in addition to the preferential tariff. So in spite of the implementation of these two pro-competitive policies into

the international dairy market, international markets and prices do not affect domestic production.

Many economists believe that the Canadian dairy industry should become more liberal and open to trade. However, that may not be an easy task. In the first instance, the high over-tariff quota duty needs to be substantially decreased along with a reduction in the import quota on dairy products, which, in turn, means an increase in the MACs. As Beghin and Sumner (1999, p.2) stressed

“one outcome of such changes could easily be an expansion of unsubsidized exports, especially if the Canadian dollar remains below US \$0.70.”

However, removing export subsidies would be difficult for two reasons; *i*) there are many exogenous factors that determine the exchange rate and therefore retaining a target exchange rate is very difficult; and *ii*) once supply management is established, dairy farm political lobbies will endeavor to preserve it for as long as possible.

The Canadian Dairy Commission (CDC), on behalf of the federal government, has been forced to modify a number of dairy policies since the 1980s. These were necessary so that Canada could meet its legal commitments to international economic organizations such as the World Trade Organization (WTO), formerly GATT, as well as meeting direct international commitments on trade like the URAA. In fact, these commitments have created many problems for international trade since 1995. In the next section we briefly review those policies and problems, drawing much of the discussion from the work of Barichello (1999).

4.2.3.1 Farm Milk Price Policy

The CDC determines farm milk prices annually staying mindful of the restrictions imposed on cross-border trade for dairy products. Fluid milk price may be determined by the provincial milk marketing board or through provincial legislation. Fluid milk price is derived from a base milk price, which is related to the

cost of primary milk production. Primary milk production cost is affected by the price of grain concentrates, forage, labor, and other purchased inputs.

Barichello (1999, p.46) reviewed the procedure used in February 1, 1999 as an example of how milk price is determined in Canada. At that time, the estimation showed that dairy farmers should receive a net price of \$C56.27 per hectolitre. If the current amount of direct dairy subsidy (\$C2.21 per hectolitre) was subtracted from that value, one could obtain an industrial milk price (\$C54.06 per hectolitre). The industrial milk price can also be determined by adding wholesale milk prices that go into butter, i.e., \$C24.86 per hectolitre, to the wholesale milk prices going into skim milk powder, i.e., \$C38.51 per hectolitre, and subtracting processor margin, i.e., \$C9.31 per hectolitre. If the conversion rates between hectolitre to hundredweight and Canadian to U.S. dollar were, respectively, set to be 2.27 (cwt./hl.), and \$0.68U.S./\$C1.00, then the estimated net price to dairy farmers would be equal to \$16.86 U.S. per hundredweight.. Barichello (1999) expressed that this price has increased steadily since 1995 due to a decrease in the federal government's budget. The federal government decreased its direct subsidy payment to dairy farmers from \$C6.04 to \$C2.21 per hectolitre. The increase in support prices offered by the CDC, up to \$C3.67 per hectolitre, has compensated for this reduction, and this policy has been implemented primarily by increasing the skim milk powder support price.

The price determination for industrial milk is computed nationally considering farm milk production costs. This is not a simple easy task, for two reasons. First, meeting the *acceptable* level for farm milk prices depends on two policies, i.e., *direct subsidy* and an *offer-to-purchase* or *support price*. Second, there are different prices used for all major milk products (both table and industrial milk). These prices are determined by a system called *end-use classified pricing*. Butter and skim milk powder prices represent floor prices, supporting a structure of higher prices for other industrial products such as condensed milk, cheese, ice cream and soft products like yogurt. The provincial milk marketing board determines the price of these processed products in addition to the price for fluid milk. Nevertheless, both fluid and

industrial milk prices are above the producers' marginal cost because farm quotas are binding and take on a significant value (Barichello, 1999, p.47). As a result of this, one may never observe farm milk prices below the floor prices. A similar method of cross-subsidization is also found in the U.S. dairy industry.

There is another farm milk pricing policy, known as the *pooling pricing system*. In the pooling pricing system, dairy farmers receive a pooled average of milk prices derived from three prices: fluid milk, all the industrial classes of milk, and world market prices. This means dairy farmers receive a pre-determined price level for the portion of their production falling within their quota. Barichello (1999, p.47) reported that product prices in this system tend to follow world market prices. Such market prices are adjusted by a processing margin for the lowest-value products. In 1999, farm level prices in this category was in the range of \$C20-25 per hectolitre (Barichello, 1999).

Farm milk price policy is one policy implemented by the CDC on behalf of federal government. The second major dairy policy deals with controls over the quantity of milk production, as discussed in the next section.

4.2.3.2 Farm Milk Quota Policy

Farm milk quota policy intentionally restricts domestic milk production by equalizing the quantity of milk marketed (at the predetermined prices) with the level of expected domestic consumption. The production quotas are administered through a joint federal-provincial agreement known as the National Milk Management Plan (NMMP) directed by the Canadian Milk Supply Management Committee (CMSMC). The jurisdiction over all aspects of fluid milk production is given by the NMMP, while all control over industrial milk is under federal jurisdiction. Prior to 1995, dairy farms were not allowed to ship milk to other provinces. The CMSMC placed such restriction in order to control provincial milk production and prevent amalgamation between the domestic milk production and the production exported from other provinces.

To determine the fluid milk quota, each provincial marketing board determines the quota volume for provincial production. In the case of the industrial milk quota, the CMSMC first estimates national demand and the aggregate level of domestic consumption using foreseeable wholesale milk product prices. Then, a buffer *sleeve*², which usually accounts for 8-10 percent of total domestic demand for industrial milk, is added to the total industrial milk quota (Barichello, 1999, p.47). The historical production of dairy farmers in each province determines the provincial quota allocations. Changes in the total market-sharing quota for each province are made each year, and the provincial marketing board adjusts producer quotas accordingly with provincial increases or decreases. In fact, quota is traded between the incumbents and new entrants. The quota trade gives farmers the opportunities they need to get into the milk market. To find more about farm milk quota policy, see Barichello (1999) and Morris (1998, 2001).

To this point, we have reviewed the Canadian dairy industry and the policies that impact the performance of dairy producers. In the next section, we look at the American dairy industry and explain briefly the various policies that impact U.S. dairy producers' performance.

4.3 The U.S. Dairy Sector

4.3.1 Background

During the 1900's, the structure of the United States dairy industry changed considerably. Initially, it was a centralized market chain characterized by minimal intervention from regional or federal government. Gradually, the U.S. dairy industry has evolved to a more commercialized market chain, which ultimately prompted government intervention. Given the time period studied in this thesis, the structure of the U.S. dairy sector should be divided into two major groups of producers (Outlaw and Knutson, 1996):

² The buffer sleeve is an over-production of milk, which compensates for unexpected

- Farms with an average herd size of 500 cows and greater, located in the West, Southwest and Florida,
- Farms with an average herd size less than 70, located in the Northeast quadrant of the U.S. bounded by Minnesota, Missouri, Kentucky, and Maryland.

Presently, the U.S. Federal Milk Marketing Order Board (FMMOB) has assigned eleven milk producing regions. They are the Pacific Northwest, West, Arizona and Las Vegas, Southwest, Central, Upper Midwest, Mideast, Southeast, Northeast, Appalachian, and Florida. This classification was made to add stability to market conditions, offer gains to producers and consumers, and ensure adequate production with no time lag.

In general, farms have become more specialized and have benefited from relatively high and stable milk prices. Due to overproduction and continuously increasing milk production costs, the U.S. federal government stopped supporting the dairy industry in the mid-1980s. Instead, it implemented a new series of dairy policies, including restrictions on production along with lowering output prices to the one-fourth of conventional prices. These were done to limit rising milk production and therefore offset the loss of the direct support program. These changes put substantial pressure on U.S. dairy farms to adjust their production structure. In some places where average dairy herds were less than 70 head of cattle, many farmers found they could not compete and were closed. Clearly, this structural adjustment did not affect all U.S. dairy farms equally. For example, during this time California surpassed Wisconsin as the largest U.S. dairy producing state. Concurrently, large farms in drylot areas began to expand outside of Western regions and Florida.

However, none of these changes reduced total U.S. dairy production. Increasing dairy cow numbers in the West and Southwest led to the establishment of the voluntary *dairy termination program* (DTP) that was available to help farms that

increases in demand or short-term reductions in production.

were less efficient at dairy production. Dairy farms that adjusted to these structural changes survived by expanding their farm size, lowering their production costs, and enhancing their technical performance. Many farmers managed to expand farm size by buying their fringe competitors' younger cows and heifers, improving the managerial skills, and obtaining progressive technological tools, equipment, and updated knowledge (Reimund et al., 1987).

A continuous increase in milk production despite a decrease in farm milk prices led to calls to reinstate U.S. dairy price support and U.S. federal milk order programs. A primary policy concern was the ability of the U.S. dairy industry to compete internationally while being supported by these policies. Such concerns have led to the investigation of deregulation policies that are designed to make the dairy industry a more market-oriented sector (GAO, 1993).

4.3.2 Structural Change in the U.S. Dairy Sector (Producer Viewpoint)

Dairy farms operate in every state in the U.S. Although they all produce a relatively homogenous product (milk), production behavior varies from region to region. For instance, small family farms in the Upper Midwest and Northeast are characterized by diversification in crop/livestock activities. In contrast, in the West and Southwest, large commercialized dairy farms with average of 1000 cows per farm are located.

In this study, the focus is on the number of farms and the number of cows on these farms (or herd size) as the main characteristics of structural change in the dairy industry. As well, there are other factors such as changes in asset values, and/or employment rates on a dairy farm that may contribute to structural change. But for more than forty years, there has been a gradual yet significant reduction in the number of the U.S. dairy farms. This phenomenon is concurrent with substantial increases in average herd size. These events are not specific to a particular region of the country.

To show the trends in the number of dairy farms and the average herd size, there are three separate statistical sources that could be used. All of these sources have a different definition of a dairy farm. The sources are *i*) the Census of Agriculture, *ii*) Standard Industrial Classification, and *iii*) farm sales. For this study, we chose the Census of Agriculture's definition of a dairy farm, which states that every farm with at least one dairy cow is considered to be a dairy farm. The weakness of this definition is that we may find farms with only one dairy cow whose milk is used for home consumption. Clearly, this definition will overestimate the number of dairy farms in the United States. But no matter which statistical source is used, one fact cannot be hidden: gradual decreases in the number of dairy farms and gradual increases in average herd size.

Using the Census definition, Table 4.2 shows the number of U.S. dairy farms, dairy milk cows and cows per farm from 1954 to 1997. Table 4.2 indicates that the number of dairy farms decreased from 2.9 million to 0.12 million. This translates into 2.07 per cent annual reduction in the number of dairy farms. Table 4.2 also indicates that the number of milk cows has also decreased from 20.2 million to 9.1 million, a 1.79 per cent annual decrease in the number of the U.S. dairy cows.

Table 4.2 shows the situation regarding the average number of cows per farm. Unlike the total number of dairy farms and milking cows, the average number of cows per farm has increased approximately by 23.6 percent per year from seven to 78 between 1954 and 1997. The greatest change occurred between 1964 and 1969 when the number of cows per farm increased by 53.8 percent from 13 to 20.

Table 4.2 Number of U.S. Dairy Farms, Cows on Farms and Cows per Farm

Year	Farms	Cows	Cows per Farm
1954	2,935,842	20,182,803	7
1959	1,792,393	16,522,026	9
1964	1,133,912	14,622,604	13
1969	568,237	11,174,036	20
1974	403,754	10,654,516	26
1978	312,095	10,221,692	33
1982	277,762	10,849,890	39
1987	202,068	10,849,890	54
1992	155,339	9,491,818	61
1997	116,874	9,095,439	78

Source: The United States, Census of Agriculture, various issues, 1964-97.

4.3.3 United States Dairy Policy

Although liberalizing policy changes have been made in the dairy sector, the U.S. dairy industry is not free of governmental intervention. In fact, the U.S. dairy industry operates under a series of mixed dairy policy regimes. These policies are either consumer-and/or producer-oriented or a combination of both. The dairy sector, as we shall see, is one of the most highly regulated industries among agricultural activities in the U.S. There is no supply management doctrine in the U.S. dairy industry, but U.S. dairy farmers have benefited from a set of producer-oriented policies. In addition, these policies have supported U.S. consumers by imposing sanitary regulations on the production side. The following is a list of the most influential U.S. dairy policies:

- *dairy price support program,*
- *pooled price discrimination program,*
- *import barriers,*
- *exports subsidies program,*
- *federal milk marketing order program*

Aside from California, whose dairy policy is unique in the United States (Cropp, 1995), the implementation of each one of these policies, or a combination of them has, at some point in time, affected the U.S. dairy industry. A short review of each policy is offered in the following section and interested readers are referred to appropriate literature for additional details (see, e.g., Outlaw and Knutson, 1996; Sumner, 1999; Westhoff and Brown, 1999; and Gorter and Boughner, 1999).

4.3.3.1 Dairy Price Support Program

The dairy price support program was initially legislated by the Agricultural Act of 1949, and it was the dominant dairy policy for a long time. The U.S. federal government carried a variety of dairy price supports through the late 1970's and early 1980's. The dairy price support program has provided a baseline for determining the price structure of all milk produced in the United States.

The original intent of price support policy was to base dairy farm prices at 75-90 percent of parity prices. Interestingly enough, this policy gave a hundredweight (cwt.) of milk the same purchasing power in the present day as it had in the 1910-14 base period! The parity price program did not work well and was finally cancelled in 1981. As might be obvious now, the program could not take into account any adjustments that should have been made to reflect technological changes, which in turn would lead to decreases in the support price level (Knutson et al., 1995). So since 1981, the United States government has improved every dairy farm bill by continuously legislating a new level of dairy support prices. In 1999, the dairy support price was \$9.90 US per hundredweight (Sumner, 1999, p.6).

Staying mindful of the recent 1995 Farm Bill debate, there is no consensus as to whether to maintain or completely remove the dairy price support program. On one hand, many economists believe that eliminating this program will have adverse consequences for the U.S. dairy industry. Others state that no adverse effects will occur because the price of industrial dairy products is now determined above the support level. A third group emphasizes the role of the Commodity Credit

Corporation (CCC) of the United States Department of Agriculture (USDA) in buying particular manufactured dairy products like butter. Since the CCC continuously purchases butter, some researchers believe that if the price support for butter is dropped for any reason, it will lower the price support level for milk. Moreover, a final group emphasizes the role that the U.S. federal government can play in marketing dairy products to stabilize prices. This view corresponds with some reports emphasizing the volatility of prices in the absence of government intervention (Gruebele, 1978). In fact, the present U.S. dairy price support program now appears to have little impact on the U.S. dairy industry. The dairy price support program was terminated in 1999 (Westhoff and Brown, 1999, p.19).

4.3.3.2 The Pooled Price Discrimination Program

The pooled price discrimination program is a more international market-oriented policy rather a domestic market-chain program. It was established to reduce U.S. dairy output prices so that they are more compatible with international dairy product prices. The pooled price discrimination policy has two major objectives: to increase U.S. milk production and to motivate dairy farmers to produce more by reducing the incentives for imports and strengthening the scope for exports (Sumner, 1999).

4.3.3.3 Import Barriers Policy

The third policy is the import barriers program planned by the U.S. government to meet sanitary as well as non-sanitary goals. But implementing such regulations in the U.S. dairy industry has caused restrictions on the import of dairy products. And for roughly the past three decades, the United States federal government has allowed the volume of imported dairy products to be up to two percent of total domestic consumption. One outcome of such policy is that U.S. dairy products prices remain stable above the world market price.

4.3.3.4 Export Subsidies Program

Since 1989, the Dairy Export Incentive Program (DEIP) has offered explicit price subsidies to help finance a portion of export expenditures (Ackerman et al., 1995). This policy is often associated with the international food aid plan. Previous dairy policies, such as the price support program, led to a massive accumulation of dairy products. Otherwise, the market would not have absorbed this over-production.

4.3.3.5 Federal Milk Marketing Order Program

The final policy to be discussed here is the federal milk marketing order program (FMMOP). This was authorized by the Agricultural Marketing Agreement Act of 1937. The Act was designed to establish new dairy policies, except dairy price policy, in the United States. To start, the FMMOP has established a classification *pricing system*, which includes four different classes to determine dairy product prices. As Outlaw and Knutson (1996) stated “the FMMOP sets minimum Grade *A* milk prices that processors would pay to dairy farmers or their cooperatives.” Federal milk marketing orders can be found all over the U.S. (with the exception of California), and each assigns different prices. The federal milk marketing orders coordinate all the local administrations, which set prices for 70 percent of U.S. milk production. The four classes of milk in each marketing order are as follows:

- Class I → milk used directly for fluid consumption as whole, low-fat or skim milk.
- Class II → milk used as fluid cream or in soft dairy products, such as cottage cheese and frozen desserts.
- Class III → milk manufactured into cheese and butter.
- Class IIIA → milk manufactured into nonfat dry milk.

In fact, the price for Class I milk is usually higher than other classes charged to the processors. Dairy producers in each marketing order district are paid an average

price based on the percentage of milk used in the order for each of the four milk classes. For example, Outlaw and Knutson (1996) reported that the percentage of Class I milk for all milk produced under the FMMOP was set about 40 percent in 1994. This means that producers in the district orders with higher percentage of Class I milk receive a higher blend price. More information about the U.S. dairy product pricing system and the classification system are contained in Richardson et al. (1995); Outlaw and Knutson (1996); Sumner (1999); Westhoff and Brown (1999); and Gorter and Boughner (1999).

The U.S. dairy industry functions under a mix of the last four major production and consumption policies, with an emphasis on the FMMOP policy. Although subsets of these policies have been enforced at any particular time, the general consensus is that this mix of policies has created a more liberalized market than that found in Canada. But it would not be the dairy industry if we did not still see new policies impacting some aspect of the industry. For example, a model of production quota and import barriers similar to policies in Canada (the so-called *tariff-rate quotas* or TRQ's) has become the most dominant policy in the U.S. dairy industry at the moment. As in Canada, under this new policy the quantity of imported dairy products can be increased to a certain pre-specified level, but over-quota imports will face prohibitive tariffs.

Clearly, the dairy industries in both Canada and the U.S. face different governmental regulations. Regardless of what type of policies and regulations are employed, dairy farms will react in a manner that affects their production. A key element in the study of production economics is to best determine how efficient producers are in combining inputs and services to obtain a given level of output.

CHAPTER V

EMPIRICAL APPLICATIONS

5.1 Introduction

In this chapter we present the empirical analysis of the stochastic nonparametric frontier model that we built in chapter three. Specifically, we present the results of the estimation procedure described in section 3.5 and 3.6. We estimate the technical efficiency of Canadian (Ontario and Quebec) dairy producers, and then compare the results with those obtained from American (New York and Wisconsin) dairy farmers. The areas of the study, i.e., Ontario, Quebec, New York, and Wisconsin have not been chosen coincidentally. Our reasons for choosing these four regions are as follows:

(i) Quebec and Ontario dairy farmers produced 110.47 and 94.04 million kilograms of butterfat in the dairy year 1999-2000 (Canadian Dairy Commission), respectively. In other words, these two provinces produced 72.3 percent of Canadian total milk production (282.92 in million kilograms of butterfat) in 1999-2000 (Canadian Dairy Commission). Quebec and Ontario also have the largest percentage of milking cows in the country. According to a Canadian Dairy Commission (CDC) report, there were 10,614 and 7,617 milking cows, respectively, in Quebec and Ontario in 1997-98. In the year under study, the Canadian dairy industry had a total of 22,696 milking cows in all provinces meaning the two provinces studied here contained 80.3 percent of the Canada's total milking cows. These numbers are a strong indication of how important Quebec and Ontario are to the Canadian dairy industry.

(ii) New York and Wisconsin have some strong similarities to their Canadian counterparts. For instance, Quebec and Ontario are similar to New York and

Wisconsin in terms of production technology, equipment and techniques used in producing milk, as well as the climatic conditions (Morris, 2001).

The concept of measuring efficiency only makes sense when decision-making units are at the firm level; otherwise the inherent problem of working with aggregate data prevents one from analyzing the performance of the economic unit. Working with aggregate data to measure all kinds of efficiencies will cause problems interpreting the results. For example, when we use aggregate data, irrespective of whether the data is consistently aggregated or not, there is still no guarantee that we would be able to reproduce the results on aggregate in a firm-level model. In this regard, a number of researchers and practitioners have reported problems working with aggregate data in the efficiency literature (see, e.g., Anderson et al., 1996, pp.226-227). In order to avoid such problems in this study, the data was collected at the farm level for all four regions of the study; therefore, the problem with aggregated data is not applicable to our data set.

We divide this chapter into five parts. First, we briefly describe the sources of the data. Second, we introduce the dependent (response) and independent variables (predictors) that are used in our analysis. Third, we present a descriptive analysis of the variables in the data sets that are used in the model. Fourth, we present the technical efficiency estimates obtained from selected model structures and selected assumptions for the regions. Statistical inference and testing the results comprise the fifth part of this chapter.

5.2 Sources of Data

To estimate and compare technical efficiency between the selected regions of Canada (Ontario and Quebec) and U.S. (New York and Wisconsin) dairy producers, we assembled farm-level databases for all four regions in an unbalanced panel data context.

We obtained the Ontario and Quebec data from Agriculture and Agri-Food Canada, which collects data annually from the Ontario dairy farm project (ODFAP) and the Quebec dairy farm project (QDAFP). The Ontario database contains 751 observations related to 277 dairy farms during 1992-1998. The Quebec data set is larger than the Ontario one, and contains 17,982 observations related to 3,118 dairy farms during 1987-1998.

We obtained the United States dairy databases in our study from two separate sources. The New York data set comes from the dairy farm business project (DFBP), part of Cornell university's Cooperative Extension's Agricultural Educational program in New York. The data is collected each year by the Department of Agriculture, Resource and Managerial Economics at Cornell University in association with County Extension staff. The New York data set contains 6,085 observations related to 1,504 dairy farms during 1985-1998. The Wisconsin data set is collected by the Centre for Dairy Research in the Department of Agricultural, Resource, and Managerial Economics at the University of Wisconsin-Madison. The Wisconsin data set comprises 489 observations on 214 dairy farms during 1993-1998. Fortunately, the design of each questionnaire was very similar. Therefore we did not have any problems merging and working with the two databases.

In total, we have used a large data set for this study containing 25,307 observations related to 5,113 dairy farms throughout all four regions. The richness of this data set allows us to estimate the technical efficiency of dairy producers through our proposed model, i.e., stochastic nonparametric frontier analysis as well as perform other statistical analysis by scrutinizing the databases for different purposes. Table 5.1 summarizes the basic information from our data set.

Table 5.1 Descriptive Characteristics of the Data Set

Region	Time Series	No. of Years	No. of Farms	No. of Observations
New York	1985-1998	14	1,504	6,085
Wisconsin	1993-1998	6	214	489
Ontario	1992-1998	7	277	751
Quebec	1987-1998	12	3,118	17,982
Total			5,113	25,307

Source: Agriculture and Agri-Food Canada (Ontario and Quebec) & Cornell University (New York), and University of Wisconsin-Madison (Wisconsin).

5.3 Variable Descriptions

As described in previous chapters, the *curse of dimensionality* problem exists in any nonparametric regression analysis whose smoothing parameter is comprised of *kernel estimators*. Being mindful of the curse of dimensionality problem, we chose three explanatory variables including land, labor, and total feed costs, which to some extent, play important roles in producing dairy products to explain variations in the dependent variable that is annual total milk production. In this study, land is measured as annual total (owned and rented) tillable area (hectares). Lack of data prevents us to consider area under pasture. Labor is measured as an annual total equivalent worker unit. Total feed costs, which could vary from year to year, is the third independent variable. To obtain this variable, we consider the total feed purchased by farmers and add the values of equivalent amount of feed that is produced by dairy farmers. Total feed costs are measured in Canadian dollars, deflated by the appropriate *Producer Price Index* (PPI). Annual total milk production is measured as hundredweight (cwt.) of 3.6 and 3.7 percent fat content for fluid milk, respectively for Canada and the United States. All the dependent and independent variables used in this analysis are in logarithmic form. The variables are adjusted by farm size by dividing each by the number of milk cows on the farm.

5.3.1 Data Descriptive Analysis

Despite of the extensive data, we only present conventional statistic descriptions of the variables in our models for all four regions. This information helps to reveal the differences that currently exist in the dairy industries of the both countries. Table 5.2 presents the statistical descriptions of the variables adjusted per number of cows. In the following sections, we briefly review each variable in the study.

5.3.1.1 Milk Output

As Table 5.2 shows, the sample mean of milk production per cows in Wisconsin is slightly higher than the other three regions of the study. The sample average of milk production per cows in the Canadian areas of the study is equal to each other. Table 5.2 also indicates that Quebec has a higher sample standard deviation among the regions of the study. The sample standard deviation of milk production per cows for Quebec, i.e., .047 is greater than the Ontario (0.32) data set, which is equal to the sample standard deviation of Wisconsin data set. The Wisconsin dairy producers also have the highest minimum, i.e., .07 (000 cwt.), record of milk production per cows amongst their counterparts whilst the maximum amount of milk produced per cows is represented by the Quebec sample farmers with .47 (000 cwt.). One can see from Table 5.2 that Ontario has a higher minimum volume of milk production per cows when compared to New York and Quebec.

5.3.1.2 Land

Annual total tillable area, measured in hectare, is one of the independent variables in the model. This measure contains both owned and rented tillable areas, except pasture areas, in the all four regions of the study. Table 5.2 indicates that Wisconsin has the highest average tillable arena (2.3 Ha.) per cows in the sample size in comparison to its counterparts. The Ontario dairy sample also has a higher average total tillable land per cows (1.9 Ha.) compared to the New York and Quebec

regions, whose mean arable land per cows is, respectively, 1.4 and 1.2 hectares. In general, the average total tillable area per cows in the U.S. regions (1.84 Ha.) is approximately 1.2 times greater than of the Canadian regions (1.56 Ha.). In our sample, Ontario has the highest minimum size of total tillable area per cows (.30 Ha.) of all regions in the study. In comparison, the maximum size of arable land per cows in Quebec (11.0 Ha.) is slightly greater than of New York (10.2 Ha.) and Ontario (9.3 Ha), but is largely higher than of Wisconsin (6.7 Ha.).

5.3.1.3 Labor

In our sample, labor is considered as the second independent variable, based on the annual total equivalent worker unit (herein, ewu.). This variable contains both hired and family labor forces as well as the operator labor force where it is applicable. Table 5.2 shows that average labor used per cows in Ontario dairy farms (.056 ewu.) is higher than Quebec (.038 ewu.), Wisconsin (.036 ewu.), and New York (.035 ewu.). This means that milk production in Ontario is more labor-intensive than the other regions. Similar pattern is seen when one compares the average labor used per cows in milk production between two countries. Table 5.2 shows that U.S. average labor used per cows in dairy farms (.0355 ewu.) at the sample observations is approximately 1.32 times less than average labor used in milk production per cows in Canada (.047 ewu.). The Ontario data has the highest sample standard deviation of labor used per cows among all regions of the study followed by Quebec, New York, and Wisconsin. Finally, the highest minimum and maximum labor used per cows in the sample data, respectively, is seen in Wisconsin (.02 ewu.) and New York (.39 ewu.).

5.3.1.4 Total Feed Costs

Total feed costs is the last independent variable in our model. Total feed costs are deflated by the producer price index (PPI) in the both countries and converted to the Canadian currency by the appropriate exchange rate obtained from the Central Bank of Canada. Feed cost is an important factor in producing milk at the farm level, which could vary from one farm to the other and year to year. Feed

costs approximately contain 40-60 per cent of dairy production costs at each region (USDA). Total feed costs is obtained by adding total feed purchased by farmers to the equivalent values of feed that is produced by dairy farmers. Table 5.2 indicates that dairy producers in Quebec and Ontario paid more than Wisconsin and New York for purchasing feed and other necessary supplements for their cattle nutrients. The average mean of total feed costs per cows for Quebec dairy producers is 1.3 (000 \$CAN) as compared to Ontario dairy farmers who paid, on average, .92 (000 \$CAN) per cows for feeding their milk cows. Wisconsin dairy producers on average paid .63 (000 \$CAN) per cows, which is less than what New York dairy farmers paid, i.e., .74 (000 \$CAN) for each milk cow to purchase feed and other nutrients supplements.

5.3.1.5 Number of Milk Cows

The number of milk cows in each region of the study is important because it is necessary to adjust the model for the farm size by dividing the entire dependent and independent variables by the number of dairy cows. In spite of having data for the number of heifers we decide not to use these numbers because we intend to compute the annual total milk produced per dairy cow and consider the new data series as the model's response (dependent variable). Table 5.2 summarizes the number of milk cows in each region of the study. Table 5.2 shows that the average number of milk cows in New York dairy farms, 122 (head), is higher than that of the Wisconsin, Ontario, and Quebec, respectively, with 95, 48, and 44 (head). Historically, the average herd size in the U.S. dairy industry is higher than the Canadian average herd size. Our sample data supports this statement. The sample data shows that the average herd size in both U.S. dairy regions, 109 (head) is approximately 2.4 times greater than of the two Canadian regions, i.e., 46 (head). A similar pattern in the average herd size can also be seen in the maximum herd size for our sample data, however this observation is not made for the minimum herd size (Table 5.2).

Table 5.2 Statistical Description of the Variables (per Cows)

Variable	Mean				Standard Deviation				Min.				Max.			
	NY	WI	ON	QC	NY	WI	ON	QC	NY	WI	ON	QC	NY	WI	ON	QC
Output	.17	.18	.15	.15	.031	.032	.032	.047	.03	.07	.04	.02	.28	.31	.24	.47
Land	1.4	2.3	1.9	1.2	.6	1.04	1.01	.5	.026	.047	.30	.09	10.2	6.7	9.3	11.0
Labor	.035	.036	.056	.038	.012	.010	.042	.017	.008	.02	.0001	.009	.39	.08	.28	1.2
Feed	.74	.63	.92	1.3	.28	.31	.28	.62	.083	.08	.27	.19	2.3	2.1	2.8	2.5
Cows	122	95	48	44	149	97	28	18	6	22	14	2	2658	754	382	321

Source: Sample data. Output is annual total fluid milk production of 3.6 and 3.7 percent fat content, respectively for Canada and U.S. (000 cwt.), Land is annual total tillable area (Hectare), Labor is annual total equivalent worker unit, and Feed is annual total feed costs in (000 \$CAN).

5.4 Results

Using the methodology proposed in sections 3.5.1- 3.5.2, we estimate the mean response function f in equation [3.18], using stochastic nonparametric frontier analysis. The estimation procedure is conducted by writing program codes in S-Plus version 3.4 in the Unix Operation System. As mentioned earlier, there are many *stochastic* approaches to analyze non-parametric estimations. Some of most popular methods are *artificial neural network models*, *Kernel estimations*, *additive models* and *generalized additive models* (GAMs). Out of these methods, we chose to use GAMs, which are briefly described in chapter three. Specifically, we model the estimation of technical efficiency in a generalized additive model by using the *backfitting algorithm* introduced by Friedman and Stuetzle (1981), and subsequently modified by Breiman and Friedman (1985) as the *iterative smoothing process*. The smoothing estimators are very popular in nonparametric regression analysis (see, e.g., Hardle, 1990; Hastie and Tibshirani, 1990; Wahba, 1990; Hardle, 1991; Pagan and Ullah, 1999; and Schimek, 2000). We use two types of smoothing process in our study: the *locally regression model* and *spline smoothing*.

As mentioned earlier, we utilize stochastic nonparametric frontier analysis in this study because efficiency scores obtained from different stochastic parametric frontier functions could vary for two main reasons. First, they might be varied because of the selected functional forms (see, e.g., Anderson et al., 1996 and Giannakas et al., 2003a). The choice of various distribution assumptions on the composed error terms, indicating technical inefficiency effects, is another source of variation in the obtained efficiency scores (see, e.g., Bravo-Ureta and Rieger, 1990; Giannakas et al., 2003b and Kumbhakar and Tsionas, 2002). These variations in results occur because the obtained efficiency scores are data specific. In order to check the nonparametric results, we also utilize a flexible parametric functional form, i.e., *transcendental logarithmic function*, also known as *translog function*. A translog function proposed by Christensen et al. (1971, 1972 and 1973) is a second order Taylor-series expansion logarithm of a true but unknown technology around a point of approximation.

With the described model structure, we estimate technical (in)efficiency of individual dairy producers in all the four regions of the study based on equations [3.28] through [3.33] in section 3.6. In particular, we use the method of COLS, proposed by Richmond (1974) to estimate the technical efficiency of dairy producers in both the nonparametric and the parametric translog models. For the latter model the technical efficiency scores are also estimated through using the frontier method of Battese and Coelli (1992). Since our study covers four different areas each with various time periods and observations, we initially construct two different models, i.e., *between* and *within*, for each region to estimate the mean response function. The between-region model refers to a comparison of the estimated technical efficiencies between the dairy producers of the two countries. Conversely, the within model does not examine cross-border performance and only explores the individual achievements of dairy farmers within each region. Thus, with the estimated parameters obtained in the first step, we compute the technical (in)efficiencies of dairy producers for each of the four regions. The frontier method of Battese and Coelli (1992) is only examined in the between-region model.

It is clear that such division is trivial for the within case, yet it is very important for the between case since in the second model, given the particular year, the number of observations must be kept equal for all the regions. This is the case because the cross-border comparison only makes sense when the number of farms is equal for a specific period of time. By doing this, we avoid obtaining biased results for estimated technical efficiencies due to the impacts of sample size. Therefore, for the between-region analysis, a sub-sample of data is randomly generated to maintain equal time periods and observations.

Comparing different methodologies (parametric and nonparametric) and dissimilar model specifications (within-and between region) means that we will discuss results corresponding to each of the scenarios described. Therefore, we present the results through the rest of the chapter as follows. First, we present the results of the within-region model, followed by the results of the between-region model. In each of these models, the results are organized as follows. First, the estimated technical efficiency resulting from nonparametric econometric estimation approaches, i.e., LOWESS and spline smoothing are discussed. Subsequently, we present the results obtained using the same structural model estimated using a parametric econometric framework.

5.4.1 Within-Region Results

The results obtained from the within-regions models preclude a cross-border efficiency comparison. These results only indicate the dairy producers' performance for each region. Tables 5.3, 5.4, and 5.5, respectively, list the estimated technical efficiencies of Canadian (Ontario and Quebec) and American (New York and Wisconsin) dairy producers obtained by implementing LOWESS, spline smoothing, and finally a parametric (translog function) model for the within-region model, in turn, classified by the group mean performance (hereafter, efficiency class interval). Herein, the results are briefly discussed.

- Mean Technical Efficiency

The results for the LOWESS model shows that the mean technical efficiency of Quebec dairy farmers is 0.697 while for New York this amount is 0.675. The estimated technical efficiency for Ontario and Wisconsin, on average, is 0.640, and 0.561, respectively (see Table 5.3). Using the method of spline smoothing, Table 5.4 indicates that the mean technical efficiency of Quebec dairy farmers, 79.1 per cent, is greater than the other three regions of the study. Following Quebec, the mean technical efficiency of New York dairy farmers (66.3 percent) is just better than Ontario dairy farmers performance (63.6 percent), while Wisconsin dairy farmers are 53.4 percent efficient. Finally, the estimated mean technical efficiency for the parametric translog production function model is presented in Table 5.5. The results show that the mean technical efficiency of Quebec dairy farmers is 66.2 per cent, followed by Ontario dairy farmers at 64.8 per cent efficiency. The mean technical efficiency of New York and Wisconsin dairy farms falls at 63.3 and 54.7 per cent, respectively. The latter result indicates that it does not fall into the same pattern as the nonparametric approaches (Tables, 5.3 and 5.4).

- Efficiency Class Interval

Table 5.3 displays that, except for Wisconsin farmers, the magnitude of the estimated differences between the mean technical efficiencies is small, in the range of four to six percent. In addition, the variability of efficiency scores approximately follows a similar pattern. Except for Wisconsin, where we find a majority (68.7 percent) of dairy farms are less than 60 percent efficient, the majority of dairy farms in all other regions fall in a category of 60-80 percent technical efficiency, with at least 60 percent of all farms in the three regions included in this class. Approximately 83.6 percent of Quebec dairy farms in the sample fall in the efficiency class interval of 0.60-0.80, while for Ontario this amount is 64.9 percent and both are higher than New York dairy farms at 62.4 percent. However, more than 12.5 percent of New York dairy farms in the sample are better than 80 percent at

producing milk. Whereas, the equivalent results for Quebec, Wisconsin and Ontario dairy farms is 6.5, 4.2, and 4.0 percent, respectively. In the most inefficient class interval, we find that almost 1.1 percent of Quebec dairy farmers operate at less than 50 percent efficiency, whilst the percentage for the same class interval is 6.5 percent for New York, 11.2 percent for Ontario, and 32.8 percent for Wisconsin. Finally, on average, the pooled-mean technical efficiency of Canadian dairy farmers is 0.693 compared to 0.660 for American farmers.

By comparing Tables 5.3 and 5.4, we see that the efficiency rankings among the regions have not changed. However, Table 5.4 indicates that the variability of the estimated efficiency scores obtained from the spline-smoothing model, unlike the LOWESS model, is not homogeneous. For example, Ontario and Wisconsin results show that 62.8 and 48.1 percent of dairy farms are located in the 50-70 percent efficiency class interval. On the contrary, the majority of Quebec and New York dairy farms reside in the 60-80 percent technical efficiency category, where more than 62 percent of New York and 79 percent of Quebec dairy farms are included in this class. These results also indicate that more than 13 percent of Quebec dairy farms in the sample are greater than 80 percent efficient in producing milk, while for New York, Ontario, and Wisconsin dairy farms this result is 11, 4.7, and 2.4 percent, respectively. Nearly 42 percent of Wisconsin dairy farms in the sample are less than 50 percent efficient, followed by Ontario dairy farmers among whom 12 percent are less than 50 percent efficient. In Quebec, only one percent of dairy farmers is less than 50 percent efficient. In sum, the pooled-mean technical efficiency of Canadian dairy farmers is 71.2 percent, while the mean efficiency is 0.647 for their U.S. counterparts.

Similar to the LOWESS results, with the parametric estimates we observe that except for Wisconsin dairy farms, the magnitude of the differences in the estimated mean technical efficiency among the other three regions is small and in the range of one-three percent (see Table 5.5). And the variability of the estimated parametric efficiency scores follows a similar regional pattern. The majority of

American dairy farms in the sample fall in the category of 50-70 percent technical efficiency. More than 64 percent of New York dairy farms and 54 percent of Wisconsin dairy farms are included in this efficiency class. In contrast, the results show that the majority of Canadian dairy farms fall in the category of 60-80 percent technical efficiency. Specifically, over 79 percent of Quebec dairy farms and more than 65 percent of Ontario dairy farms are found in this efficiency class interval. Table 5.5 also shows that close to seven percent of Ontario dairy farms in the sample are greater than 80 percent efficient in producing milk, while for New York, Wisconsin and Quebec this result is 4.4, 3.4, and 2.0 percent, respectively. Conversely, 2.4 percent of Quebec dairy farmers are categorized as operating at less than 50 percent efficiency while the percentage of their counterparts in the same class interval is 37.4 percent for Wisconsin, 12.3 percent for Ontario, and 9.9 percent for New York. Finally, on average, the results show that the parametric pooled-mean technical efficiency of Canadian dairy farmers is 0.661 while in the U.S. it is 0.623.

Table 5.3 Technical Efficiency of Dairy Producers (Within-Regions: LOWESS)

Efficiency Class Interval	NY			WI			ON			OC		
	Farms	Percent	Mean Efficiency	Farms	Percent	Mean Efficiency	Farms	Percent	Mean Efficiency	Farms	Percent	Mean Efficiency
<= 0.50	98	6.53	0.445	70	32.71	0.429	31	11.19	0.452	33	1.06	0.421
0.51 – 0.60	278	18.48	0.559	77	35.98	0.549	55	19.86	0.563	275	8.82	0.566
0.61 – 0.70	492	32.71	0.651	36	16.82	0.644	116	41.88	0.651	1183	37.94	0.657
0.71 – 0.80	447	29.72	0.746	22	10.28	0.750	64	23.10	0.739	1424	45.67	0.742
> 0.80	189	12.56	0.856	9	4.21	0.887	11	3.97	0.866	203	6.51	0.835
Total	1504	100.00	0.675	214	100.00	0.561	277	100.00	0.640	3118	100.00	0.697

Source: Sample data.

Table 5.4 Technical Efficiency of Dairy Producers (Within-Regions: Spline Smoothing)

Efficiency Class Interval	NY			WI			ON			QC		
	Farms	Percent	Mean Efficiency	Farms	Percent	Mean Efficiency	Farms	Percent	Mean Efficiency	Farms	Percent	Mean Efficiency
<= 0.50	111	7.38	0.446	90	42.00	0.427	33	11.91	0.445	33	1.06	0.419
0.51 – 0.60	291	19.35	0.560	72	33.64	0.544	60	21.66	0.563	185	5.93	0.566
0.61 – 0.70	566	37.63	0.651	31	14.48	0.655	114	41.16	0.652	932	29.90	0.659
0.71 – 0.80	372	24.74	0.746	16	7.48	0.748	57	20.58	0.741	1547	49.61	0.748
> 0.80	164	10.90	0.841	5	2.40	0.886	13	4.69	0.858	421	13.50	0.836
Total	1504	100.00	0.663	214	100.00	0.534	277	100.00	0.636	3118	100.00	0.719

Source: Sample data.

Table 5.5 Technical Efficiency of Dairy Producers (Within-Regions: Translog)

Efficiency Class Interval	NY			WI			ON			OC		
	Farms	Percent	Mean Efficiency	Farms	Percent	Mean Efficiency	Farms	Percent	Mean Efficiency	Farms	Percent	Mean Efficiency
<= 0.50	149	9.90	0.443	80	37.38	0.422	34	12.27	0.451	75	2.41	0.438
0.51 – 0.60	402	26.73	0.559	59	27.57	0.552	46	16.61	0.567	500	16.04	0.564
0.61 – 0.70	567	37.70	0.649	57	26.64	0.640	111	40.07	0.655	1573	50.45	0.655
0.71 – 0.80	320	21.28	0.744	10	4.67	0.735	68	24.55	0.740	908	29.12	0.735
> 0.80	66	4.39	0.841	8	3.74	0.863	18	6.50	0.844	62	1.98	0.835
Total	1504	100.00	0.633	214	100.00	0.547	277	100.00	0.648	3118	100.00	0.662

Source: Sample data.

5.4.2 Between-Region Results

In this section, we present the estimated technical efficiency of dairy farms for the between-regions model. This analysis allows us to directly compare the performance of Canadian and American producers. First, we have to equalize the sample size in all regions for each year. To accomplish this, we consider the shortest length of time period of data among the four regions of study as the base line for the comparison. Using a random generation method to choose sample dairy farms, we pared down the full sample of dairy farms into a sub-sample equal to the minimum number of observations available. All variables in this particular estimation were converted to appropriate Canadian units. Table 5.6 depicts the equivalent number of dairy farms in the sample data set for each of the four regions.

Table 5.6 Equivalent Number of Sample Dairy Farms (Between-Regions)

Year	No. of Farms	Total No. of Observations
1993	44	176
1994	93	372
1995	101	404
1996	108	432
1997	67	268
1998	64	256
Total	477	1,908

Source: Sample data.

Comparing Tables 5.1 and 5.6, we use only 9.33 per cent of the total dairy farm observations (477 out of 5,113) and 7.54 per cent of the total number of observations (1,908 out of 25,307) to estimate technical efficiency of Canadian and U.S. dairy producers in the between-region model. Our procedure for the between-region analysis proceeds as follows. For each year, we pool the sample observations, estimate the models with three techniques, and obtain separate results. Therefore, in total we estimate 18 separate econometric models in order to identify the technical

efficiency of the dairy farms in the sample. We present and discuss the results showing the percentage distribution of dairy farms among the efficiency class intervals for the three approaches in the between-region model.

Tables 5.7, 5.8, and 5.9, respectively, illustrate the estimated technical efficiency of dairy farmers in both countries obtained by implementing LOWESS, spline, and parametric (translog function) methodologies for the between-region models classified by the efficiency class interval (i.e., group mean performances). The method of estimating the efficiency scores for all three Tables is the corrected ordinary least squares (see section 2.2). Like the within-region models, a brief discussion of the results is presented.

Table 5.7 Technical Efficiency of Dairy Producers (Between-Regions: LOWESS)

(Percent)

Efficiency Class Interval	New York						Wisconsin						Ontario						Quebec					
	93	94	95	96	97	98	93	94	95	96	97	98	93	94	95	96	97	98	93	94	95	96	97	98
<= 0.50	4.5	8.6	16.5	15.7	16.4	14.1	2.3	4.4	5.0	3.7	4.5	4.7	13.6	19.3	28.2	26.8	17.9	14.1	4.5	10.8	10.6	8.3	9.0	7.9
0.51 – 0.60	27.3	29.0	35.9	31.5	26.9	28.1	2.3	12.9	15.4	15.7	17.9	12.5	36.4	30.1	28.2	24.1	32.8	35.9	27.3	23.6	17.5	21.3	37.3	39.0
0.61 – 0.70	40.9	44.3	34.0	34.3	35.8	37.5	31.8	35.5	34.9	35.2	46.3	37.5	34.1	34.4	28.2	30.6	32.8	34.4	47.7	38.7	42.7	37.9	38.8	42.2
0.71 – 0.80	20.5	15.9	11.7	16.7	17.9	17.2	45.4	26.8	24.3	24.1	16.4	23.4	11.4	14.0	13.5	15.7	10.4	14.1	20.5	26.9	28.2	31.5	14.9	10.9
> 0.80	6.8	2.2	1.9	1.8	3.0	3.1	18.2	20.4	20.4	21.3	14.9	21.9	4.5	2.2	1.9	2.8	6.1	1.5	0.0	0.0	1.0	1.0	0.0	0.0
Mean	.650	.622	.603	.609	.617	.623	.726	.703	.694	.704	.675	.694	.602	.590	.570	.582	.591	.593	.629	.630	.634	.640	.609	.610
Total Mean	0.621						0.699						0.588						0.625					

Source: Sample data.

Table 5.8 Technical Efficiency of Dairy Producers (Between-Regions: Spline Smoothing)

(Percent)

Efficiency Class Interval	New York						Wisconsin						Ontario						Quebec					
	93	94	95	96	97	98	93	94	95	96	97	98	93	94	95	96	97	98	93	94	95	96	97	98
<= 0.50	4.5	10.8	6.8	6.5	4.5	4.7	2.3	4.3	3.0	2.8	3.0	3.2	11.4	34.4	30.0	29.6	25.4	25.0	2.3	16.1	9.7	10.2	5.9	6.3
0.51 – 0.60	13.6	33.3	30.0	33.3	22.3	23.5	2.3	17.2	10.6	9.3	3.0	3.2	34.1	34.4	32.0	32.4	29.8	31.2	13.6	38.7	39.8	38.8	28.4	26.5
0.61 – 0.70	34.1	47.3	47.6	44.4	41.8	40.6	13.6	39.8	40.8	39.8	32.8	32.8	36.4	26.8	31.0	29.6	31.3	29.7	45.4	35.5	37.8	38.0	43.3	46.8
0.71 – 0.80	36.4	7.5	14.6	14.8	26.9	26.5	43.2	25.8	31.0	33.3	32.8	32.8	16.1	2.2	4.0	5.6	9.0	9.4	29.6	7.5	9.7	10.2	19.4	17.2
> 0.80	11.4	1.1	1.0	1.0	4.5	4.7	38.6	12.9	14.6	14.8	28.4	28.0	2.3	2.2	3.0	2.8	4.5	4.7	9.1	2.2	3.0	2.8	3.0	3.2
Mean	.689	.607	.622	.621	.659	.658	.785	.679	.694	.697	.731	.731	.620	.545	.558	.560	.587	.586	.681	.591	.607	.608	.633	.634
Total Mean	0.643						0.719						0.576						0.626					

Source: Sample data.

Table 5.9 Technical Efficiency of Dairy Producers (Between-Regions: Translog)

(Percent)

Efficiency Class Interval	New York						Wisconsin						Ontario						Quebec					
	93	94	95	96	97	98	93	94	95	96	97	98	93	94	95	96	97	98	93	94	95	96	97	98
<= 0.50	4.5	4.3	4.0	3.7	6.0	6.3	2.3	3.2	3.0	1.8	3.0	3.2	15.9	21.5	19.4	19.4	16.4	17.2	4.5	5.3	5.0	5.6	4.5	4.7
0.51 – 0.60	34.1	29.0	16.5	17.6	17.9	20.3	2.3	4.3	4.0	2.8	4.5	4.7	43.2	33.2	26.2	26.0	32.8	34.4	34.1	32.3	26.2	25.0	26.8	28.1
0.61 – 0.70	34.1	39.8	41.7	41.7	29.8	29.7	34.1	36.6	31.0	32.4	23.9	26.5	25.0	25.8	30.0	30.6	29.9	26.5	47.8	43.0	41.7	42.6	49.3	50.0
0.71 – 0.80	22.8	23.7	32.0	32.4	40.3	35.9	34.1	36.6	30.0	31.5	34.3	32.8	13.6	17.2	19.4	19.4	16.4	17.2	13.6	17.2	22.1	22.2	16.4	14.0
> 0.80	4.5	3.2	5.8	4.6	6.0	7.8	27.2	19.3	32.0	31.5	34.3	32.8	2.3	2.2	5.0	4.6	4.5	4.7	0.0	2.2	5.0	4.6	3.0	3.2
Mean	.647	.644	.669	.667	.672	.667	.740	.719	.745	.746	.754	.747	.592	.590	.609	.610	.609	.604	.621	.623	.648	.646	.639	.632
Total Mean	0.661						0.742						0.602						0.635					

Source: Sample data.

- Mean Technical Efficiency

Table 5.7 displays the results obtained from the LOWESS model. The mean technical efficiency of Wisconsin dairy producers, 0.699, is the highest value amongst the other three regions. This might occur because the Wisconsin dairy farmers benefited from the economies of size that they have in feed costs. Table 5.2 shows that the Wisconsin dairy farms at the sample observations have the lowest total feed costs as compared to the other regions. The magnitude of the difference between Quebec's mean technical efficiency, 0.625 with New York dairy farms' mean technical efficiency, 0.621, is very small. Based on the LOWESS result, Ontario dairy farms have the worst performance (58.8 percent efficient) compared to the other regions. This result is considerably below the estimated mean technical efficiency scores for Ontario dairy producers (0.92) that Weersink et al. (1990) reported (see section 2.3.1.2). In three regions of study (except Quebec) the sample data shows that dairy farmers performed best in 1993. Quebec farmers had their best performance in 1996. Table 5.9 also illustrates that New York and Ontario have their lowest mean technical efficiency in 1995, while for the other two regions the poorest performances were in 1997.

The mean technical efficiency of Wisconsin dairy producers, 0.719, which is obtained by using the spline smoothing technique, is the highest among the other three regions (Table 5.8). This result is below the one that Ahmad and Bravo-Ureta obtained for Vermont dairy farms (77 percent efficient) in 1995, but much above of what Battese and Coelli (1988) estimated for Victoria dairy producers (63 percent efficient) in Australia. Unlike the LOWESS results, the magnitude of the difference between New York's mean technical efficiency, 0.643 (as second place), and Quebec dairy farms' mean technical efficiency, 0.626 (as third place), is not trivial. The technical efficiency scores obtained for New York dairy farmers in the spline smoothing approach is different with what Tauer and Belbase estimated (69.3 percent) in 1987 for the same region. This pattern is also seen in the estimated mean technical efficiency for Quebec dairy farms. While this index is .626 in the case of spline smoothing, Cloutier and Rowley (1993) and Mbagwa et al. (2000), respectively,

found that Quebec dairy producers were 91.3 and 92.2 per cent technical efficient. The results of the latter studies should be close to each other since both studies used the nonparametric deterministic method of estimating the technical efficiency. Nevertheless, the pooled-variance two-tailed t-test value (0.944) at the .05 level of significance shows that there is statistically no difference between the two means. Like the LOWESS result, we find Ontario dairy farms (.576) are the worst performers compared to other regions. Without exception, the spline smoothing results show that all regions of the study have their highest and lowest mean technical efficiency in 1993 and 1994, respectively.

Table 5.9 presents the results obtained from the parametric translog production function. Similar to the results of the nonparametric approaches, the mean technical efficiency of Wisconsin dairy producers (0.742) is the highest among the other three regions. This result is slightly below of what Battese and Coelli estimated for New South Wales' dairy producers (77 percent) in 1988, but it is higher than the British dairy farmers whose technical efficiency scores (72 percent) were estimated by Russell and Young (1983). The results also show that Ontario dairy farmers are the worst performers compared to other regions. These results conform to what we found in the LOWESS and the spline smoothing approaches. The U.S. dairy farmers have their best performance in 1997, whereas for Canadian dairy producers the best performance was occurred in 1995 and 1996 for Quebec and Ontario, respectively. Table 5.9 also illustrates that New York, Wisconsin and Ontario have their lowest mean technical efficiency in 1994, while for Quebec the poorest mean technical efficiency was in 1993.

Table 5.10 shows the sample correlation coefficient of the estimated mean technical efficiency among the four regions obtained from the LOWESS, spline smoothing, and the parametric translog function. To obtain figures in Table 5.10, first the sample correlation coefficient of the estimated technical efficiency scores is computed for each year. Then by taking average over the period of study, the sample correlation coefficient at the mean level is obtained. As Table 5.10 shows, there is a

high correlation between the estimated mean of technical efficiency of all four regions of the study. This pattern is seen in both nonparametric and parametric estimation techniques. To examine the null hypothesis of no difference in the sample correlation coefficient of the estimated technical efficiency between two regions, per say New York and Wisconsin (0.975), the Fisher test of correlation (see, Levine et al., 1999) is conducted. The computed Z-test value (19.18) rejects the null hypothesis at the .01 level of significance.

Table 5.10 Sample Correlation Coefficient of the Estimated Mean Technical Efficiency

	New York	Wisconsin	Ontario	Quebec
New York	1.000	0.975	0.989	0.961
	1.000	0.976	0.992	0.988
	1.000	0.976	0.991	0.979
Wisconsin	0.975	1.000	0.980	0.977
	0.976	1.000	0.964	0.983
	0.976	1.000	0.969	0.989
Ontario	0.989	0.980	1.000	0.976
	0.992	0.964	1.000	0.984
	0.991	0.969	1.000	0.977
Quebec	0.961	0.977	0.976	1.000
	0.988	0.985	0.984	1.000
	0.979	0.989	0.977	1.000

Source: Sample data. For each region, the figures show the sample correlation coefficient of the estimated mean technical efficiency obtained, respectively, from LOWESS, spline smoothing, and the parametric translog function.

To compare the estimated technical efficiency scores from the nonparametric techniques and the parametric translog function, obtained from the COLS approach, the model is also run using the stochastic parametric frontier model of Battese and Coelli in 1992 by applying the sample observations to the frontier 4.1. The results show that the estimated technical efficiency for all four regions varied between 0.889 for Ontario in 1995 and 0.996 for New York in 1994. The overall mean technical efficiency was found to be 0.989 and 0.978, respectively, for U.S. and Canada between 1993 to 1998. This implies that the stochastic parametric frontier model of Battese and Coelli (1992) overestimated the mean technical efficiency of dairy producers. Table 5.11 shows the estimated technical efficiency of dairy producers in all four regions using the stochastic parametric frontier model of Battese and Coelli (1992) assuming a half-normal distribution for the one-sided non-negative error term.

Table 5.11 Technical Efficiency of Dairy Producers (Battese-Coelli Model)

	New York	Wisconsin	Ontario	Quebec
1993	0.978	0.980	0.982	0.984
1994	0.996	0.994	0.993	0.991
1995	0.993	0.992	0.889	0.976
1996	0.992	0.990	0.987	0.984
1997	0.988	0.986	0.986	0.984
1998	0.990	0.988	0.990	0.988
Total Mean	0.989		0.978	

Source: Sample data.

- Efficiency Class Interval

As Table 5.7 shows, the distribution of dairy farms within the efficiency class interval in the sample follows a homogeneous pattern in the LOWESS model. For all regions, the majority of dairy farms are crowded into a technical efficiency category between 61-70 percent, which is the median of the efficiency class intervals. However, this pattern is not seen in the spline smoothing approach. Except for Wisconsin dairy farms, Table 5.8 indicates that the majority of dairy farms for the regions fit into the technical efficiency category between 0.51-0.70. For the parametric translog function model, as Table 5.9 displays, the majority of dairy farms for the regions are crowded into the technical efficiency category of between 61-70 percent, except for Ontario.

- Statistical Inference

The pooled-mean technical efficiency of U.S. dairy farmers for LOWESS, spline, and the translog function models are 0.660, 0.681, and 0.701, which are, on average, higher than that of Canadian dairy producers 0.607, 0.601, and 0.619, respectively, during the study. Once again, we perform two conventional statistical tests for each of these models to examine whether the variances and the means, respectively, of the computed technical efficiencies in both countries are equal. First, an F-test rejects any discrepancies between the two variances of the computed technical efficiency at the .01 level of significance. The computed F-values for the LOWESS, spline smoothing, and the translog estimates models are 0.263, 0.518, and 0.211, respectively. The two-tailed pooled-variance t-test also rejects any equality between the technical efficiency means of Canadian and U.S. dairy producers at the .01 level of significance. The computed t-test values for the LOWESS, spline smoothing, and the translog models are 3.786, 4.324, and 5.942, respectively. This finding might hint that the different policies implemented in the two countries significantly affected performance in the dairy sector. Furthermore, the direction of the performance impact is sensible; the tighter regulations in Canada over the sample period hurt the performance of Ontario and Quebec dairy farmers in comparison to

their U.S. counterparts. This conclusion, however, should be interpreted with cautious since there are other variables involved in dairy production, which were not used in this study. Table 5.12 summarizes the results of the above comparisons.

**Table 5.12 Summary of the Estimated Technical Efficiency of Dairy Producers
(Between-Regions)**

	LOWESS		Spline Smoothing		Translog	
	U.S.	Canada	U.S.	Canada	U.S.	Canada
	Pooled-Mean	0.660	0.607	0.681	0.601	0.701
Pooled-Variance	0.0019	0.0005	0.0027	0.0014	0.0019	0.0004
Sample Variance Ratio	0.263		0.518		0.211	
Sample Mean Difference	0.053		0.080		0.082	
Computed t-test Value	3.786**		4.324**		5.942**	

Source: Sample data. ** 0.01 level of significance.

For each of the nonparametric approaches and the parametric translog function model, we investigate any variation among mean technical efficiency by adding a time trend in each country and individual region. This test, which can be performed by using a two-factor way of ANOVA test (with no replication), shows there is no variation among the efficiency class intervals and the time trend. We find similar results for both countries and each region of the study. For Canadian sample data, the F-test values for the LOWESS, spline, and the translog function models are 8.598, 3.978, and 13.568, respectively. For the U.S. data, the F-test values are 11.663 (LOWESS), 2.904 (spline), and 5.142 (translog). These figures reject any equality among the efficiency class intervals and the time trend at the .05 level of

significance indicating that dairy farms' performance varied significantly from year-to-year.

We also examine the null hypothesis of no evidence for a relationship between efficiency class intervals and time trend in each region of the study. This is done using a chi-square test. This test allows us to investigate whether the efficiency class intervals and time trend are independent of each other (see, Levine et al., 1999). In the LOWESS model, we found different results for each region. The chi-square test values with 20 degrees of freedom fails to reject any relationship between efficiency class interval and time trend at a 95 percent confidence level for New York (22.02) and Ontario (20.725) dairy farms. Conversely, the computed chi-square values for Wisconsin (36.02) and Quebec (37.37) reject the null hypothesis at the .05 level of significance. This indicates that the performance of dairy farms in a particular year, on average, varies from year to year. The result for Quebec is also statistically meaningful at .01 level of significance.

For the spline and translog models we found similar results for all regions. In the former model, the chi-square test value with 20 degrees of freedom rejects any relationship between efficiency class interval and the time trend at 95 percent confidence level for New York (66.506), Wisconsin (67.599), Ontario (31.653), and Quebec (63.486) sample dairy farms. These results indicate that farmers' efficiency in a particular year, on average, is different from the following year. In the latter model, we fail to reject the null hypothesis of no relationship between efficiency class intervals and time trend in each region of the study at the .05 level of significance. The computed chi-square values are 27.181 (New York), 11.569 (Wisconsin), 11.956 (Ontario), and 13.511 (Quebec). Table 5.13 summarizes the results of the above comparison.

Table 5.13 Summary of the Independent Test between Efficiency Class Intervals and Time Trend

	LOWESS	Spline Smoothing	Translog
New York	22.02	66.50 **	27.18
Wisconsin	36.02 **	67.60 **	11.57
Ontario	20.72	31.65 **	11.95
Quebec	37.37 **	63.48 **	13.51

Source: Sample data. ** 0.05 level of significance.
 Chi-square value with 20 degrees of freedom = 31.4104.

By looking at the results illustrated in Tables 5.7, 5.8, 5.9, and 5.11 a few points are worth highlighting. First these results show that the transcendental logarithmic flexible functional form, as a representative of parametric functions appears to overestimate the mean technical efficiency of the dairy farms examined here. The total mean technical efficiency obtained using the translog function for all regions of the study (reported in Table 5.11) is higher than the corresponding nonparametric estimates shown in Tables 5.7, 5.8, and 5.9. Second, the calculated pooled-variance t-test for the translog function is higher than of the two nonparametric approaches; this statistic verifies the differences between the farms' performance in the two countries. Third, the parametric model, unlike the nonparametric approaches, fails to reject any relationship between efficiency class intervals and a time trend. Fourth, both parametric and nonparametric estimates indicate that there is a significant difference between the mean technical efficiency of dairy farms in the two countries. This latter result implies that various agricultural policies implemented in both Canada and the U.S. significantly affected farm efficiency in the dairy sector. The direction of these differences in efficiency is in favor of U.S. dairy farmers who consistently produced milk more efficiently than their Canadian counterparts.

5.5 Testing Procedure

Following the statistical test described in section 3.7, we examine whether our nonparametric model satisfies the implicit assumption of additive separability of the predictors. To conduct the analysis, we introduce a new independent variable obtained from the product of land and total feed costs, the two independent variables that are expected not to be separable (Castle and Watkins, 1984). We can readily introduce this new independent variable because the problem of curse of dimensionality is not applicable to our model. Then, using the likelihood ratio (LR) statistic we test the null hypothesis of additive separability of the predictors in the nonparametric estimates (restricted model) as opposed to the alternative hypothesis, specifying that this new independent variable adds more information to the model (unrestricted model). We conducted separate tests for each year in the between-region models for 1993-1998. The computed p -values of the chi-square ranged between 0.9920 to 0.9985, which means in all years, we failed to reject the null hypothesis at the .05 level of significance. The new variable did not add any information to the non-parametric model, so the additive separability assumption of the predictors holds.

A few other points are worth mentioning. The question might arise as to why we did not examine instead the cross effect of labor and feed costs and/or labor and land. To address this, we need to consider the type of technology that is used in the process of producing milk. In North America, on average, labor could be viewed as a minor input in dairy production because various technologies associated with different equipment in feeding dairy cows can be used. In other words, no matter what the level of herd size is, very little labor can readily feed dairy cows provided that appropriate feeding technology is being used.

The final point worth mentioning deals with the issue of separability. Sono (1945; 1961) and Leontief (1947a; 1947b) proposed the notion of functional separability independently to deal with aggregation problems in consumer and producer theory, respectively. Generally, if we can separate technology into several

stages, that technology is described as *separable*. In the theoretical analysis of separability in production functions, we note that not all technologies are separable, and that the concept of separability is most easily described in the context of continuously differentiable technologies (Chambers, 1997, p. 42). We consider these two points in our methodology and discussion.

In section 3.5.1 we assumed that the mean response variable f_i is smooth enough to be differentiable at least twice, which is also a crucial assumption to any nonparametric regression analysis. Using the LR statistic test, we concluded that the additive separability assumption concerning the predictors holds statistically. Input separability is derived from how the marginal rate of technical substitution (MRTS) between two input variables, i.e., the slope of an isoquant in the two-dimensions space, is affected by the changes in another input variable available in a third dimension. Statistically, by failing to reject the null hypothesis, we constructed here, we conclude that any changes in the labor force in the sample may alter the degree of smoothing in the space of labor input, but it doesn't change the span value (i.e., the degree of smoothing) between land and feed costs. In fact, it means that labor changes do not affect the ratio between the marginal product of land and feed costs. Therefore, the dairy production data is a special case, since weak separability holds among the chosen explanatory variables.

In summary, this study constitutes a somewhat special case where the additive separability assumptions hold for agricultural production. This fact does not diminish the applicability of the proposed econometric model to other production studies. Moreover, we strongly recommend to researchers who want to use the generalized additive model as a nonparametric approach to estimate the response function in production studies efficiency to first test the additive separability hypothesis since additive separability is inherently part of the structure of the nonparametric estimators proposed here.

CHAPTER VI

SUMMARY AND CONCLUSIONS

6.1 Motivation and Method

Microeconomic theory suggests that efficiency can be measured in three ways: technical, allocative or total efficiency. Given that improving efficiency is one way to increase productivity, in this thesis we focused on the technical portion of efficiency measurement, reflecting of firms to obtain maximal output from a given set of inputs.

The historical discussion concerning the measurement of productivity and efficiency in the economic literature started with contemporaneous papers by Debreu (1951) and Koopmans (1951). Subsequently, Farrell (1957) extended this work in an attempt to operationalize the measurement of productivity and efficiency. From Farrell's work, we define the productivity of an economic agent as the scalar ratio of outputs to inputs used by the agent in its production process. An agent's productivity may vary based on differences in production technology, through the efficiency of the production process, via the institutional environment in which production occurs, or in the quality of inputs used by the agent. Alternatively, efficiency is defined as a comparison between observed versus optimal values of the agent's outputs and inputs. This comparison comes in two forms. The first is the ratio of observed to maximum potential output obtainable from a given level of input. The second is defined by considering first the given level of input, and is measured as the ratio of minimum potential to observed input required producing the given output.

Prior to Farrell's work, efforts were made to measure efficiency by interpreting the average productivity of inputs. In the 1950s, economists and agricultural economists found that this method of measuring efficiency was

unsatisfactory as it ignored other inputs used in the process of production. To circumvent the multiple input problem, several researchers constructed efficiency indices using index numbers. However, this method suffered from other drawbacks, such as a) data aggregation; b) an a priori assumption that all firms produce efficiently; c) no allowance for random noise in measurement; and d) little or no knowledge about the functional form of production and the values of the parameters of the underlying technology. Finally in the 1970's, with the seminal papers of Aigner et al. (1977) and Meeusen and van den Brock (1977), econometricians developed a statistically and theoretically sound method for measuring efficiency, a method now known as stochastic frontiers. In this case, a stochastic frontier is defined as the locus of best performing agents within a data set. The other data points of the other firms are located "below" this estimated frontier. The relative distance measured between this best performance and the other data points is interpreted as inefficiency.

Frontiers can be estimated in different ways. In general, they are classified into three main groups: parametric, nonparametric, and semiparametric. Parametric frontier models are particular analytical functions with an a priori fixed number of parameters. Conversely, there is no prespecified functional form and no distributional assumptions with respect to errors with nonparametric frontier estimates. Thus, these types of models are robust to and are not constrained by the predetermined choice of function in their structure. Finally, semi-parametric frontier models contain a little of both parametric and non-parametric frontier estimates. There is no prespecified functional form when estimating a nonparametric frontier, thus these models are robust to the predetermined choice of function in their structure.

A frontier function can also be classified according to how one interprets the deviation of a group of agents or firms from the best performing agents in the sample. In this sense, frontier functions can be either deterministic or stochastic. In a deterministic production frontier model, output is bounded from above by a

deterministic production function. Any deviation from the best performance is imputed to inefficiency, which means random noise is not accounted for. On the contrary, in a stochastic production frontier model, output is bounded from above by a stochastic production function. Therefore the error term in a stochastic frontier estimate contains two parts: one is a two-sided term representing randomness or statistical noise, and the other is a one-sided term representing technical inefficiency. Further, depending on what types of data are used, these models can be further subdivided into cross-sectional, panel data, and dual frontiers.

Our motivation for using stochastic nonparametric frontier estimates comes from the fact that there are problems inherent in the structure of stochastic parametric frontier models. Specifically, the literature has shown that the efficiency scores are sensitive to the choice of both functional forms and the distribution assumptions made about the one-sided random component of the composed error term. One outcome of such sensible distinction is that the estimated technical efficiencies obtained from these estimates are not robust. Statistically, one solution to this problem is to employ stochastic nonparametric frontiers, where neither the condition of imposing a functional form nor the predetermined assumption of random error distribution is applied. For such models, it can be said that we let the data speak for themselves.

Nonparametric frontiers are estimated using different methods. A simple nonparametric method of estimating a regression function is known as the local averaging approach, which gives an approximately unbiased estimate of a function $v(x)$ within a closed interval of $x \in [0,1]$. One advantage of the local averaging approach is to reduce the variation arising from the random shocks. The most well-known and widely accepted method of estimating nonparametric frontier models is through the use of kernel functions. A kernel estimator is a variation of the local averaging approach, whereby the simple averaging procedure is replaced with a function containing the summation of pre-defined weights. In turn, these define a neighborhood around the point of estimation x , i.e., a grid point.

Flexibility in functional form and mathematical tractability are the advantages of kernel estimators. Despite such advantages as compared to the local averaging approach, kernel functions are not without their drawbacks; boundary bias, lack of local adaptivity, an inclination to flatten out peaks and valleys in functions, sensitivity to the form of the chosen kernel function (which determines the shape of smoothing), and an over-reliance on a smoothing parameter (called the bandwidth) regulating the degree of smoothness for kernel estimates, are all potential problems with kernel estimation.

In applied economic production studies, we seldom see a single input producing output. However, this is precisely when the kernel estimation method can be applied in a tractable fashion. Thus, there is little point in using kernel estimators to estimate frontier functions. In the thesis, we highlight this problem using kernel estimators for frontier studies and propose a methodology where the so-called “curse of dimensionality” problem is avoided. Specifically, the method developed in this thesis is derived from the theory of generalized additive models, an extension of the theory of generalized linear statistical models. In a generalized additive stochastic frontier model, we maintain an additivity assumption in the function, but relax linearity. Thus, the new model contains a flexible structure without using an a priori predetermined functional form.

To solve this econometric model, we utilize an iterative procedure called a smoothing process. This lets us estimate the mean response function and its parameters. The smoothing process takes an average (locally in the neighborhood) of any fixed points of the predictors in the multidimensional vector of the regressors in the model. As a result, the estimated mean function becomes the mean of the dependent variable for all predictors in the procedure. Our motivation for using this smoothing procedure is that none of the known kernel functions in a nonparametric regression analysis can handle the estimation of a multi-dimensional matrix of covariates. Therefore, using a specific method of smoothing called locally scoring smoothing, and a particular algorithm for estimating parameters called the backfitting algorithm to start the estimation process, we are able to estimate the

parameters of the regression function in a nonparametric fashion. The latter is formally accomplished using two separate techniques: locally weighted scatterplot smoothing (LOWESS), also known as a local regression model (LOESS), and spline smoothing, also known as a cubic smoothing spline. After estimating the response function and its parameters, we can finally compute technical efficiency scores.

Employing the theory of generalized additive models and the derived estimation procedure (the smoothing process) is not without cost. The necessary additivity assumption and the determination of the smoothing degree, respectively, are important restrictions encountered in applying these techniques. In the relevant econometrics literature, cross validation and generalized cross validation are two methods that have been suggested for fixing the second restriction. In this study we used the cross validation approach by removing the observation method each time in the process of estimating the mean response function to provide consistent estimators. In order to examine the additive separability assumption of the model, we used an analysis of residual deviance. This value for the model is simply the logarithm of the likelihood ratio. Therefore, the relevant statistical test of significance has an asymptotic chi-squared distribution.

The goals of this study can be summarized into two main themes, theoretical and applied in nature. First, an effort was made to address the sensitivity of efficiency scores to the choice of functional form and distributional assumptions of the one-sided non-negative random error term in parametric stochastic frontier models. Second, we introduced various methods of estimating parameters of a function in a nonparametric fashion and highlighted their shortcomings. Finally, we proposed a new model for estimating the technical efficiency of North American dairy farms.

In the applied section, we compared the technical efficiency of Canadian dairy producers (Ontario and Quebec) with U.S. dairy farmers (New York and Wisconsin). This constitutes an interesting cross-border comparison. For a comparison, we also estimated a stochastic flexible translog function to obtain the

base technical efficiency of the dairy producers. We compared the results from this simple model with the results estimated using nonparametric techniques, i.e. LOWESS and spline smoothing. We then divided the discussion into two separate categories based on location. In the first category, called the within-regions model, we did not consider a cross-border comparison. Instead, dairy farmers at each region were compared with their own-region counterparts. However, an examination of cross-border efficiencies was contained in the so-called between-regions model.

6.2 Major Policy Findings

We focus here on summarizing the results for the between-region models because these econometric models allow cross-border comparisons by expressing the variation in estimated technical efficiency between the two countries. While important to the theoretical portion of this thesis, the within-region models are for calibration purposes only and do not measure important aspects of dairy policy. The calibration results from the within-region model were extensively discussed in section 5.4.1.

These are the key policy findings of this study, derived from the between-regions model:

- (i) The stochastic parametric translog function overestimated the mean technical efficiency of dairy farms during the period of study. The overall mean technical efficiency obtained from translog function for all regions is higher than that of the corresponding values obtained from the nonparametric approaches (see Tables 5.11 and 5.12).
- (ii) The calculated pooled-variance t-test in the translog function is higher than of the nonparametric approaches, indicating that the statistical test confirms differences between the dairy farms' performance in the two countries.

(iii) Both parametric and nonparametric methodologies indicated evidence of differences between the mean technical efficiency of dairy farms in all regions. This indicates that various policies implemented in the two countries significantly impacted the performance of dairy producers. The direction of these differences was in the favor of U.S. dairy farmers, who produced milk more efficiently than their Canadian counterparts.

(iv) Interpreting (iii), we find that the regulated dairy industry in Canada has led to lower technical efficiency of Canadian dairy farmers. Canada's commitments to international agreements such as the WTO may no longer readily allow the federal government and the provinces to pursue supply management policy.

6.3 Areas for Further Research

We can categorize the potential arena for further research based on both theoretical and applied aspects of this study. For the theoretical aspect, we recall the problems stemming from the smoothing technique. In order to estimate the mean response function and the parameters of this model, we used two nonparametric approaches, i.e., LOWESS and spline smoothing. For both techniques, we utilized an iteration process called the backfitting algorithm to project the initial estimate of the mean response function. However, with this methodology, finding the optimal choice of smoothing degree is an important issue. This is not only time consuming but involves considerable computational burden. We circumvented this problem by using the cross validation method. This procedure provides an optimal smoothing parameter that leads to consistent estimators, but it is not an efficient method in the sense of computer time and memory use. One way to better get around this problem would be to use the method of marginal-integration for generalized additive models, which is a direct method of estimation with no iteration. The marginal integration method is proposed independently by Newey (1994), Tjøstheim and Auestad (1994), and Linton and Nielsen (1995).

With respect to the applied portion of this study, following points need to be addressed. First, there is a need to estimate the technical efficiency of dairy producers in all Canadian provinces across time. The first critical period dates back to the 1960s, when there was no supply management policy. The second critical period of time is when supply management was implemented in the 1970's. The last critical period of time is after 1995, when Canada was forced to change its milk pricing policy due to the signing of the North American Free Trade Agreement (NAFTA) and the World Trade Organization (WTO) agreement. These policies were designed to reduce trade barriers among the geographical regions in question. This meant the dairy supply management policy could not be validated any more to protect the industry. Clearly, the various policies impacted the performance of Canadian dairy producers over time, and dairy farmers' reactions to these policies can be measured by estimating their technical efficiency. The results of such a study, in particular through the post-1995 period, may be useful to farming on the Canadian prairies since this region tends relatively to have the lowest production cost in Canada. If the Canadian dairy industry is forced to sell their products at the world price upon removal of the supply management policy, then the Prairies could be the first place to expand the dairy industry due to the lower production costs. The more rapid expansion in the average herd size in the Prairies may also be changing the level of technical efficiency of these Canadian provinces. Perhaps the Prairie provinces should be compared to growth areas of the U.S. in a subsequent study.

We note that the second suggestion is best conducted by estimating allocative and economic efficiency for the regions of the study. Lack of input and output price information from the dairy industry prevents us from measuring these efficiency indices. Ultimately, it would be more appropriate to compare the performance of dairy farmers in all the regions in question from an allocative and economic efficiency point of view to determine if the technical efficiency found here are still valid.

There is a potential obstacle for new entrants in dairy industry. This refers to the quota values. Quota values may act as a capital barrier to entry that new entrants initially may face it. Such barriers vary from one province to another. Historically, Saskatchewan placed a limit on the quota that could be held by an individual firm. Other provinces, such as Manitoba, declared that new entrants should not pay anything for quota, only facilities. Irrespective of types of attitudes, quota values may constrain the rate of growth in dairy farm size. Therefore, a study that evaluates the relationship between quota values and the expansion of dairy farm size in all provinces is suggested.

Finally, in this study labor force is used as a physical quantity and it was not converted to dollar values. A question might be raised and that is how sensitive the results of this study were if labor force would have been considered as dollar values. Specifically, if labor force were converted to dollar values at a prevailing wage rate in each country, would the results of this study be changed? Thus, a study of estimating the technical efficiency of dairy farms in all four regions considering labor in dollar value is recommended.

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