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PARAMETRIC MODELS FOR DYNAMIC EFFICIENCY MEASUREMENT

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Abstract

The efficiency measurement literature has been almost exclusively based on a static view of the firm. In this static context the optimality of decisions is measured against the best practice frontier in a period-by-period basis and without any connection along time. This dissertation departs from the techniques used by static models of efficiency measurement and accounts for the intertemporal nature of the decision-making process at the firm level. The cost associated with the adjustment of the stock of quasi-fixed production factors is identified as the link between current decisions and future production possibilities. The objective of the firm is assumed to be intertemporal cost minimization.

Two parametric models for efficiency measurement are developed and estimated. The first model is based on the argument that when the adjustment of quasi-fixed factors is costly, dynamic optimization may prescribe a plan that would force a technically inefficient firm to remain partly inefficient in the short run. The implication of intertemporal cost minimization is that inefficiency in static models is likely to persist over time. This implication is incorporated to the techniques used for static efficiency measurement and estimation of a reduced-form model is proposed within the state-space modeling framework. The applicability of the model is illustrated using two panels of dairy farms from Germany and the Netherlands.

The second model is centered around efficiency measurement with respect to capital stock. The firms' managers are assumed to form rational expectations with respect to future prices and minimize the expected discounted cost of producing a given stream of output. Estimation is based on a system of equations consisting of the variable cost function, the cost-share equations and the derived Euler equations. A relatively new econometric technique is employed for the estimation which combines regression and factor analysis. The structural model is applied to a panel of food-processing plants from Mexico.

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Chapter 1

Introduction

1.1 General Background on Production Theory and Efficiency

Modern microeconomic theory maintains as an assumption that producers are successful optimizers. At a first stage, given a rule for transforming inputs into outputs, producers choose the amount of production factors to employ in order to produce a given level of output such that production cost is minimized. At a second stage, producers choose the amount of output to be produced such that another objective is achieved. Usually this objective is profit maximization.

Cost minimization or profit maximization are behavioral assumptions imposed on the production units. Both are based on the rationale that if producers fail to optimize, then competition would drive them out of business. The empirical appeal of these behavioral assumptions comes from their flexibility to accommodate different situations and market structures. This is mainly because of the fact that, even if high-level assumptions are not satisfied, the assumptions on the previous stages could still hold. For example, profit maximization implies cost minimization behavior, but not the other way around. A firm can be minimizing the cost of producing a given level of output, but this level could be chosen not such that it maximizes profit but according to another criterion. Cost minimization in turn implies that producers operate at a specific region of the transformation rule. More specifically, given that production factors have non-negative rental prices, the producers will choose to employ a bundle of inputs that can produce a predetermined level of output, but if contracted in any direction this bundle will no longer be able to produce the same level of output. Again this implication does not work in the other direction. That is, non-wasteful input usage does not necessarily imply cost minimization unless the relative input prices are taken into consideration.

These behavioral assumptions provide a rigid framework for explaining production decisions at the microeconomic level and are accompanied by results, such as duality theorems, that facilitate inference. In reality, however, it is not necessary that all producers always make the optimal decisions. Firms maybe using suboptimal production methods because government regulations protect them from competition, or simply because the industry dynamics have not yet caught up with them. In other words, "survival of the fittest" in an economic environment would imply that in the long run the firms that will continue to produce are the most successful optimizers. But it could be that, due to the changing environment, this long-run equilibrium will never be attained.

After accepting the fact that at any point in time the firms that are active in an industry are not guaranteed to be perfect decision-making units, it follows that a measure of the discrepancy between what is optimal and what is observed should be defined. Two very similar definitions of what is known today as productive efficiency appeared as early as 1951. One is due to Koopmans (1951) and the other to Debreu (1951). Both authors work at a theoretical and very general level, describing economies with multiple inputs and outputs. The first applied study that measures efficiency was conducted by Farrell (1957), but again the analysis was not done at a microeconomic level.

By providing the necessary definitions and tools, the three articles mentioned above inspired a vast literature on efficiency measurement. The original question of measuring efficiency and comparing the efficiency scores between economic agents soon extended to include other interesting issues. Some of these issues include the decomposition of efficiency into its components, such as productive and allocative efficiency, and the study and explanation of the driving forces of inefficiency. But is it failure to optimize that has been measured by the studies in this literature? The next section argues that when applied research is considered, what is termed as inefficiency depends heavily on the modeling assumptions.

1.2 A Closer Look at Inefficiency

When the measurement of efficiency of a group of firms is undertaken, the researcher faces some challenges and decisions. First of all, in order for the comparison of the performance between the firms to be meaningful, these firms should have access to the same technology. It is not necessary that the firms actually employ the same technology, as there exist models that can measure efficiency even when different production techniques are used. In fact, when this is the case, a study on the factors affecting the choice of technique is usually interesting. What is important is that the choice of the technology is under the control of the firm. Otherwise one would be measuring the optimality of decisions made by firms facing different restrictions on their action sets.

The choice of the behavioral assumptions is also of great importance. If a researcher undertakes the measurement of profit efficiency of a group of firms that have an objective other than profit maximization, then the firms will be inefficient according to the criterion falsely chosen by the researcher. Depending on the market structure and the industry under consideration different objectives can be assumed. In agriculture for example, maximization of expected utility of profits with risk-averse agents appears to be a more appropriate objective than maximization of profits under risk-neutrality. In oligopolistic markets, deterrence of potential competitors plays an important role in the objective of the firm. Maximization of short-term profits is inappropriate as a behavioral assumption in this case. In general, cost minimization is a milder assumption and it is more likely to hold under a variety of circumstances.

In an extreme case, if all the conditions that are not under the control of the firm could be modeled and all the heterogeneity between the firms could be accounted for, then inefficiency could be considerably downsized. In this case inefficiency would measure the pure effect of failure to optimize with respect to the true objective of the manager. But, even if data were available to build a model like this, the model would be extremely complicated; hence, the applied analyst's dillemma of a trade-off between model parsimony and ease of interpretation of the results.

A rather extreme argument against the existence of inefficiency in total is made by Stigler (1976). In his critique of models that assume that producers are not perfectly efficient he states:

> "The first assumption [that monopolists do not maximize profits] is an abandonment of formal theory, and one which we shall naturally refuse to accept until we are given a better theory."

Of course, what is "a formal theory" can be different in different circumstances, even in different points in time. The theory that requires firms to be maximizing profits has proven a useful framework, but there is mounting evidence that this objective is not achieved in practice.

There exists no general rule for solving these problems and inefficiency will most likely be present in almost any empirical application. However, it can be said that if a restriction on the firm's action set is presumed to be present for a large number of producers in the industry under consideration, then it should be explicitly modeled. Also, when there is a high degree of heterogeneity between the firms in the sample, either with respect to the objective or with respect to unobserved factors, then using a subsample for the inference could be justifiable, trading in this way external for internal validity.

1.3 Efficiency in a Dynamic Context

In the past years theoretical results and empirical studies on efficiency measurement have been based almost exclusively on a static view of the firm. But, although useful for illuminating many ideas about decision making at the firm level, this static theoretical construct is not representative of reality. Firms' decisions are intertemporal in nature with present actions affecting both today's outcomes and future possibilities. In this case, the modeling issues mentioned above become particularly relevant. When moving from a static to a dynamic context both the objective of a firm and the constraints are different.

The producer in a dynamic model has to make a plan of production so that an objective that extends far in the future is optimized. Examples are maximization of discounted cash flows over a period of time or minimization of discounted costs. All decisions have to be made under the uncertainty of future prices and the adoption and diffusion of implementable technologies. At the core of this argument is the question: can we tag a producer as inefficient for not being able to predict the evolution of uncertain quantities in the future, given that there is a given amount of variability associated with future conditions? Of course when a producer consistently under- or over-estimates some quantity, this could be treated as inefficiency, since the expectation-formation mechanism is probably flawed. Conversely, can we term a producer efficient for optimizing in the short term and completely disregarding the effect that today's decisions have in future outcomes? Yet, this is what would happen under a static measure of efficiency.

The additional restriction that is imposed when modeling the dynamic behavior of a firm is the evolution of capital stock over time. In the static context capital is treated either as fixed in short-run models or as freely adjustable in long-run models. There is hardly any connection between those two extremes. In a dynamic model capital is adjusted according to an equation of motion that depends on the rate of depreciation of existing capital and investment in new capital. This equation is the link between current decisions and future production possibilities. If investment is allowed to be positive or negative, and no cost is associated with the adjustment of capital, then there is no real restriction for the firm. Along with the constraint, the intertemporal nature of the problem vanishes. But capital can rarely be considered as freely and costlessly adjustable. This idea has its roots in the adjustment cost theory of investment that was developed as a response to the failure of the neoclassical investment theory to predict the observed investment behavior of firms.

In what follows we make a distinction between positive and negative gross investment (disinvestment). First of all, there are some costs associated with the change of the capital stock of the firm beyond the acquisition costs or rental prices of capital. One category includes the costs of learning to use the new equipment. Although they are termed costs, they are usually measured in terms of output loss due to the time and resources devoted to learning. These costs are also relevant in the case of disinvestment, although arguably not as important. Depending on whether these costs are convex or concave with respect to gross investment, capital stock adjustment can be smooth or discrete. In the case of positive investment there may also be fixed installation costs for new capital. This is a special kind of non-convexity that gives rise to lumpy adjustment.

Secondly, although in principle disinvestment is always possible (in a worst case scenario capital could be left idle), it is frequently impractical from an economic point of view. It is obvious that no firm would invest in machinery that has high probability of being left idle. But in the case that this happens, the under-utilized equipment could still have a salvage value. In many cases, however, investment is fully or partially irreversible. This could happen when the markets for used capital are not well developed, either because the capital is industry-specific or the market for these capital goods is small. In general, selling prices of almost new equipment are much lower than those of new. Based on this irreversibility of investment decisions, investing in a project can be seen as a call option. Under uncertainty, managers may very well have an incentive to wait until the state of the world is revealed before investing.

The differences between static and dynamic models of efficiency measurement do not stop here. The entire nature of the exercise changes when decisions over time are considered. In a static context there are clear definitions of what efficiency is, mainly based on the distance of the observed quantities from a boundary (production, cost, revenue or profit frontier). In a dynamic context when multiple, if not infinite, decisions are considered, two natural definitions of efficiency arise. The first is associated with measuring dynamic efficiency as the deviation of an observed path from the optimal path of capital stock adjustment. This deviation could be upwards or downwards and thus cannot be measured against a frontier.[1] The discrepancy between the optimal and observed trajectories gives rise to a stock notion of inefficiency, with the effect of suboptimal decisions accumulating through time. In the second approach dynamic efficiency is perceived as a flow. In this case inefficiency would measure the failure

[1]This is not a problem *per se* but it complicates the econometric measurement of efficiency since such a deviation is hard to distinguish from deviations due to random noise.

to optimize in the current period, where the firm always operates. But the long-run objective of the firm is taken into consideration in the definition of the optimal current-period action.

1.4 Objectives and Research Questions

Given the appeal of the dynamic theory of the firm, it is rather surprising that efficiency measurement has been based primarily on a static perception of the environment in which firms operate. On the other hand, there seems to be an increasing interest during the last few years in modeling investment decisions at the firm level and measuring efficiency within the dynamic framework. Progress in the field, however, is rather slow. This is due to two reasons. First, duality theory, that has proven very useful in static modeling of efficiency, becomes much more complicated when dynamics are introduced, especially when these dynamics are combined with uncertainty about the future economic environment. Second, the static models of efficiency measurement are not very flexible in admitting modifications that are suggested by the dynamic theories. By extending the primal static models in a dynamic context, one has to deal with more complex estimation techniques and more computationally demanding procedures. As a result most applied studies on dynamic efficiency measurement take a non-parametric approach.

The objective of this study is to contribute to this growing literature in a specific way: by developing and estimating parametric models for dynamic efficiency measurement. At a first stage, the theoretical implications of the adjustment costs and investment irreversibilities hypotheses are examined. Then a reduced-form model is developed to test whether these implications manifest themselves in practice. At a second stage, a structural dynamic efficiency model is built. From this model the optimal short-run decisions with respect to input usage and investment are derived. The deviation of observed from optimal decisions is measured in a parametric system of equations.

The underlying questions of the study are the following:

- Is there persistence in the inefficiency scores of a firm along time?

- Are there any considerable gains in understanding how firms behave by moving from static to dynamic modeling?
- Is there a feasible way to model the optimality of current-period firm decisions that reflect intertemporal optimality?

Two focused applications are undertaken to study firm-level decisions in a dynamic context. The first one uses farm-level input use and output data for a sample of dairy farms in Germany and the Netherlands to estimate a reduced-form model of firm behavior. The sample covers the period 1995-2005, but each farm is observed on average for a period of 5 years. In the second application data from Mexico's Annual Industrial Survey are used to estimate a structural model. A balanced panel of food- processing plants, observed for the period 1984-1990, is extracted from the database. This dataset contains information on input quantities and prices, as well as value of output and cost of investment.

1.5 Outline

The main focus of this dissertation is on models that are appropriate for dynamic efficiency measurement. Emphasis is given to the connection of the models developed here to the already available techniques for efficiency measurement and to their ability to be operationalized. The next chapter, therefore, reviews the literature of efficiency measurement from the early static models to the more elaborate static and recent dynamic models. The presentation is done mainly from a technical point of view. Techniques for measuring productive and allocative efficiency are considered, although profit and revenue frontiers can be obtained as direct extensions. Special attention is given to the extentions that will prove useful for developing the dynamic models in the following chapters. A comparison between the parametric and non-parametric methods is carried out along the way.

Chapter 3 examines the implications of adjustment costs for technical efficiency measurement. A reduced-form model is developed and estimated within the state-space modeling framework. In Chapter 4 a structural model of dynamic efficiency measurement is developed. Two alternative formulations are proposed, which lead to different estimation techniques. Chapter 5 provides an application of the structural model. Finally, Chapter 6 presents some concluding comments, along with a summary of the empirical findings and suggestions for further research.

Chapter 2

Efficiency Measurement: A Review of the Literature

2.1 Introduction

This chapter reviews the methodological advances in efficiency measurement. The definitions of static efficiency are given in the next section, along with some basic assumptions about the representation of a production technology. Non-parametric methods for efficiency analysis are described in section 2.3. Since the focus of this study is on parametric methods of efficiency measurement, the non-parametric methods are only briefly reviewed. Efficiency measurement via parametric methods is presented in sections 2.4 and 2.5. Technical efficiency is considered first. Then techniques for the estimation and decomposition of cost efficiency are described and special emphasis is given to the role of duality theory. Extensions to the basic models are presented in section 2.6. Up to this point all presentations are made under a static view of the firm. Therefore, only cross-sectional models are considered. The presentation of panel data models starts in section 2.7. Then, the dynamic efficiency measurement literature is reviewed in greater detail. Finally section 2.8 places this study on the literature map.

2.2 Basic Definitions

2.2.1 Representations of a Technology

Production analysis is conducted with respect to a technology. There exist different mathematical representations of a technology that describe what is possible to be produced from a given amount of inputs. The most general representations of a technology are given in terms of sets. Two sets that are equivalent in describing the technology are the *input requirements set* and the *output possibilities set* and they are defined bellow. The presentation in this subsection is based on Lovell (1993).

Definition 2.1. Let $\mathbf{x} \in \mathbb{R}_{+}^{N}$ be a vector of inputs and $\mathbf{y} \in \mathbb{R}_{+}^{M}$ a vector of outputs. The *input requirements set* $\mathtt{L}(\mathbf{y})$ is the set of input vectors that can produce $\mathbf{y}$.

Definition 2.2. The *output possibilities set* $\mathtt{P}(\mathbf{x})$ is the set of output vectors that can be produced by $\mathbf{x}$.

Typically, convexity or concavity assumptions are placed on these sets, along with disposability of inputs and outputs. A particularly important assumption is that the sets are closed and bounded. These properties allow for another representation of technology. The definitions above are useful for defining efficiency and measuring it, especially with non-parametric methods. For parametric analysis of efficiency the notion of distance functions is used instead.

Definition 2.3. An *input distance function* is a function $D_I : \mathbb{R}^M \times \mathbb{R}^N \to \mathbb{R}$ defined as:

$$D_I(\mathbf{y}, \mathbf{x}) = \max\left\{\lambda : \frac{\mathbf{x}}{\lambda} \in \mathtt{L}(\mathbf{y})\right\} \tag{\textbf{D}.2.3}$$

An input distance function gives the maximum linear contraction of an input vector so that this vector reaches the boundary of the input requirements set for given $\mathbf{y}$. Closeness and boundedness of the input requirements set is required for the maximum in the definition to be attained. The input distance function assumes values in the interval $[1, \infty)$ and the locus of points for which $D_I(\mathbf{y}, \mathbf{x}) = 1$ defines the boundary of the input requirements set. A particularly useful (for purposes of parametric estimation) property of the input distance function is that is it linearly homogeneous in inputs.

Definition 2.4. An *output distance function* is a function $D_O : \mathbb{R}^N \times \mathbb{R}^M \to \mathbb{R}$ defined as:

$$D_O(\mathbf{x}, \mathbf{y}) = \min\left\{\theta : \frac{\mathbf{y}}{\theta} \in \mathtt{P}(\mathbf{x})\right\} \tag{\textbf{D}.2.4}$$

An output distance function gives the maximum linear expansion of an output vector so that this vector reaches the boundary of the output possibilities set for given $\mathbf{x}$. Contrary to the input distance function, the output distance function assumes values in the interval $(0, 1]$. The locus of points for which $D_O(\mathbf{x}, \mathbf{y}) = 1$ defines the boundary of the output possibilities set. From the definition it is obvious that the output distance function is linearly homogeneous in $\mathbf{y}$.

Input and output distance functions are equivalent ways of representing a technology where multiple inputs are used to produce multiple outputs. In the special case where a single output is produced the notion of a production function is useful for empirical analysis.

Definition 2.5. A *production function* is a function $f : \mathbb{R}^N \to \mathbb{R}$ defined as:

$$f(\mathbf{x}) = \max\{y : y \in \mathtt{P}(\mathbf{x})\} \qquad (\mathbf{D}.2.5)$$

The production function gives the maximum amount of output that can be produced by a given $\mathbf{x}$. That is, it gives the boundary of a single-output possibilities set explicitly.

2.2.2 Definitions of Efficiency

Koopmans (1951), Debreu (1951) and Farrell (1957) are the first to define technical efficiency in a static context. Koopmans gives the conditions for a feasible input-output combination to be efficient but his definition is not operational in terms of efficiency measurement. Debreu uses the notion of distance functions to give a unidimensional measure of efficiency and Farrell uses an almost identical definition and conducts the first empirical application of efficiency measurement. Farrell defines the technical efficiency of an input-output combination as the inverse of the maximum linear contraction of the input vector such that the output vector is feasible. The input distance function is at the center of this definition of efficiency. In fact, efficiency as it is defined by Farrell, is the inverse of the input distance function.

Definition 2.6. The *input oriented efficiency* of an input-output combination $(\mathbf{x}, \mathbf{y})$ is defined as:

$$\mathrm{TE}_I(\mathbf{y}, \mathbf{x}) = \frac{1}{D_I(\mathbf{y}, \mathbf{x})} \qquad (\mathbf{D}.2.6)$$

This is an input-contracting view of technical efficiency. An output-expanding view leads to the following definition.

Definition 2.7. The *output oriented efficiency* of an input-output combination $(\mathbf{x}, \mathbf{y})$ is defined as:

$$\mathrm{TE}_O(\mathbf{x}, \mathbf{y}) = D_O(\mathbf{x}, \mathbf{y}) \tag{\textbf{D}.2.7}$$

Both measures assume values in the interval $(0, 1]$.[1] In general the two measures will not give the same result for a given input-output combination, except in the special case of a constant returns to scale technology.

A graphical representation of the input and output oriented measures of efficiency for the simple case of a single output and two inputs is given in Figure 2.1. Here the efficiency of the input-output combination $(\mathbf{x}, y)$ is under consideration. The input oriented efficiency score of $(\mathbf{x}, y)$ is given by the ratio $\frac{\|\mathbf{x}^*\|}{\|\mathbf{x}\|}$. The output oriented measure of efficiency is given by the ratio $\frac{y}{y^*}$.

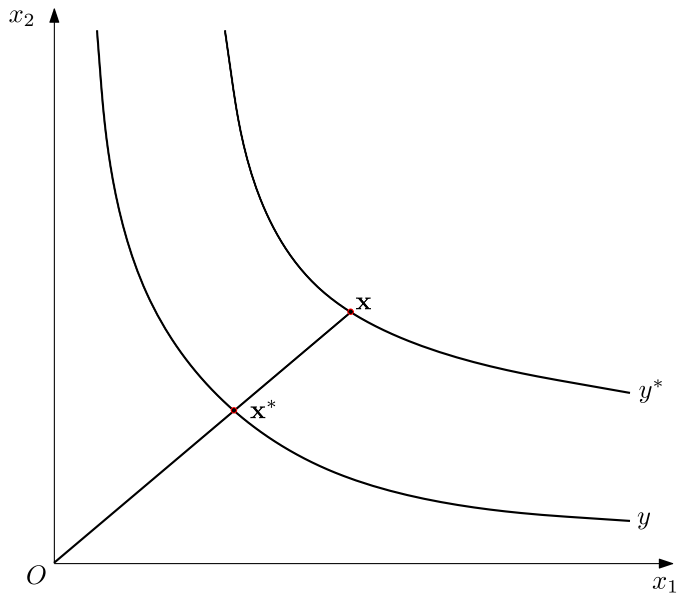

Fig. 2.1: Input and Output Oriented Technical Efficiency

[1] In most places in the literature the output oriented efficiency measure is defined as the inverse of the output distance function. Then $\mathrm{TE}_O \in [1, \infty)$.

If producers are assumed to be minimizing cost, then the cost efficiency of an input-output combination can be defined.

Definition 2.8. The *cost efficiency* of an input-output combination $(\mathbf{x}, \mathbf{y})$ given a vector $\mathbf{w} \in \mathbb{R}_+^N$ of input prices is defined as:

$$\mathrm{CE}(\mathbf{x}, \mathbf{y}, \mathbf{w}) = \frac{c(\mathbf{y}, \mathbf{w})}{\mathbf{w}'\mathbf{x}} \tag{D.2.8.1}$$

where $c(\mathbf{y}, \mathbf{w})$ solves the cost minimization problem:

$$\begin{aligned} \min_{\mathbf{x}} \quad & \mathbf{w}'\mathbf{x} \\ \text{s.t.} \quad & \mathrm{TE}_I(\mathbf{y}, \mathbf{x}) \leq 1 \\ & \mathbf{y} \ \text{ given} \end{aligned} \tag{D.2.8.2}$$

From this definition it is apparent that for an input-output combination to be cost efficient two conditions have to hold: 1) it is technically efficient 2) the minimization problem is solved appropriately. In practice it is possible for both conditions for cost efficiency to fail. In that case the economic efficiency can be decomposed into (input oriented) technical efficiency and allocative efficiency. The latter is defined below.

Definition 2.9. The *allocative efficiency* of an input-output combination $(\mathbf{x}, \mathbf{y})$ given a vector $\mathbf{w} \in \mathbb{R}_+^N$ of input prices is defined as:

$$\mathrm{AE}(\mathbf{x}, \mathbf{y}, \mathbf{w}) = \frac{\mathrm{CE}(\mathbf{x}, \mathbf{y}, \mathbf{w})}{\mathrm{TE}_I(\mathbf{y}, \mathbf{x})} \tag{D.2.9}$$

This definition of allocative efficiency coinsides with the one given by Farrell (1957). Again, for the simple case of a technology with a single output and two inputs, a graphical representation of the decomposition of cost efficiency is possible. This is done in Figure 2.2. The efficiency of the input-output combination $(\mathbf{x}, y)$ is under consideration. The market prices of inputs are given by vector $\mathbf{w}$. Given that amount y of output is produced, the input vector $\mathbf{x}^*$ is technically efficient and given the market input prices the cost efficient input vector is $\mathbf{x}^{**}$. The cost efficiency of $\mathbf{x}$ is therefore $\frac{\mathbf{w}'\mathbf{x}}{\mathbf{w}'\mathbf{x}^{**}}$.

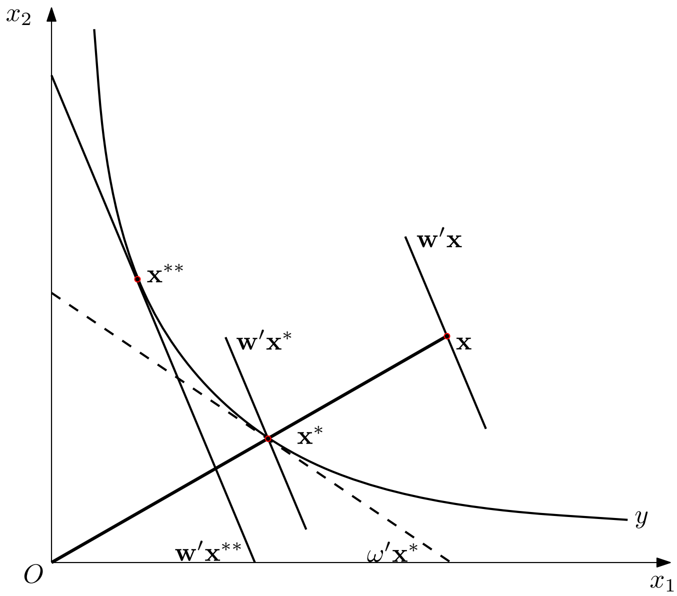

Fig. 2.2: Decomposition of Cost Efficiency

The move from $\mathbf{x}$ to $\mathbf{x}^{**}$ can be broken into to two parts, a move from $\mathbf{x}$ to the technically efficient $\mathbf{x}^*$ and a move along the isoquant of y, from $\mathbf{x}^*$ to the cost efficient $\mathbf{x}^{**}$. Note that the input vector $\mathbf{x}^*$ is allocatively efficient with respect to the shadow prices ω. The discrepancy between the real market prices and the shadow prices is pivotal in measuring allocative efficiency in the shadow-cost approach.

With these definitions at hand, two major approaches for efficiency measurement were developed in parallel, a parametric and a non-parametric. Note however that the entire analysis in this section was done under the assumption that the production technology is known to the researcher in the form of an input or output distance function. The challenge in practice is not only to measure efficiency but, at the same time, to recover the frontier against which efficiency is measured. The non-parametric methods for accomplishing this task are briefly reviewed in the following section. More attention is given to the parametric methods for efficiency measurement which are presented in sections 2.4 and 2.5.

2.3 Non-parametric Methods

Farrell (1957), in the first empirical study of efficiency measurement employed non-parametric methods. Some of the restrictions his model imposed on the data were relaxed by Charnes et al. (1978) and Banker et al. (1984). The technique that became known as Data Envelopment Analysis (DEA) uses linear programming to construct the production frontier by linearly mixing efficient producers. Therefore, the set of efficient input-output combinations is a piece-wise linear surface that envelops all the observations. The efficiency score of every producer is measured against this frontier.

The first applications of DEA measured the technical efficiency of production units. Färe et al. (1985) are the first to discuss cost efficiency in a non-parametric setting. The application again involves solving linear programming models and measuring efficiency against a piecewise linear frontier. Allocative efficiency can be calculated by the multiplicative formula in definition 2.9, after cost and technical efficiency are calculated separately. Banker and Maindiratta (1988) use a revealed-preference approach to develop a similar decomposition of profit efficiency into technical and allocative efficiency. The cost efficiency decomposition was extended by Cooper et al. (1999) in additive models (a slight modification of the original DEA models).

DEA does not require the specification of production or cost frontiers, although some convexity or concavity and disposability assumptions are made about the input requirements or output possibilities sets. If efficiency measurement and ranking of the production units is the sole objective of the exercise, DEA provides the means of reaching this goal. However, it does not provide any estimates of measures that are usually of interest to economists, such as marginal products or marginal costs.

As most nonparametric methods, DEA is subject to the criticism that it produces results which are very sensitive to measurement error. In fact, a measurement error at the quantities of an efficient production unit would shift the frontier enough to render most units in the sample inefficient. Furthermore, the efficiency scores of the production units are deterministically generated rather than estimated, i.e. there is nothing stochastic about them. In an attempt to remedy this, Banker (1993) shows that DEA can be regarded as a stochastic approach leading to maximum likelihood estimates if the calculated inefficiency scores are treated as random draws from a probability distribution. Inferences about the estimated efficiency scores can be made based on the assumed probability distribution. A different approach is taken by Simar and Wilson (1998, 2000). They use bootstrapping with DEA to empirically generate distributions of the firm-specific efficiency measures. These distributions can then be used to draw inferences about the efficiency scores, even in the case where only small samples are available.

DEA can accommodate production processes with multiple inputs and outpus. Since it is a non-parametric method one does not have to worry about degrees of freedom. This led to the practice of using DEA in empirical applications when the number of production units is small compared to the number of inputs and outputs. However, the dimensions of the enveloping surface increase along with the number of inputs and outputs. Thus, the number of vertices that describe the surface will increase and the number of production units that will define these vertices will be a larger portion of the sample. In a sample with very few production units, the majority of them will appear as perfectly efficient. Thus, the interpretation of efficiency scores in such a case is different: efficiency measurement is not done under the best possible practice but more appropriately the production units are ranked against one another.

2.4 The Stochastic Frontier Model and Extensions

The parametric methods for efficiency measurement also have their roots in Farrell's seminal paper. In his discussion of Farrell's paper, Winsten (1957) suggested that a valid way to estimate a production function would be to correct the Ordinary Least Squares estimator so that the resulting frontier envelops rather than going through the data. In fact, under the assumption of productive inefficiency, the OLS estimator is unbiased for all the parameters except the constant term, which is biased towards zero due to the non-zero mean of the errors. To correct for this bias, the estimated production function can be shifted upwards so that it envelops the most extreme observation. The firm-specific efficiency scores are measured against this frontier.

Corrected Least Squares did not become a popular method of estimation *per se*, but because of its computational ease it was included in studies of comparison of alternative estimators. A modified version of least squares was proposed by Afriat (1972) and later implemented by Richmond (1974). Again it involved shifting the production frontier (estimated by least squares) upwards, but this time the amount by which it is shifted is calculated as an expectation. More specifically, the error term is assumed to be distributed as gamma and after the least squares estimation, the frontier shifts upwards by an amount equal to the expectation of the error term. The important idea that this method introduced is the treatment of efficiency as a random variable with a distribution known up to a vector of parameters. On the other hand the frontier that is estimated is deterministic, in the sense that the frontier is fixed and every deviation from it is interpreted as inefficiency.

A natural extension was presented in two very similar papers, that were published almost simultaneously, one by Aigner et al. (1977) and the other by Meeusen and van den Broeck (1977). The model became known as stochastic frontier because, apart from the one-sided error term that captures inefficiency effects, it contains another, symmetric error, designed to capture random noise. It has been applied to a variety of situations and extended to measure cost and allocative efficiency. These models are presented below.

2.4.1 Technical Efficiency

The Single-Output Case

Consider a technology where N inputs are used to produce a single output according to the production function $f(\mathbf{x};\boldsymbol{\beta})$, assumed to be known up to a vector of parameters. Suppose that data on the amount of inputs used and the output produced are available for a sample of I firms. The output-oriented measure of efficiency for firm i is defined as:

$$\mathrm{TE}_i = \frac{y_i}{f\left(\mathbf{x}_i;\boldsymbol{\beta}\right)} \tag{2.1}$$

Technical efficiency is treated as a random variable and replaced by e^{-u_i}. Distributional assumptions are imposed on u_i. For these assumptions to be consistent with the fact that $\mathrm{TE}_i \in (0,1]$ the assumed density of u_i has to have support only on the interval $[0,\infty)$. By using this transformation, taking the natural logarithm of both sides of (2.1) and rearranging one obtains:

$$\log y_i = \log f\left(\mathbf{x}_i;\boldsymbol{\beta}\right) - u_i \tag{2.2}$$

This is the deterministic stochastic frontier with u_i being the one-sided error term. A second, two-sided error term is added to capture random noise:

$$\log y_i = \log f\left(\mathbf{x}_i;\boldsymbol{\beta}\right) + v_i - u_i \tag{2.3}$$

In order for the parameters of the stochastic frontier model to be estimated the following assumptions are necessary:

- a specification of the functional form of the production function,
- a specification of the distribution of the v_is, along with the assumption that they are independently and identically distributed,
- a specification of the distribution of the u_is that has support on the set of positive real numbers, along with the assumption that they are independently and identically distributed.

Given that v_i and u_i are independent, the distribution of their convolution ($\varepsilon_i = v_i - u_i$) can be obtained, although not always in closed form. Then the parameters of the production function along with any parameters in the distributions of two error terms can be estimated by maximum likelihood.

Typically, v_i is assumed to have a normal density with mean zero, since its role in the model is to represent random noise. The distributional assumption on u_i is more arbitrary. In the literature, u_i has been assumed to have a half-normal (Aigner et al. 1977), truncated normal (Stevenson 1980), exponential or Gamma distribution (Greene

1990). More elaborate distributions have also been assumed but they will be discussed in section 2.6.

In this formulation of the problem, the technical efficiency of firm i is a random variable and, therefore, has a distribution. Different point estimates of this technical efficiency can be derived. One can obtain information about TE_i from the expectation of $u_i|\hat{\varepsilon}_i$ (Jondrow et al. 1982) or its mode. An advantage of using the mode instead of the expectation is the ease with which the point estimate of TE_i can be obtained from the mode estimate of u_i, given the monotonic relationship between the two quantities. Battese and Coelli (1988) proposed directly using the expectation of $e^{-u_i}|\hat{\varepsilon}_i$ to get a point estimate of technical efficiency.

The Multiple-Outputs Case

Consider a technology where N inputs are used to produce M outputs. In this case distance functions are used to measure efficiency. Färe and Grosskopf (1990) appear to be the first to propose efficiency measurement in a parametric way using distance functions. The output oriented measure of technical efficiency is given by the output distance function itself. As in the single-output case, the technical efficiency of firm i is treated as a random variable and replaced by e^{-u_i}. The analog to (2.3) is:

$$\log D_O\left(\mathbf{x}_i, \mathbf{y}_i; \boldsymbol{\beta}\right) = v_i - u_i \tag{2.4}$$

The linear homogeneity of the output distance function is used to put (2.4) in an estimable form:

$$\log y_i^m = -\log D_O\left(\mathbf{x}_i, \frac{\mathbf{y}_i}{y_i^m}; \boldsymbol{\beta}\right) + v_i - u_i \tag{2.5}$$

where y_i^m is the m-th output, chosen to be the normalizing output. Any output or any function of the M outputs, can be used for the normalization. The choice of a single output is made usually on the basis of reducing the endogeneity problem that is present due to the fact that the same quantity appears on both sides of the equation to be estimated

The analysis from now on is very similar to the single-output case. An input oriented measure of efficiency can be generated by estimating an input distance function instead and using the linear homogeneity in inputs for deriving an estimable form.

2.4.2 Cost Efficiency

When the objective is the estimation of cost efficiency, the econometric analysis does not change much. Suppose again that a dataset of I firms is available. The cost efficiency of firm i is defined as:

$$\mathrm{CE}_i = \frac{c\left(\mathbf{y}_i, \mathbf{w}_i; \boldsymbol{\beta}\right)}{\mathbf{w}_i' \mathbf{x}_i} \tag{2.6}$$

Using the same transformations as in the case of technical efficiency one obtains an equation in estimable form:

$$\log \mathbf{w}_i' \mathbf{x}_i = \log c\left(\mathbf{y}_i, \mathbf{w}_i; \boldsymbol{\beta}\right) + v_i + u_i \tag{2.7}$$

The only difference in terms of econometrics between (2.3) and (2.7) is the sign on the inefficiency component of the error term. All the analysis of the previous subsection applies here as well.

The challenge in the case of estimating cost inefficiency is its decomposition into technical and allocative inefficiency. Duality theory has been traditionally employed to achieve this task. Christensen and Greene (1976) are the first to formulate and estimate a system composed of the cost function and the cost-share equations:

$$\log \mathbf{w}_i' \mathbf{x}_i = \log c\left(\mathbf{y}_i, \mathbf{w}_i; \boldsymbol{\beta}\right) + v_i + u_i \tag{2.8a}$$

$$\frac{w_i^j x_i^j}{\mathbf{w}_i' \mathbf{x}_i} = \frac{\partial \log c\left(\mathbf{y}_i, \mathbf{w}_i; \boldsymbol{\beta}\right)}{\partial \log w_i^j} + \eta_i^j \quad , \quad j = 1, 2, \ldots, N-1 \tag{2.8b}$$

The $N-1$ cost-share equations follow from Shephard's lemma. One share equation is excluded from the system because it is redundant, since the cost-shares add to unity.

In their original application Christensen and Greene did not consider inefficiency, and thus did not include u_i in the specification. The other error terms, v_i and η_i^j, were assumed to capture random noise. The seemingly unrelated regressions technique was used for the estimation of the parameters to account for possible correlation between the error terms in each equation.

When u_i is included in the specification maximum likelihood has to be employed to estimate the parameters of the model. But this is not a trivial task. For the likelihood function to be tractable, in general u_i will have to be assumed to be distributed independently of the η_i^js. As Greene (1980) noted, this can only happen if the η_i^js represent pure random noise, not allocative inefficiency. This is because the inefficiency component of the error term u_i, will consist partly of the η_i^js. Except in the case of a Cobb-Douglas specification of the cost function (Schmidt and Lovell 1979), the way in which u_i depends on the η_i^js is very complicated. Kumbhakar (1997) derived these expressions for the translog case analytically, but another inconsistency with the stochastic frontier approached appeared: if allocative inefficiency is firm-specific and if u_i in (2.8a) consists partly of this inefficiency, then it cannot be assumed that u_i has a distribution with common mean and variance across firms. Nevertheless, the exact relationship between the η_i^js and u_i as derived by Kumbhakar was implemented consistently byKumbhakar and Tsionas (2005) in a Bayesian framework and by using panel data.

As a response to the correlation between the cost inefficiency and allocative inefficiency error terms Schmidt (1984) proposed an *ad hoc* decomposition of u_i into two parts: 1) u_{T_i} that captures pure technical inefficiency and which is independent of the η_i^js, and 2) u_{A_i} that captures pure allocative inefficiency and is deterministically defined by the η_i^js. This procedure has the advantage of decomposing cost efficiency multiplicatively into technical and allocative efficiency (after the cost frontier is exponentiated) as the definition of cost efficiency requires. The main disadvantage is that the decomposition remains an approximation to the exact decomposition provided by Kumbhakar (1997). Additionally, both decompositions, exact and approximate, assume no noise in the cost-share equations.

The method proposed by Schmidt (1984) was extended by Ferrier and Lovell (1990) to allow for random noise along with allocative inefficiency effects in the cost-share equations. This generalization, however, comes at the cost of restricting the allocative inefficiency component of the error term to be equal across firms, at least in the case where only cross-sectional data are available.

A somewhat different approach was proposed by Rodrigez-Álvarez et al. (2004). In their formulation of the problem, an input distance function is specified and the duality with respect to it is exploited to estimate allocative inefficiency. In this model, the inefficiency component of the error term in the distance function measures only technical efficiency and thus it can be assumed independent of the allocative inefficiency terms in the cost-share equations. However, cost efficiency is not decomposed to its ingredients in a way consistent with its definition (definition 2.9).

2.5 The Shadow-Cost Approach

Another parametric approach for allocative efficiency measurement that is based on optimality conditions was first proposed by Lau and Yotopoulos (1971) under a profit maximization assumption. Toda (1976) applied the same ideas to the case where firms are assumed to be minimizing cost. This method does not have direct connections to the stochastic frontier literature and is in general easier to implement from an econometric point of view. In its original form it relaxed the distributional assumptions necessary for the stochastic frontier models, at the cost of a technical efficiency assumption.

In loose terms the method involves specifying a cost frontier and deriving the first order conditions for cost minimization. These first order conditions imply firm-specific shadow price ratios for the inputs. The discrepancy between the shadow and the observed (market) price ratios is used as a measure of allocative inefficiency. More specifically, the allocative efficiency coefficient for inputs k and ℓ is defined as a scalar $\theta_{k\ell}$ such that the following relationship holds:

$$\frac{\omega_k}{\omega_\ell} = \theta_{k\ell} \frac{w_k}{w_\ell} \tag{2.9}$$

where ω_ℓ is the shadow price of input ℓ and w_ℓ is its market price. The left-hand side of the previous expression can be calculated using a production or an input distance function by noting that at a technically efficient point $\mathbf{x}^*$ the first order conditions for optimization imply:

$$\frac{\partial D_I\left(\mathbf{y},\mathbf{x}^*\right)/\partial x_k}{\partial D_I\left(\mathbf{y},\mathbf{x}^*\right)/\partial x_\ell} = \frac{\omega_k}{\omega_\ell} \tag{2.10}$$

The shadow-cost method is designed to measure primarily allocative efficiency and as such, works with cost or profit functions. Therefore, duality theory could become a useful tool in terms of providing additional information about efficiency scores as well as increasing the degrees of freedom in empirical applications. Atkinson and Halvorsen (1980) are the first to make heavy use of duality theory by deriving the factor demand functions from a cost function and estimating all equations in a system. In this approach the allocative efficiency coefficients appear as parameters to be estimated. These parameters can be interpreted as coefficients on the variables of a function that relates the actual to the shadow prices of inputs. Stefanou and Saxena (1988) extend the method by adding explanatory variables on the levels of efficiency, other than just a constant term.

When only cross sectional data are available, the dual shadow-cost approach provides very limited information compared to the stochastic frontier models. With the availability of panel data, Atkinson and Cornwell (1994) re-introduced technical inefficiency and showed how firm- and input-specific allocative inefficiency can be estimated.

2.6 Incorporating Environmental Variables

The efficiency measurement literature reached a point where more interesting questions about efficiency could be asked. Apart from measuring efficiency and ordering the firms according to their efficiency scores, there is particular interest in identifying the driving forces of inefficiency, either technical, cost or allocative.

The first two studies that addressed this issue were conducted by Kalirajan (1981) and Pitt and Lee (1981). Both studies used a two-step procedure to examine the effect on efficiency of variables that are outside the control of the firm. Estimates of the firm-specific efficiency scores are obtained in the first step and these scores are then regressed on a set of environmental variables. Byrnes et al. (1988) present a similar model where the efficiency scores are obtained using DEA.

Many empirical applications followed that investigated the role of environmental variables on efficiency using these two-step models. However, this modeling approach posed consistency problems for both the parametric and non-parametric branches of efficiency measurement. Considering the stochastic frontier approach, one of the assumptions on the distribution of the inefficiency component of the error term is that it is identically distributed. This assumption is used in the first step to calculate the efficiency scores. In the second step the efficiency scores are assumed to depend on exogenous variables, and thus not being identically distributed. In the non-parametric setting, the efficiency scores are deterministically generated instead of being estimated and, therefore, they permit no stochastic component. In the second stage, however, a data generating process is implicitly assumed by regressing the scores on the exogenous variables.[2]

Stefanou and Saxena (1988) and Deprins and Simar (1989) developed models that were entirely built around the purpose of measuring the effect of the environmental variables. The first study measured allocative efficiency within the shadow-cost framework, while the second used a deterministic frontier. In the stochastic frontier literature, Battese and Coelli (1995), building on the work of Kumbhakar et al. (1991) and Reifschneider and Stevenson (1991), developed a technique for measuring efficiency and its dependence on exogenous variables in one step, by relaxing the assumption of an identically distributed inefficiency error term. More specifically, they assumed that the distribution of the inefficiency component of the error term follows a normal distribution which is truncated from below at zero and which mean is given by $\boldsymbol{\gamma}'\mathbf{z}_i$. In the last expression $\mathbf{z}_i$ is a vector of environmental variables for the firm and $\boldsymbol{\gamma}$ is a vector

[2] Although the term regression is used here, only a few studies used least squares to estimate the marginal effects of exogenous variables on efficiency scores. Usually maximum likelihood is employed to estimate truncated regressions due to the fact that the estimated efficiency scores are restricted to be either in the interval $(0, 1]$ or $[1, \infty)$.

of parameters to be estimated. Other specifications have been proposed since, but all move along the lines of assuming a distribution for u_i conditional on the the exogenous variables.

It is not surprising that the problem of incorporating environmental variables in efficiency measurement models was first solved within the parametric framework. This is because stochastic models can better accommodate the problem, which is stochastic in nature. However, Simar and Wilson (2007) showed that the role of environmental variables can be properly addressed in non-parametric models as well. In their approach a data generating process is assumed to have generated all inputs, outputs and environmental variables. Then bootstrapping is used to estimate the efficiency scores for each firm and the marginal effects of the environmental variables on these scores.

2.7 Dynamic Efficiency Measurement

The efficiency measurement literature was initially developed under a static theory of the firm. When empirical applications utilizing panel data started appearing, the weakness of this approach became apparent. With multiple observations per firm at hand, the researcher has to decide what is the true nature of efficiency. One approach is to use fixed- or random-effects techniques to measure firm-specific efficiency, which is modeled as being constant along time (see Schmidt and Sickles (1984) for an application). That is, it is assumed that the producer retains the same degree of inefficiency throughout the period for which data are available, without the possibility of improving or even becoming worse. In such a model the one-sided error term that represents inefficiency is absorbed by the firm constant term and firm-specific efficiency is measured in a way similar to the Corrected Least Squares models. Models with time-invariant inefficiency have been estimated with maximum likelihood as well (Pitt and Lee 1981), but this approach is subject to the incidental parameters problem when the time dimension of the panel is short.

On the other extreme one can completely ignore the panel nature of the data and assume that the firm realizes a new draw from the distribution of u in every period. Such models never became popular because, although the firm was modeled within a static framework, it was realized that inefficiency is likely to follow a more complicated, dynamic process. Kumbhakar (1990), Cornwell et al. (1990), Battese and Coelli (1992) and Lee and Schmidt (1993) developed and estimated models were the inefficiency component of the error term explicitly depends on time. All four models are very similar in their approach, with the primary difference being the specification of the distribution of u conditional on time. The restriction that these models impose is that efficiency evolves through time in the same way for every firm. In this way, only inferences about the evolution of the industry on average can be made. They are not dynamic at the firm level in the sense that they completely disregard the dynamic nature of the decision-making process.

The next two paragraphs review truly dynamic models for efficiency measurement. The reduced-form models do not define explicitly a mathematical representation of dynamic behavior of the firm, but the implications of such an underlying model can be incorporated into static models of efficiency measurement. The econometric estimation, however, is far from trivial. The structural models on the other hand make explicit the dynamic structure of the firm's problem. The objective of the firm is optimization of some quantity in time under dynamic constraints (equation of motion). Direct estimation of the structural models is not possible in most cases, either due to data availability or because of computational restrictions. Therefore, most estimation techniques rely on dynamic duality theory.

2.7.1 Reduced-Form Dynamic Models

Static techniques for efficiency measurement, if appropriately extended, can be used to evaluate the performance of firms that operate in a dynamic setting. To start with, consider a dynamic model of firm behavior. The objective of the manager is to maximize the discounted flow of utility from profits over time. Under risk neutrality this objective can be replaced by maximization of net cash flows. The optimization is done under technological restrictions and the adjustment of fixed inputs is subject to an equation of motion, involving the depreciation rates and gross investment in new fixed inputs. The level of fixed inputs is under the control of the firm but the adjustment is costly. Now consider a firm that at some point in time is inefficient, either because of bad management in previous periods or because of random conditions. If the cost of reorganization so that the firm becomes efficient in the next period is high, then the optimal policy might be to remain inefficient in the short-run. For data observed in reality this would imply that inefficiency is likely to persist along time.

Using this argument, Ahn et al. (2000) develop a model where the inefficiency component of the error term is autocorrelated. Their theoretical model consists of a production frontier:

$$y_{it} = x_{it}'\boldsymbol{\beta} + \beta_0 + \gamma \cdot t + v_{it} - u_{it} \tag{2.11}$$

and an AR(1) process for u_i:

$$u_{it} = \left(1 - \rho_i\right) \cdot u_{i,t-1} + \xi_{it} \quad , \quad \mathrm{E}\left(\xi_{it}\right) \geq 0 \tag{2.12}$$

In this formulation ρ_i represents firm i's ability to adjust its inefficiency level from last period. In practice, however, in a dataset with many firms, the number of parameters to be estimated would be very large. The authors restrict ρ to be the same across all firms in the dataset and provide specification tests for such a restriction. Due to the dynamic nature of the model the Generalized Method of Moments (GMM) is employed for the estimation, with a very large number of instruments in some models. With this specification the authors derive the expected long-run efficiency levels for each firm in their dataset.

Although the estimation within the GMM framework avoids many distributional assumptions, a criticism of the model could be that it does not restrict u_{it} to be non-negative, except only in expectation. Another criticism is that it does not allow for environmental variables to play a role in the determination of the efficiency levels.

A related model was developed by Tsionas (2006). Based on a similar argument about adjustment costs, his specification includes a typical production frontier and an AR(1) process for the logarithm of u:

$$\log u_{it} = \mathbf{z}_{it}'\boldsymbol{\gamma} + \rho \log u_{i,t-1} + \xi_{it} \quad , \quad \xi_{it} \sim \mathrm{N}\left(0, \sigma_w^2\right) \tag{2.13}$$

Here $\mathbf{z}_{it}$ is a vector of environmental variables. Maximum likelihood estimation of this model is particularly complicated due to the fact that the composed error term is no longer independently distributed along time. Tsionas uses Bayesian inference instead and he is able to estimate firm- and time-specific efficiency scores.

A somewhat different approach is taken by Löthgren (1998). Although not based on an underlying dynamic model, he assumes that the inefficiency component of the error term depends on the entire past disturbance term, both inefficiency and random noise components. With his formulation maximum likelihood estimation appears to be simpler, but all the difficulties associated with the estimation of Generalized Autoregressive Conditional Heteroskedasticity models are most likely to be magnified, given the more complicated form of the likelihood function.

Choi et al. (2006) carry the argument of adjustment costs further. They argue that the transition from an inefficient towards an efficient input bundle is associated with increasing and convex transition costs. In their model there is no distinction between variable and quasi-fixed inputs, but the existence of transition costs associated with each input becomes a testable hypothesis. The proposed method is based on the shadow-cost rather than the stochastic frontier approach. The objective of the firm is specified as the minimization of discounted cost for the period for which data are available:

$$\begin{aligned} V = \quad & \min_{x(t)} \left\{ \int_0^T e^{-\rho t} \left[\mathbf{w}^T \mathbf{x}_t^b \left(\mathbf{w}^*, y_t, \eta \right) + \Psi \left(\Delta \mathbf{x} \right) \right] \mathrm{d}t \right\} \\ \text{s.t.} \quad & \dot{\mathbf{x}} = -\Delta \mathbf{x} \\ & \mathbf{x}_0 \ \text{ given} \end{aligned} \tag{2.14}$$

where $\mathbf{x}_t^b \left(\mathbf{w}^*, y_t, \eta \right)$ are the input demand functions derived from a static shadow-cost minimization problem and $\Psi \left(\Delta \mathbf{x} \right)$ is the transition cost function. After the behavioral input demand quantities are estimated, they are replaced into the optimality conditions of (2.14) to recover the parameters of $\Psi \left(\Delta \mathbf{x} \right)$.

2.7.2 Structural Dynamic Models

The models reviewed above can provide evidence for the dynamic nature of the decision-making process at the firm level. But they provide little guidance on how efficiency should be defined and measured in a dynamic setting. Explicit structural models of firm behavior are indispensable in that respect.

In greatest generality, the intertemporal problem of the firm has the following structure:

$$\begin{aligned} J = & \max_{\mathbf{I}(t),\mathbf{x}(t)} \mathrm{E}_t \left\{ \int_0^\infty e^{-\rho t} g\left(\mathbf{y},\mathbf{x},\mathbf{k},\mathbf{I}\right)\, \mathrm{d}t \right\} \\ \text{s.t.} \quad & \dot{\mathbf{k}} = \mathbf{I} - \boldsymbol{\delta}\mathbf{k} \\ & (\mathbf{x},\mathbf{I}) \in \mathtt{L}\left(\mathbf{y};\mathbf{k}\right) \\ & \mathbf{k}_0 \ \text{ given} \end{aligned} \tag{2.15}$$

In this formulation, the objective of the firm is to maximize over time the expected discounted flow of an instantaneous reward function g. This reward function could be simply the instantaneous profit (under risk neutrality) or the negative of production cost. In any case, the objective should incorporate information about prices of inputs and outputs and in general, an expectation-formation mechanism for these prices that uses information available at time t. The set of inputs is divided into two subsets, variable ($\mathbf{x}$) and quasi-fixed ($\mathbf{k}$) inputs. The choice variables are the levels of variable inputs to be employed and the level of investment in quasi-fixed inputs ($\mathbf{I}$).

The equation of motion describes the evolution of capital through time. It depends on the constant rate of depreciation of existing quasi-fixed inputs and the gross investment in new capital. The second restriction is a representation of the technology in terms of an input requirements set. This is a modification of the input requirements set of Definition 2.1 to account for adjustment costs. Given the level of quasi-fixed inputs, this set describes the vectors of outputs that can be produced from a given vector of variable inputs and gross investment. In a parametric approach the representation of the technology could be given in terms of a production function $F\left(\mathbf{y},\mathbf{x},\mathbf{k},\mathbf{I}\right) = 0$. The properties of this production function are stated in many places in the literature (see for example Epstein (1981)).

The production function formulation of the adjustment cost theory of investment was introduced by Eisner and Strotz (1963). Lucas (1967), Gould (1968) and Treadway (1969, 1970) are early contributors to the adjustment cost literature. All these studies assume profit maximization behavior and work at a theoretical level. The possibility of inefficiency at the firm level is not considered. The objective of this line of literature is not only to generate estimates of the parmeters of a production function augmented to allow for adjustment costs, but primarily to provide a framework for studying the response of firms to exogenous conditions, mainly prices changes. Although these papers predate Lucas' seminal paper (1976), the goal is to estimate the "deep" parameters of the model so that the projections of firm behavior are not subject to the Lucas critique.

Econometric estimation of such dynamic models is difficult since the optimal control problem rarely has a closed-form solution. In response to this problem, two distinct approaches were developed, both avoiding explicitly solving the problem. The first is based on dynamic duality theory, first discussed by McLaren and Cooper (1980) and Epstein (1981). McLaren and Cooper derive the demand functions for variable inputs and investment from the value function, J. Epstein establishes duality between the value and the production functions. He then proceeds by deriving the curvature conditions for the supply function and the demand functions for variable inputs and investment. But duality in a dynamic model becomes particularly complicated. Flexible functional forms require the estimation of a very large number of parameters. Therefore, Epstein restricts attention to less flexible functional forms, with the first empirical application provided by Epstein and Denny (1983).

A maintained assumption in most dynamic models is that the firm's manager forms static expectations about future prices. That is, the manager assumes the current prices to persist indefinitely. An extension to non-static expectations in the dynamic duality framework was provided by Luh and Stefanou (1996). The generalization of the expectations mechanism comes at the cost of an even larger number of parameters to be estimated. Pietola and Myers (2000) extend the model by removing some of the linearity assumptions made by Luh and Stefanou.

Lasserre and Ouellette (1999) derive the factor demand functions from a dynamic cost minimization problem with an unspecified expectation-formation mechanism. Again the number of parameters to be estimated is large, but imposition of cross-equation restrictions that are implied by theory can increase the degrees of freedom. From the parameter estimates of the demand system the authors are able to recover returns to scale and technical change parameters. Ouellette and Vigeant (2001) extended this method by allowing for additional restrictions on the firm's action set to be incorporated in the optimization problem. Two applications followed by the same authors (Ouellette and Vigeant 2003; Ouellette et al. 2005).

The analysis in all the studies reviewed above is done under the assumption of perfectly efficient producers. Rungsuriyawiboon and Stefanou (2007) conducted the only study to date where efficiency is modeled and estimated in the duality framework. They develop a dynamic shadow-cost approach for efficiency measurement after deriving approximations to the variable inputs and investment demand functions under static expectations.

The second procedure for parametric estimation of the model in (2.15) is originally developed by Hansen and Sargent (1980). In their approach the problem is reformulated in discrete time. The objective and adjustment cost functions are specified as quadratic, and uncertainty enters the model in terms of autoregressive production and price shocks. Given their specification the authors explicitly solve the Euler equations and derive the factor demands. Then maximum likelihood is employed for the estimation of the model parameters.

The framework developed by Hansen and Sargent has proven very inflexible in the sense that minor modifications in the specification lead to difficulties in obtaining a closed-form solution. Pindyck and Rotemberg (1983a,b) use a more flexible specification that does not admit a closed-form solution. Instead of estimating the implied decision rule, they work directly with the Euler equations, i.e. the first order conditions for optimization. Although this approach has been used and extended in numerous studies (see for example Chavas (1994) and Gardebroek and Oude Lansink (2004)), none of them explicitly modeled inefficiency.

To date, the issue of dynamic efficiency measurement has been more successfully addressed in a non-parametric setting. This is because the non-parametric methods do not require explicitly solving the firm's optimization problem. As it is the case in the static framework, a statement about the objective of the firm is enough to form the piecewise linear efficient frontier.

Using this flexibility of non-parametric methods, Nemoto and Goto (1999, 2003) state as the objective of the firm the minimization of the discounted total cost of producing an observed stream of outputs during the period for which data are available. The adjustment costs are incorporated in their model by treating the observed capital stock at time t as output for period t and as input for period $t+1$. Therefore, they construct an input requirements set similar to the one in (2.15), with k_{t-1} replacing investment.

By restricting attention to the period for which the firm is observed they avoid one of the main restrictions inherent to dynamic efficiency measurement from a primal point of view: data availability. Specifically, they contract the time span of the objective and manage to measure the efficiency of the firms against a frontier that requires only finite amount of data. This approach, however, has a shortcoming. The optimization problem is interrupted abruptly in the last period for which data are available. Nothing is assumed for the objective of the firm beyond T, but at the same time nothing can be said about whether the firm is following a long-run efficient plan. The transversality conditions are important for answering this question. The authors explicitly say that:

> "...the terminal values follow the natural boundary condition; that is, T is fixed but k_T is free".

But if a firm continues to operate after T then capital will have a positive shadow value. Furthermore, this shadow value will be different for each firm. The approach examines whether a firm has been technically and economically efficient when moving from k_0 to k_T, but whether this terminal level of capital is optimal with respect to the long-run objective cannot be determined.

A different approach is taken by Silva and Stefanou (2003, 2007). Using a revealed preference formulation they recover information about the production process from an intertemporal cost minimization problem. This approach explicitly considers the adjustment path of the firm with an infinite time horizon in view. The efficiency measures that they propose, however, are temporal, in the sense that they measure the efficiency of a firm at specific locations on the adjustment path.

This temporal nature of efficiency seems to be the appropriate way to measure efficiency in dynamic models. Stefanou (2009) views temporal efficiency as a flow notion of dynamic efficiency. He argues that firms operate in the short-run but with a view to the long-run. Therefore, efficiency should be measured at the level where the decisions are made, taken into account the information available at the time these decisions are made. Furthermore, if dynamic efficiency is based on the comparison between optimal and observed paths of adjustment as a stock notion, then this would hide a lot of information about why firms are inefficient. This is because with a stock measure of efficiency it is hard to distinguish whether a production unit is inefficient because of suboptimal decisions at a specific point in time (which would change the entire adjustment path) or because of consistently making suboptimal decisions.

2.8 The Place of this Study in the Literature

This study aims at contributing to the literature on dynamic efficiency measurement via parametric methods. At the reduced-form branch of this literature, a stochastic frontier model similar to the one proposed by Tsionas (2006) is specified and the feasibility of estimation and inference within the framework of classical statistics is demonstrated. The persistence of inefficiency along time, which is implied by the existence of adjustment costs, becomes a testable hypothesis.

At the structural branch of the dynamic efficiency measurement literature, this study develops a model which accounts for inefficiency and at the same time takes into consideration the intertemporal nature of the decision-making process. The proposed model provides extensions of existing models either by incorporating inefficiency in dynamic models of firm behavior, or by relaxing the static expectations assumption made in previous studies. Efficiency is defined at the level the decisions are made, i.e. in the short-run and, therefore, it is treated as a flow notion.

The point of departure for the models proposed here is the existing static models for efficiency measurement. These models are appropriately extended to accommodate the additional implications or restrictions that are imposed on the data when moving from a static to a dynamic view of the firm's problem.

Chapter 3

A Reduced-Form Model for Dynamic Efficiency Measurement

3.1 Introduction

Both irreversibilities of investment decisions and fixed adjustment costs imply that investment will take place in irregular intervals. Factors that affect the efficiency score of a firm may not be adjusted frequently, even if they are under the control of the firm, if the adjustment costs are high. In a dynamic setting, the optimal decision rule for the firm could prescribe an action that would force it to remain inefficient in the short-run. This in turn implies that inefficiency would persist from one period to the next.

This fact has been recognized in the stochastic frontier literature. Early attempts to take into account the time-dependence of inefficiency include Kumbhakar (1990), Cornwell et al. (1990) and Lee and Schmidt (1993). In general, the issue has been largely ignored. However, Alvarez et al. (2006) note that most of the parameters of a stochastic frontier model remain consistent even if the correlation between the efficiency scores among periods is ignored. But neither the firm-specific efficiency scores nor a measure of the degree of persistence of inefficiency can be consistently estimated from these misspecified models. More recently Ahn et al. (2000) and Tsionas (2006) specify inefficiency in a "true" autoregressive form. The primary focus of these two studies is the estimation of the autocorrelation parameter(s). Both studies find very strong autocorrelation, or persistence, in the efficiency scores.

In this chapter the stochastic frontier model is put in a state-space form. This formulation opens an array of possibilities for estimating the parameters of the model, as well as the hidden state, i.e. the efficiency scores for every firm. The model specification builds on the one Tsionas (2006) uses, with the main differences concentrating on distributional assumptions and estimation methods.

3.2 State-Space Formulation of the Problem

Consider the following stochastic frontier model[1]:

$$y_{it} = \mathbf{x}'_{it}\boldsymbol{\beta} + v_{it} + \log\left(\mathrm{TE}_{it}\right) \qquad , \quad v_{it} \sim \mathrm{N}\left(0, \sigma_v^2\right) \tag{3.1}$$

In the equation above, v_{it} is the typical error term, assumed to be homoskedastic and not correlated across either time or cross-section dimensions. $\log\left(\mathrm{TE}_{it}\right)$ is the natural logarithm of efficiency for firm i in period t, and will be treated as a random variable, as in a typical stochastic frontier model. By definition, $\mathrm{TE}_{it} \in (0, 1]$ and in order to put it in a familiar autoregressive form we need to functionally transform the variable that represents efficiency. We define $s_{it} = \log\left(\frac{1-\mathrm{TE}_{it}}{\mathrm{TE}_{it}}\right)$, and assume the following autoregressive process in s_{it}:

$$s_{it} = \delta + \rho s_{i,t-1} + w_{it} \quad , \qquad w_{it} \sim \mathrm{N}\left(0, \sigma_w^2\right) \tag{3.2}$$

$$s_{i1} = \mu_1 + w_{i1} \qquad , \qquad w_{i1} \sim \mathrm{N}\left(0, \sigma_{w1}^2\right) \tag{3.3}$$

The quantity inside the logarithm in the definition of s_{it} is the ratio of inefficiency to efficiency. This quantity is non-negative and its logarithm can assume any value in $\mathbb{R}$. Using this transformation we can allow for a normally distributed error term in (3.2) and, therefore, have a typical autoregressive model. At the same time, technical efficiency remains restricted in the unit interval, and δ and ρ are parameters to be estimated. In this specification, ρ is the elasticity measuring the percentage change in the inefficiency to efficiency ratio that is transferred from one period to the next.

[1] For simplicity a production frontier is considered in this section. In revenue and profit frontiers the skewness of the error term is the same as in production frontiers. Therefore, the estimation technique for such frontiers remains unchanged and only the dependent and independent variables are different. The extension to cost frontiers involves only minor sign changes.

Equation (3.3) initializes the stochastic process. If one is willing to assume that the process is stationary, then the two additional parameters, μ_1 and σ^2_{w1} are determined by ρ, δ and σ^2_w by the following relations:

$$\mu_1 = \frac{\delta}{1-\rho} \tag{3.4}$$

$$\sigma^2_{w1} = \frac{\sigma^2_w}{1-\rho^2} \tag{3.5}$$

However, stationarity maybe a restrictive assumption. If the observed data cover a period of adjustment the stochastic process will be non-stationary as the firms represented by the sample become less or more efficient. In such a case ρ will be greater than unity and the variance in the initial period will be undefined. In general, allowing for the two additional parameters in (3.3) leads to a more robust model, in which the assumption of stationarity can be tested rather than imposed.

There exists a large and growing literature on unit-root and stationarity tests in panel data settings. A variety of tests have been derived under different assumptions on the asymptotics. For a typical micro-panel, a likelihood ratio test for the ability of the data to support (3.4)-(3.5) can be used. Such a test is valid for $N \to \infty$ with fixed T (Hsiao 1986, p. 90). A likelihood ratio test requires the estimation of the model both with and without imposing stationarity.

In terms of estimation, TE_{it} is not observed. In a state-space model equation (3.2) represents the hidden *state equation*. Equation (3.1) is the corresponding *measurement equation* for the model. The task is to estimate the parameters in equations (3.1)-(3.3) along with the technical efficiency scores, given only the observed data in equation (3.1).

Prior to estimation, some additional independence assumptions are imposed on the two processes:

- The density of y_{it} depends only on $\mathbf{x}_{it}$ once we condition on s_{it}:

$$\mathrm{p}\left(y_{it}|\mathbf{x}_{i,1:T}, y_{i,1:t-1}, s_{i,1:t}\right) = \mathrm{p}\left(y_{it}|\mathbf{x}_{it}, s_{it}\right) \tag{3.6}$$

- There is no feedback from the y_{it} process to the s_{it} process. That is, once we condition on $s_{i,t-1}$ we obtain:

$$f\left(s_{it}|\mathbf{x}_{i,1:T}, y_{i,1:T}, s_{i,1:t-1}\right) = f\left(s_{it}|s_{i,t-1}\right) \tag{3.7}$$

where:

$$\ell_{1:\tau} \equiv \left\{\ell_1, \ell_2, \ldots, \ell_\tau\right\} \tag{3.8}$$

3.3 Estimation Techniques

Once the model is placed in a state-space form, Kalman filtering techniques (Kalman 1960) can be applied to jointly estimate the hidden states and the parameters. These filtering techniques are very flexible, allowing for firm-specific intercepts and time-varying parameters. For a panel of N firms, each observed for T periods, in every time period there is one observation per firm to estimate one hidden parameter (s_{it}). But restrictions can be imposed on the model so that all or a subset of the structural parameters (slope coefficients and constant terms) are equal among the firms.

The original Kalman filtering assumptions, however, are very restrictive. First, the error terms in both measurement and state equations have to be normally distributed. Additionally, the state variable has to be linearly incorporated in the measurement equation. It is obvious that the model specified in (3.1)-(3.3) does not satisfy both assumptions simultaneously. If s is considered as the state variable, then it has to undergo a one-to-one but nonlinear transformation before added to the measurement equation. On the other hand, if TE is considered as the state variable then it does not follow a normal distribution. This problem can be dealt with by using a non-linear filtering technique. The extended or the unscented Kalman filters could be used for dual estimation (Wan et al. 2000). These techniques can estimate all the parameters of the model except for the variances of the two error terms.

These techniques represent the “computational view” or “engineering view” of the Kalman filter, where in every period the beliefs about the hidden state and the values of the parameters are updated based on data available for that period. In econometrics, however, the data are available once and the analysis is usually based on the information contained in the entire sample.

For this study the "statistical view" of Kalman filtering is used. This view is based on the probabilistic origins of the technique. As opposed to the "computational view" of Kalman filtering, here the likelihood function is specified using all observed data and the parameters are estimated using all the information contained in the dataset. The hidden state can then be estimated using the maximum likelihood estimates of the parameters.

To start, note that the likelihood can be based only on observed data, y_{it} and $\mathbf{x}_{it}$. Given the independence assumption in the cross-section dimension of the data, the likelihood can be written as:

$$\mathscr{L}(\boldsymbol{\theta}|\mathbf{y},\mathbf{X}) = \mathrm{p}(\mathbf{y}|\mathbf{X};\boldsymbol{\theta}) = \prod_{i=1}^{N} \mathrm{p}\left(y_{i,1:T}|\mathbf{x}_{i,1:T}\right) \tag{3.9}$$

where $\mathbf{y}$ and $\mathbf{X}$ are the stacked vectors of observed data over i and t, and $\boldsymbol{\theta}$ is the vector of parameters to be estimated. To simplify the notation the firm index is dropped and in the following we calculate the contribution to the likelihood of the i-th firm:

$$\mathrm{p}\left(y_{1:T}|\mathbf{x}_{1:T}\right) = \prod_{t=1}^{T} \mathrm{p}\left(y_t|\mathbf{x}_{1:T}, y_{1:t-1}\right) \tag{3.10}$$

where the last result is obtained by sequential conditioning.

In the last expression $\mathrm{p}\left(y_t|\mathbf{x}_{1:T}, y_{1:t-1}\right)$ is an unknown quantity that can be obtained by integrating-out s_t from $\mathrm{p}\left(y_t, s_t|\mathbf{x}_{1:T}, y_{1:t-1}\right)$:

$$\begin{aligned}\mathrm{p}\left(y_t|\mathbf{x}_{1:T}, y_{1:t-1}\right) &= \int \mathrm{p}\left(y_t, s_t|\mathbf{x}_{1:T}, y_{1:t-1}\right)\,\mathrm{d}s_t \\ &= \int \mathrm{p}\left(y_t|\mathbf{x}_t, s_t\right) f\left(s_t|\mathbf{x}_{1:T}, y_{1:t-1}\right)\,\mathrm{d}s_t\end{aligned} \tag{3.11}$$

Assumption (3.6) is used here to obtain the second equality. The last expression again contains an unknown quantity, but which can be calculated recursively:

$$\begin{aligned} f\left(s_{t+1}|\mathbf{x}_{1:T}, y_{1:t}\right) &= \int f\left(s_{t+1}, s_t|\mathbf{x}_{1:T}, y_{1:t}\right) \mathrm{d}s_t \\ &= \int f\left(s_{t+1}|s_t\right) f\left(s_t|\mathbf{x}_{1:T}, y_{1:t}\right) \mathrm{d}s_t \end{aligned} \tag{3.12}$$

Note that the assumption that the hidden-state stochastic process has the Markov property (assumption (3.7)) is used here. The unknown quantity in the last expression is $f\left(s_t|\mathbf{x}_{1:T}, y_{1:t}\right)$, which by Bayes' rule can be written as:

$$\begin{aligned} f\left(s_t|\mathbf{x}_{1:T}, y_{1:t}\right) &= \frac{\mathrm{p}\left(y_t|\mathbf{x}_{1:T}, y_{1:t-1}, s_t\right) f\left(s_t|\mathbf{x}_{1:T}, y_{1:t-1}\right)}{\mathrm{p}\left(y_t|\mathbf{x}_{1:T}, y_{1:t-1}\right)} \\ &= \frac{\mathrm{p}\left(y_t|\mathbf{x}_t, s_t\right) f\left(s_t|\mathbf{x}_{1:T}, y_{1:t-1}\right)}{\mathrm{p}\left(y_t|\mathbf{x}_{1:T}, y_{1:t-1}\right)} \end{aligned} \tag{3.13}$$

The last expression contains no unknown quantities:

- $\mathrm{p}\left(y_t|\mathbf{x}_t, s_t\right)$ is known by assumption (equation (3.1)).
- $f\left(s_t|\mathbf{x}_{1:T}, y_{1:t-1}\right)$ can be calculated recursively from (3.12) given that $f\left(s_1|\mathbf{x}_{1:T}\right)$ is known by assumption (equation (3.3)).
- $\mathrm{p}\left(y_t|\mathbf{x}_{1:T}, y_{1:t-1}\right)$ can be calculated from (3.11).

Equations (3.12) and (3.13) represent the "prediction" and "update" steps of the Kalman filter. In (3.12) the hidden state is "predicted" based on past information. In (3.13) the belief on the hidden state is "updated" using concurrent information.

When the model is linear and both error terms are normally distributed, then the expressions in (3.11)-(3.13) are all normal densities. This is because the family of normal densities is closed under conditioning and marginalization[2]. In general, the integrals have no closed-form expressions when the assumptions of linearity or normality

[2] Another family of densities that is closed under these operations is the family of skew-normal distributions. Naveau et al. (2005) provide closed-form formulas for a Kalman filter where the distributions of the errors are skewed. The applicability of their model to stochastic frontier analysis is worth exploring.

are not satisfied. The challenge is to approximate these integrals numerically. We now turn to this subject.

3.4 Sequential Importance Sampling and Sequential Gaussian Quadratures

In order to evaluate the contribution to the likelihood of firm i's data we need to evaluate the series of integrals in (3.11). This in turn requires the evaluation of the series of integrals in (3.12). In general, numerical methods will have to be employed. With a panel of N firms observed for T periods, $2 \times N \times T$ integrals have to be evaluated. This is within the capacity of modern computers even for very large datasets. However, evaluating the integrals numerically, requires closed-form expressions of the quantities to be integrated. But in state-space models these quantities are obtained sequentially and only numerical approximations of the previous step quantities are available.

Tanizaki and Mariano (1994) propose using sequential importance sampling (SIS) to evaluate the integrals by Monte Carlo methods. The method was extended in a series of papers by the same authors (Tanizaki and Mariano (1998) and Tanizaki (1999)). In the context of the model defined in (3.1)-(3.3), the method follows the steps:

1. Define an importance density $f_p\left(s_t\right)$ as close to $f\left(s_t|\mathbf{x}_{1:T}, y_{1:t-1}\right)$ as possible. The proposal density should be such that random draws can easily be obtained. In any case, the proposal density should have "heavier tails" than the density it is approximating, otherwise some issues of numerical stability are raised.[3]

2. Define:
$$\omega\left(s_t|y_{1:t-1}\right) = \frac{f\left(s_t|\mathbf{x}_{1:T}, y_{1:t-1}\right)}{f_p\left(s_t\right)} \tag{3.14}$$
as the weight function. Note that given (3.3), the weight function for the initial period can be calculated.

[3] If the importance density is close to zero at some point where $f\left(s_t|\mathbf{x}_{1:T}, y_{1:t-1}\right)$ is large, then the ratio of the two will tend to infinity, rendering the algorithm unpredictable.

3. Rewrite (3.11) as:

$$\mathrm{p}\left(y_t|\mathbf{x}_{1:T}, y_{1:t-1}\right) = \int \mathrm{p}\left(y_t|\mathbf{x}_t, s_t\right) \omega\left(s_t|y_{1:t-1}\right) f_p\left(s_t\right) \,\mathrm{d}s_t \tag{3.15}$$

and approximate the integral using Monte Carlo methods by sampling from $f_p\left(s_t\right)$:

$$\tilde{\mathrm{p}}\left(y_t|\mathbf{x}_{1:T}, y_{1:t-1}\right) \approx \sum_r \mathrm{p}\left(y_t|\mathbf{x}_t, s_t^r\right) \omega^r \tag{3.16}$$

were s_t^r are random draws from $f_p\left(s_t\right)$ and ω^r is the weight function evaluated at s_t^r.

4. Note that by combining (3.12) and (3.13) we obtain:

$$f\left(s_{t+1}|\mathbf{x}_{1:T}, y_{1:t}\right) = \int f\left(s_{t+1}|s_t\right) \frac{\mathrm{p}\left(y_t|\mathbf{x}_t, s_t\right) f\left(s_t|\mathbf{x}_{1:T}, y_{1:t-1}\right)}{\mathrm{p}\left(y_t|\mathbf{x}_{1:T}, y_{1:t-1}\right)} \,\mathrm{d}s_t \tag{3.17}$$

Division of both sides by $f_p\left(s_{t+1}\right)$ yields:

$$\omega\left(s_{t+1}|y_{1:t}\right) = \int \frac{f\left(s_{t+1}|s_t\right)}{f_p\left(s_{t+1}\right)} \frac{\mathrm{p}\left(y_t|\mathbf{x}_t, s_t\right) \omega\left(s_t|y_{1:t-1}\right)}{\mathrm{p}\left(y_t|\mathbf{x}_{1:T}, y_{1:t-1}\right)} f_p\left(s_t\right) \,\mathrm{d}s_t \tag{3.18}$$

The last integral can be approximated by Monte Carlo Methods, using the same draws as in step 3 and $\tilde{\mathrm{p}}\left(y_t|\mathbf{x}_{1:T}, y_{1:t-1}\right)$ in place of $\mathrm{p}\left(y_t|\mathbf{x}_{1:T}, y_{1:t-1}\right)$. This provides a recurrence for updating the weight function, evaluated at the fixed sample of draws:

$$\omega_{t+1}^q = \sum_r \frac{f\left(s_{t+1}^q|s_t^r\right)}{f_p\left(s_{t+1}^q\right)} \frac{\mathrm{p}\left(y_t|\mathbf{x}_t, s_t^r\right) \omega_t^r}{\tilde{\mathrm{p}}\left(y_t|\mathbf{x}_{1:T}, y_{1:t-1}\right)} \tag{3.19}$$

5. While $t < T$, increase t by one and repeat the last two steps.

After the completion of the algorithm the approximate quantities $\tilde{\mathrm{p}}\left(y_t|\mathbf{x}_{1:T}, y_{1:t-1}\right)$ can be used for the optimization of the likelihood function. Tanizaki and Mariano (1994, 1998) report Monte Carlo simulation results where different versions of the algorithm outlined above perform well in estimating the hidden state. However, when the objective is the estimation of the model's parameters, a numerical optimization algorithm will be used to maximize the likelihood function. In this case these calculations will have to be carried out multiple times, once for each evaluation of the likelihood function. The computational burden is substantial.

Instead of using importance sampling for the evaluation of the integrals, Heiss (2008) proposed using a Gaussian quadrature. The difference between SIS and Sequential Gaussian Quadrature (SGQ) is the original calculation of the weights. In SGQ the weights in the initial period are the SIS weights times the quadrature weights obtained by an appropriate rule (Hermite, Laguerre etc. quadratures). The abscissas produced by the quadrature replace the random draws of the SIS algorithm. Of course, when an optimal rule is used to obtain the abscissas for the integration, the integrals can be better approximated with much fewer nodes. This vastly reduces the computational cost. Heiss (2008) presents a comparison of SGQ and SIS (among other methods) for an estimation of a discrete choice model. The SGQ outperforms all methods by every criterion used.

Given the computational advantages of the SGQ over the SIS technique, quadrature methods are used for the application in the next section. Since the hidden state variable is normally distributed, the integrals that need to be calculated are approximated by a Gauss-Hermite quadrature.

With the parameter estimates in hand, the hidden state can be estimated using (3.13):

$$\mathrm{E}\left(s_t|y_{1:t},\mathbf{x}_{1:T}\right)=\int s_t f\left(s_t|y_{1:t},\mathbf{x}_{1:T}\right)\mathrm{d}s_t=\int s_t f_p\left(s_t\right)\frac{\mathrm{p}\left(y_t|\mathbf{x}_t,s_t\right)\omega_t}{\mathrm{p}\left(y_t|\mathbf{x}_{1:T},y_{1:t-1}\right)}\mathrm{d}s_t \tag{3.20}$$

However, interest lies on the estimation of technical efficiency directly rather than the state variable. Since technical efficiency is a one-to-one transformation of s, we can obtain the expected value of the efficiency score by:

$$\begin{aligned}\mathrm{E}\left(\mathrm{TE}_t|y_{1:t},\mathbf{x}_{1:T}\right)&=\int\frac{1}{1+e^{s_t}}f_p\left(s_t\right)\frac{\mathrm{p}\left(y_t|\mathbf{x}_t,s_t\right)\omega_t}{\mathrm{p}\left(y_t|\mathbf{x}_{1:T},y_{1:t-1}\right)}\mathrm{d}s_t\\&\approx\sum_r\frac{1}{1+e^{s^r_t}}f_p\left(s^r_t\right)\frac{\mathrm{p}\left(y_t|\mathbf{x}_t,s^r_t\right)\omega^r_t}{\tilde{\mathrm{p}}\left(y_t|\mathbf{x}_{1:T},y_{1:t-1}\right)}\end{aligned}\tag{3.21}$$

If one assumes stationarity of the hidden state process, then the expected long-run efficiency scores can be calculated using (3.4), and the dependence of the density of TE on the parameters δ and ρ. Given the normality assumption on s, the density of TE can be shown to be:

$$f(x) = \frac{\phi\left(\log\left(\frac{1-x}{x}\right), \mu, \sigma^2\right)}{x(1-x)} \tag{3.22}$$

where ϕ is the normal density function and μ and σ are given by (3.4) and (3.5) respectively.

3.5 Application

In this section the method described above is applied to a sample of dairy farms from Germany and the Netherlands. The next two paragraphs describe the empirical specification of the model and the data respectively. Next, the results are presented and interpreted. The main findings are summarized in the concluding section.

3.5.1 Empirical Specification

Dairy farms are rarely producing a single output. Usually farms combine beef and veal with cow's milk production. Furthermore, part of the forage used is produced within the farm, with the excess amount of forage crops sold on the market. Given the multi-output nature of production in dairy farming, the production technology is better represented by a distance function rather than a production function. An output distance function is used for this application. Parametrically, this distance function is specified as translog in inputs, outputs and time:

$$
\begin{aligned}
\log D_O(\mathbf{x}, \mathbf{y}, t) = \alpha_0 &+ \sum_k \alpha_k \log(x_k) + \sum_\ell \beta_\ell \log(y_\ell) \\
&+ \frac{1}{2} \sum_k \sum_j \alpha_{kj} \log(x_k) \log\left(x_j\right) \\
&+ \frac{1}{2} \sum_\ell \sum_h \beta_{\ell h} \log(y_\ell) \log(y_h) \\
&+ \frac{1}{2} \sum_k \sum_\ell \zeta_{k\ell} \log(x_k) \log(y_\ell) \\
&+ \eta_1 t + \eta_2 t^2 + \sum_k \lambda_k t \log(x_k) + \sum_\ell \xi_\ell t \log(y_\ell)
\end{aligned} \tag{3.23}
$$

The translog is a flexible functional form that can be viewed as second-order Taylor expansion in logarithms of any function of unknown form. Imposing no restrictions on the elasticities of substitution between inputs and outputs, this flexibility is almost a necessity, at least in the output dimensions of the distance function. This is because if one restricts the interaction terms of outputs with all other variables in (3.23) to be zero, then the output-possibilities frontier would also be resticted to be convex instead of concave. This would imply that there is no combination of outputs that can maximize profits.

Time is included in the specification to capture the effect of technological progress. The interaction terms of inputs and outputs with the time variable allow for this technological progress to be non-neutral.

In order to put the distance function in an estimable form, the linear homogeneity of the function in outputs is used, as described in Section 2.4.1. The econometric version of the distance function is:

$$
\log y_{it}^m = -\log D_O\left(\mathbf{x}_{it}, \frac{\mathbf{y}_{it}}{y_{it}^m}, t; \boldsymbol{\beta}\right) + v_{it} + \log\left(\mathrm{TE}_{it}\right) \tag{3.24}
$$

where y^m is the normalizing output.

In a translog specification the parameter estimates are not directly interpretable, as they depend on the units of measurement. A convenient transformation of the data is the normalization of all inputs and outputs by their respective geometric means prior to estimation. In this way, the parameter estimates on the first-order terms in the translog distance function can be directly interpreted as elasticities evaluated at the geometric mean of the data (arithmetic mean in logarithms).

3.5.2 Data

The data used for this application come from the Farm Accountancy Data Network (FADN). FADN provides harmonized accounting information from agricultural holdings across Member States of the European Union. The data are collected regionally through the means of an annual survey that uses a common questionnaire across all Member States. The purpose of FADN is to gather information that is fit for the determination of the income of agricultural holdings as well as for business analysis of these holdings. The primary user of the dataset is the European Commission and except for some summary results coming from the dataset, it is not publicly available.

The dataset contains farm-level information on physical units (outputs and inputs), economic and financial data (revenues from specific products and product groups, expenses related to input use, subsidies, investment in quasi-fixed factors etc.), as well as some geographical characteristics and characteristics of the farm's primary operator. FADN uses a stratified, rotating sampling scheme where farms remain in the panel on average for a period of 4-5 years, but cases of farms that are interviewed for as many as 10 years are not uncommon.

The part of the dataset that is used here contains such information for dairy farms from Germany and the Netherlands, and covers the period from 1995 to 2005. For the farms selected for the analysis, the revenues from sales of cow's milk and beef and veal comprise at least 80% of their total revenues, for every year that the farm is in the sample.

The output distance function is specified in two outputs:

1. Deflated revenues from sales of cow's milk (milk).

2. Deflated revenues plus change in valuation of beef and veal, plus deflated revenues from sales of all other output (other).

The reported revenues are deflated using country-wide price indices for each category of products. Although physical units are available for the quantity of milk produced, differences in the quality of output between farms are not observed. The deflated revenues instead provide a measure of quality-adjusted output.

Six categories of inputs are used in the specification of (3.23):

1. Buildings and machinery (K) – deflated book value. It includes buildings and fixed equipment, as well as machines, tractors, cars and irrigation equipment.

2. Total labor (L) – man-hours. This measure contains both hired and family labor as reported by the operator during the interview.

3. Total utilized agricultural area (A) – hectares. It includes owned as well as land that is rented for more than a year.

4. Materials and services (M) – deflated value. This category of inputs is composed of six other sub-categories: seeds and plants, fertilizers, crop protection, crop- and livestock-specific costs, and energy. A Törnqvist index was constructed using expenditure and price indices for each sub-category. The total reported expenditure on materials and services was then deflated using the Törnqvist index.

5. Livestock (S) – animal units. This is a measure of the volume of cattle present in the farm during the year. FADN assigns weights to different categories of cattle. Dairy and cull cows are assigned a weight of 1, while younger cattle (0-2 years) are assigned weights from 0.4 to 0.6.

6. Purchased feed (F) – deflated value. This includes feed and concentrated feedingstuffs purchased, as well as expenditure for use of common or rented grazing land. It excludes the value of feed produced within the farm.

Dummy variables are used for Germany to capture differences in the soil and climatological conditions across regions that are likely to affect agricultural production.

Four dummies are used for eastern, western, northern and southern (base category) Germany. An interaction term between the time trend and farms in former Eastern Germany is also included in the specification, to test whether technological progress was faster in this region during the years covered by the data.

Some farms in Germany are specialized beef and veal producers and they report zero milk output. The translog specification can not accommodate these zero values because the logarithm of each variable is used in the estimation. The procedure proposed by Battese (1997) is used here to avoid the bias introduced by removing the observations that report zero milk output from the sample. In terms of specification the procedure consists of including a dummy variable for these observations[4].

3.5.3 Results

The complete set of results is provided in Appendix A. Table 3.1 reports the parameter estimates of the first-order terms of the distance function and the structural parameters of the hidden-state equation. All estimated elasticities have the correct sign and are highly significant.

The distance elasticities with respect to outputs can be considered as measures of the curvature of the production possibilities frontier. The high elasticity with respect to cow's milk indicates that an 1% increase in milk output (holding inputs and other output fixed) will lead to a 0.8-0.9 increase in the distance function, that is, the farms will be moved closer to the frontier. The implied (from the linear homogeneity restrictions) elasticities with respect to other output are about 0.17 for Germany and 0.1 for the Netherlands. The magnitude of these elasticities in turn implies that, at the point the elasticities are calculated, the marginal rate of transformation of milk to other output is high.

The negative elasticities of the distance function with respect to inputs state that increases in inputs push the production possibilities frontier outwards. For both

[4]This method of dealing with zero values is implicitly imposing the restriction that the differences between the production technologies that produce all outputs and those that do not can be captured by differences in the constant term. When an output is not produced the production possibilities set collapses to a smaller dimension.

	Germany			The Netherlands		
log_other	Coef.	Std. Error	p-value	Coef.	Std. Error	p-value
log_milk	0.8265	0.0020	0.000	0.9013	0.0041	0.000
log_K	-0.0539	0.0036	0.000	-0.0591	0.0058	0.000
log_L	-0.0590	0.0071	0.000	-0.0645	0.0084	0.000
log_A	-0.0168	0.0069	0.014	-0.1559	0.0111	0.000
log_M	-0.2193	0.0060	0.000	-0.1640	0.0088	0.000
log_S	-0.5029	0.0089	0.000	-0.4295	0.0147	0.000
log_F	-0.1682	0.0032	0.000	-0.2156	0.0078	0.000
trend	-0.0115	0.0008	0.000	-0.0125	0.0011	0.000
scale	-1.0201	0.0066	0.002	-1.0886	0.0064	0.000
σ_v	0.0849	0.0011	0.000	0.0615	0.0014	0.000
σ_w	0.2801	0.0063	0.000	0.2776	0.0104	0.000
δ	-0.0524	0.0122	0.000	-0.0733	0.0301	0.015
ρ	0.9574	0.0101	0.000	0.9876	0.0214	0.000
μ_1	-1.4114	0.0316	0.000	-1.7096	0.0516	0.000
σ^2_{w1}	0.5784	0.0362	0.000	0.5787	0.0643	0.000

Table 3.1: Elasticities and Structural Parameter Estimates of the Model.

countries the largest effect is that of livestock, followed by materials and purchased feed. An interesting result is the striking similarity of the magnitude for most of these elasticities for Germany and the Netherlands, indicating that the technology employed in the two countries is very similar. Large differences, however, appear in the elasticity with respect to land. A possible explanation for this is that Dutch farmers have cow's free grazing for longer periods of time on average than German farmers, and thus the amount of used land has a larger impact on output. On the other hand, the difference could be merely because these elasticities are calculated at different data points. Dairy farms in the Netherlands are smaller, on average, in terms of land, and since the point of calculation of the elasticity in smaller, the marginal effect of this input will appear larger.

Both countries experience technological progress as the production possibilities set is pushed outwards with time. The scale elasticity of the distance function is calculated by adding the distance elasticities with respect to every input. Farms in both countries appear to be operating in the increasing returns to scale part of the technology. Two-sided tests for constant returns to scale are highly rejected for both Germany and the Netherlands.

Moving to the structural parameter estimates of the inefficiency stochastic process, the large value of ρ indicates that for both countries the ratio of technical inefficiency to efficiency is highly persistent. The hypothesis of stationarity (using a likelihood ratio test for the validity of (3.4)-(3.5)) is highly rejected for the Netherlands, but marginally rejected at 5% significance for Germany (the p-value for the test is 0.048). This implies that, especially for dairy farms in the Netherlands, the hidden-state process could be divergent, with the long-run efficiency score approaching unity as time goes to infinity.

Table 3.2 contains summary statistics for the estimated efficiency scores. Farms in the Netherlands are on average more efficient than farms in Germany, a result that appears to be mainly due to the more extreme values of efficiency scores for German farms. Figure 3.1 presents histograms of the estimates for the two countries. The shape of these histograms confirms the higher variability of efficiency scores for Germany and the heavier tail of the distribution of the estimates towards zero. This result could be due to the heterogeneity of German farms, as part of it shows up as inefficiency.

Country	**# of Obs**	**Mean**	**Min**	**Max**
Germany	7475	0.7817	0.1878	0.9733
The Netherlands	2390	0.8310	0.2707	0.9844

Table 3.2: Summary Statistics of Efficiency Score Estimates.

If we treat the stochastic process of the hidden state as stationary, then, using (3.21), we can determine the expected value of the average efficiency score that will persist to infinity. For Germany this number is 0.772 and is virtually the same to the average efficiency score that appears in Table 3.2. This is another indication that the hidden state process for Germany is stationary and that the time window captured by the data found the process close to equilibrium. On the contrary, the average efficiency score far in the future for the Netherlands is 0.997. This implies that the hidden state series

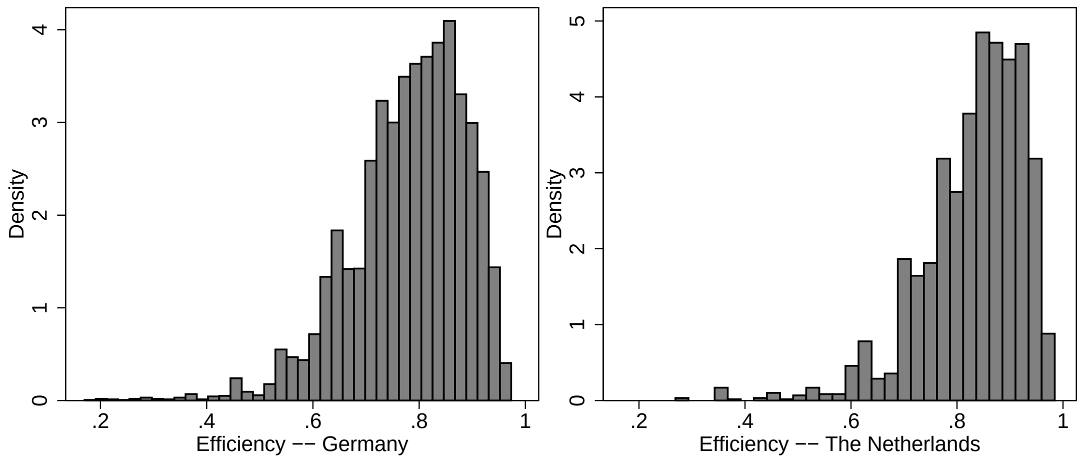

Fig. 3.1: Histograms of Efficiency Score Estimates for Germany and the Netherlands

is close to being divergent. However, these numbers depend heavily on the parameter estimates of δ and ρ. As it can be seen from Table 3.1, these two parameters cannot be estimated very accurately for the Netherlands. This uncertainty is also transfered to the estimate of the long-run efficiency level. The numbers reported in this paragraph should, therefore, be interpreted with caution.

3.6 Conclusions

In this chapter, a model for efficiency measurement was developed. The model accounts for the intertemporal nature of producer's decision-making process. It is based on the standard stochastic frontier model, but it allows for the efficiency scores of a firm to be correlated along time. The model can provide an estimate of the expected value of the efficiency score that will prevail in an industry in the long run. Under certain conditions, this long-run efficiency level will be less than unity. This result is consistent with the implications of the adjustment cost theory of investment, which suggests that, in the presence of adjustment costs, the optimal strategy for a firm could be to remain partly inefficient at any point in time.

The autocorrelated inefficiency model is developed in a state-space framework. Non-linear Kalman filtering is used to evaluate the likelihood and the technical efficiency scores. Although the integrals required to be evaluated for the Kalman filter can be approximated by Gaussian quadratures, the computations involved in the optimazition of the likelihood function are vast, but manageable.

The model is applied to a group of dairy farms from Germany and the Netherlands. An output distance function was estimated for each country separately, but the estimates of the corresponding parameters are very similar. This indicates that the technology employed by farms in the two countries are similar themselves. On the other hand, farms in Germany appear to be on average less efficient than farms in the Netherlands. Inefficiency is found to be highly persistant along time in both countries, although some variability is present in the cross-section dimension of the panel.

Chapter 4

A Structural Model for Investment Decisions and Dynamic Efficiency Measurement Under Uncertainty

4.1 Introduction

This chapter introduces a structural model for dynamic efficiency measurement. The model has origins from Pindyck and Rotemberg (1983a), although it is a generalization of it in terms of functional form. Originally assuming perfectly efficient producers, both technically and allocatively, this assumption is then relaxed to include inefficiency in the short and long run. Two approaches are proposed for completing this task, the shadow cost and a system stochastic frontier method.

4.2 Basic Model

Consider a single-output technology represented by the production function:

$$y = f\left(\mathbf{x}, K, I\right) \tag{4.1}$$

where $\mathbf{x} \in \mathbb{R}_{+}^{N}$ is the vector of variable inputs, $K \in \mathbb{R}$ is the amount of a single quasi-fixed input[1], and $I \in \mathbb{R}$ is the amount of gross investment in K. Investment enters the production function to capture the adjustment cost of the quasi-fixed input.

The following assumptions are imposed on the production function:

Assumption 1.

The production function satisfies the properties:

1. *it is twice continuously differentiable:* $f \in \mathcal{C}^2$

[1] The model can be easily extended to include more than one quasi-fixed inputs.

2. *it is increasing in* $\mathbf{x}$ *and* K *and decreasing in* I*:* $\frac{\partial f}{\partial \mathbf{x}}, \frac{\partial f}{\partial K} > 0$, $\frac{\partial f}{\partial I} < 0$

3. *concave in all its arguments:* $\frac{\partial^2 f}{\partial \mathbf{x} \partial \mathbf{x}'}, \frac{\partial^2 f}{\partial K^2}, \frac{\partial^2 f}{\partial I^2} < 0$

Let $\mathbf{w} \in \mathbb{R}_+^N$ be the vector of prices of the variable inputs and r be the rental price of capital. The short-run cost function $C(\mathbf{w}, y; K, I)$ is the solution to the problem:

$$\begin{aligned} \min_{\mathbf{x}} \quad & \mathbf{w}'\mathbf{x} \\ \text{s.t.} \quad & y = f(\mathbf{x}, K, I) \\ & y, K, I \;\; \text{given} \end{aligned} \tag{4.2}$$

$C(\mathbf{w}, y; K, I)$ is a restricted cost function. Therefore, it satisfies properties as homogeneity of degree one in variable input prices, symmetry in cross-price effects, Shephard's lemma etc. Furthermore, the properties of the production function (Assumption 1) imply that the variable cost function is non-decreasing in input prices and I, and non-increasing in K. Additionally, it is concave in input prices and convex in I and K.

The long-run objective of the firm is to minimize the expected sum of discounted flows of production cost, given that a predetermined stream of output quantities has to be produced. The minimization is subject to the equation of motion for capital stock adjustment:

$$\begin{aligned} J = \quad & \min_{I_\tau} \mathrm{E} \left\{ \sum_{\tau=t}^{\infty} \beta_\tau \left[C\left(\mathbf{w}_\tau, y_\tau; K_\tau, I_\tau\right) + r_\tau K_\tau \right] \middle| \Omega_t \right\} \\ \text{s.t.} \quad & K_\tau = (1-\delta) K_{\tau-1} + I_\tau \\ & K_t \;\; \text{given} \end{aligned} \tag{4.3}$$

In the last expression δ is the constant depreciation rate of capital and β_τ is the appropriate discount factor for evaluating the cash flows from period τ in period t values. The stochastic variables in the optimization problem (4.3) at time t are the variable input prices ($\mathbf{w}_\tau$), the rental price of capital (r_τ), and output levels for $\tau = t+1, \ldots, \infty$. The expectation in the objective is taken with respect to these stochastic variables and it is conditional on the information set available in period t, Ω_t. Economic agents are assumed to form rational expectations.

Cost minimization behavior is assumed here as a less restrictive assumption than profit maximization. This makes the model more robust to different market structures. In this context y_τ is treated as a random variable which is determined at another stage of the decision-making process of the firm. The determination of the contingency plan for the stream of output quantities is made conditional on the information about the other random variables that is available at each time period. For example, suppose that the higher-level objective of the firm is expected profit maximization[2]. In this case, future y_τ will be a deterministic function of future input and output prices. But since these prices are stochastic, y_τ will also be stochastic, as it is a function of these random variables.

Following Pindyck and Rotemberg (1983a) we derive the first-order conditions for the two minimization problems. Consider first the problem in (4.2). By Shephard's lemma we know that the demand function for each variable input j is given by the derivative of the variable cost function with respect to the input's price:

$$x_t^{*j}\left(\mathbf{w}_t, y_t; K_t, I_t\right) = \frac{\partial C\left(\mathbf{w}_t, y_t; K_t, I_t\right)}{\partial w_t^j} \quad , \quad j = 1, 2, \ldots, N \tag{4.4}$$

The Euler equations for problem (4.3) are:

$$\begin{aligned} &\frac{\partial C\left(\mathbf{w}_t, y_t; K_t, I_t\right)}{\partial I_t} + \frac{\partial C\left(\mathbf{w}_t, y_t; K_t, I_t\right)}{\partial K_t} + r_t \\ &\qquad - \mathrm{E}\left[\beta_t \left(1-\delta\right) \frac{\partial C\left(\mathbf{w}_{t+1}, y_{t+1}; K_{t+1}, I_{t+1}\right)}{\partial I_{t+1}} \middle| \Omega_t\right] = 0 \end{aligned} \tag{4.5}$$

An important note is in place here, with respect to the assumptions that are imposed upon the expectation formation mechanism. The Bellman equations have been used to derive the Euler equations. But Bellman's principle of optimality is only valid when the state variables have the Markov property. This is true for the transition equation of capital which is treated as a non-stochastic equation. But it should also be the case for all random variables at time t. These are also state variables, although not under the control of the firm. Therefore, the expectation in (4.5) should be interpreted

[2] As Pindyck and Rotemberg (1983a) note, the cost minimization problem defined here is consistent with profit maximization behavior.

as being conditional on past values of $\mathbf{w}$ and y. If a particular structure is imposed on the way these variables evolve through time, then the parameters of an expectation formation mechanism can be estimated (Hansen and Sargent 1980).

Once the short-run cost function is specified, one can proceed to derive a set of estimable equations based on the optimization conditions (4.4)-(4.5). In general the variable cost function will have a flexible functional form. If this function is specified as quadratic, then the first-order conditions are linear in the parameters and they can be estimated directly in a system. Pindyck and Rotemberg (1983a) use a translog specification. In this case the variable input cost shares rather than their demand functions are linear in the parameters:

$$S_t^j \equiv \frac{w_t^j x_t^j}{C_t} = \frac{\partial \log C\left(\mathbf{w}_t, y_t; K_t, I_t\right)}{\partial \log w_t^j} \tag{4.6}$$

The Euler equations can also be written in a form that is linear in the parameters, using the same relationship between derivatives in levels and in logarithms.

The estimation of the model parameters can be carried out by estimating the system of variable input demand functions or cost-share equations together with the Euler equations. Symmetry and homogeneity of degree zero of the variable inputs demand functions provide cross-equation restrictions for the parameters. The Euler equations together with the assumption of rational expectations provide moment restrictions that should hold in the population. Pindyck and Rotemberg use the Generalized Method of Moments (GMM) to estimate the system (Hansen 1982).

4.3 Accounting for Inefficiency in the Structural Model

The model presented in the previous section assumes that producers are perfectly efficient in solving the optimization problems. This model is now extended to account for inefficiency. We can distinguish between short- and long-run inefficiency. A firm is inefficient in the short run when its observed expenditure of variable inputs is higher than the variable cost frontier, given the levels of fixed input and gross investment. Short-run inefficiency can be decomposed further into technical and allocative inefficiency. It can be measured parametrically using either the stochastic frontier or the shadow cost methods (reviewed in sections 2.4 and 2.5).

Long-run inefficiency represents the degree of suboptimality of decisions that are related to the long-run planning of the firm. These decisions have an impact on the firm's cost that persists for many periods. With decisions always made in the short run, their optimality has to be assessed with respect to the long-run objective of the firm. Therefore, the appropriate place to measure dynamic efficiency is in the only dynamic component of the model that can be estimated; namely, the Euler equations.

The Euler equations provide a rule for the optimal level of investment in each period. They are, in fact, an intertemporal arbitrage condition. The first three terms in (4.5) measure the marginal effect of an additional unit of investment on current period's cost. This effect is decomposed into three parts: i) marginal adjustment cost, ii) marginal reduction in short-run cost because more capital is available, and iii) the rental price of the additional unit of capital. In the absence of adjustment costs terms (ii) and (iii) vanish. The last term in (4.5) is the expected marginal adjustment cost of investment that takes place in the next period.

Consider a firm for which at some point in time the Euler equation is violated upwards, i.e. the right-hand side of (4.5) is positive. In such a case the firm is overinvesting in the current period. Given the convexity of the variable cost function in capital and investment, a reduction in I_t would lead to: i) a reduction to the marginal adjustment cost[3], and ii) an increase in absolute value to the non-positive marginal effect of capital on variable cost. Therefore, for a given expected marginal cost of investment in period $t + 1$, a reduction in I_t is required for the Euler equation to be satisfied. A similar argument can be used to show that underinvestment is associated with a situation where the Euler equation is violated downwards.

Suboptimality of investment decisions can stem either from a false expectation formation mechanism about future prices or from improper optimization with respect

[3]When I_t is negative the marginal adjustment cost is also negative. A reduction in I_t here means larger disinvestment and overinvestment in this context should be interpreted as not large enough disinvestment.

to investment in the fixed inputs. Unless some structure is imposed on the expectation formation mechanism, these two effects cannot be distinguished in practice.

There are two alternative ways of introducing inefficiency in the structural model. One follows the shadow cost approach and incorporates inefficiency in the Euler equations multiplicatively. The second incorporates inefficiency additively. The next two subsections review these alternatives in terms of the information they can provide and explore the econometric feasibility of the resulting models.

4.3.1 Incorporating Inefficiency Multiplicatively

The problem of measuring dynamic efficiency using the Euler equations is similar in nature to the measurement of allocative efficiency in a static context. The Euler equations are the conditions prescribing how investment should be allocated over time such that long-term expected cost is minimized. They are the counterpart to the conditions indicating how the budget to employ production factors should be allocated among inputs in a static cost minimization problem. The shadow cost approach is, therefore, a natural choice for proceeding.

Taking this into account, consider the following version of the Euler equations:

$$\frac{\partial C_{it}}{\partial I_{it}} + \frac{\partial C_{it}}{\partial K_{it}} + r_{it} = \psi_{it}\,\mathrm{E}\left[\beta_t\,(1-\delta)\,\frac{\partial C_{i,t+1}}{\partial I_{i,t+1}}\middle|\Omega_t\right] \tag{4.7}$$

where i indexes firms and C_{it} is used as shorthand notation for $C\left(\mathbf{w}_{it}, y_{it}; K_{it}, I_{it}\right)$. The additional parameter ψ_{it} is specified to measure dynamic efficiency, with $\psi_{it} = 1$ implying perfect efficiency, $\psi_{it} > 1$ indicating overinvestment in the current period (t), while $\psi_{it} < 1$ indicating underinvestment.

This approach of incorporating inefficiency in the model introduces an estimation problem. The ψ_{it}s are parameters to be estimated and there are as many parameters as the number of observations. Unless ψ_{it} is parameterized in terms of firm- and time-specific variables, the strong assumption of a similar efficiency score across either time or firms will have to be imposed for identification.

A different approach for getting a measure of dynamic efficiency is to estimate the parameters of the model using only the variable cost function together with the variable input cost-share functions:

$$\log E_{it} = \log C\left(\mathbf{w}_{it}, y_{it}; K_{it}, I_{it}\right) + v_{it} - \log \mathrm{CE}_{it} \tag{4.8a}$$

$$S_{it}^{j} = \frac{\partial \log C\left(\mathbf{w}_{it}, y_{it}; K_{it}, I_{it}\right)}{\partial \log w_{it}^{j}} + \eta_{it}^{j} \tag{4.8b}$$

Estimation can be carried out using any of the techniques that can allow for inefficiency in the variable cost function. After the estimation the Euler equations can be evaluated using the parameter estimates and the values of the ψ_{it}s can be calculated rather than estimated. Of course in such a case the uncertainty with respect to future conditions will have to be ignored and the dynamic efficiency will be assessed assuming perfect foresight instead of rational expectations.

4.3.2 Incorporating Inefficiency Additively

Incorporating inefficiency in the Euler equations additively can be used to avoid the overparameterization of the model that arises from using the shadow cost approach to efficiency measurement. Consider the following version of the Euler equations:

$$\frac{\partial C_{it}}{\partial I_{it}} + \frac{\partial C_{it}}{\partial K_{it}} + r_{it} - \mathrm{E}\left[\beta_t \left(1-\delta\right) \frac{\partial C_{i,t+1}}{\partial I_{i,t+1}} \middle| \Omega_t\right] = \mu_{it} \tag{4.9}$$

where μ_{it} is a firm-specific and time-varying measure of intertemporal inefficiency. Of course, μ_{it} will again have to be parameterized to be identified. But since it appears as an additive term in the model it can be treated as a time-varying group effect in the technique developed by Ahn et al. (2006). In this case there is no need to explicitly specify μ_{it} as a function of covariates, but rather treat it as the outcome of the interaction of p group-specific factors with time-dependent parameters:

$$\mu_{it} = \theta_{1t}\alpha_{1i} + \theta_{2t}\alpha_{2i} + \ldots + \theta_{pt}\alpha_{pi} = \sum_{\ell=1}^{p} \theta_{\ell t}\alpha_{\ell i} \tag{4.10}$$

This approach combines factor analysis with regression analysis. Not all θ_{pt}s can be identified but with an appropriate normalization an estimate of μ_{it} can be recovered after the estimation. To be more specific, define:

$$u_{it} = \frac{\partial C_{it}}{\partial I_{it}} + \frac{\partial C_{it}}{\partial K_{it}} + r_{it} - \beta_t (1-\delta) \frac{\partial C_{i,t+1}}{\partial I_{i,t+1}} \tag{4.11}$$

Then (4.9) can be written as:

$$\mathrm{E}\left[u_{it}|\Omega_t\right] = \mu_{it} \tag{4.12}$$

implying the following data generating process:

$$u_{it} = \mu_{it} + \epsilon_{it} \qquad \mathrm{E}\left[\epsilon_{it}|\Omega_t\right] = 0 \tag{4.13}$$

where ϵ_{it} is a disturbance term. In a simple rational expectations model (4.13) would be estimated using moment conditions derived from the fact that any variable in the information set at time t is orthogonal to ϵ_{it}:

$$\mathrm{E}\left[\epsilon_{it} z_{it}\right] = \mathrm{E}\left[\mathrm{E}\left[\epsilon_{it}|\Omega_t\right] z_{it}\right] = 0 \qquad \forall z_{it} \in \Omega_t \tag{4.14}$$

Typically the instrument set (zs) would consist of a constant term that forces ϵ_{it} to be zero in expectation and any other variable that could be used by the economic agents to predict the future conditions that are relevant to the problem.

In the case where time-varying group effects are included in the right-hand side of (4.13) a transformation of the data should be used prior to estimation. Define:

$$\underset{T\times p}{\mathbf{\Theta}} = \begin{bmatrix} \mathbf{\Theta}_1 \\ -\mathbf{I}_p \end{bmatrix} \qquad \text{and} \qquad \underset{T\times(T-p)}{\mathbf{H}} = \begin{bmatrix} \mathbf{I}_{T-p} \\ \mathbf{\Theta}_1' \end{bmatrix} \tag{4.15}$$

where $\mathbf{\Theta}_1$ is a $(T-p)\times p$ matrix of time- and factor-specific parameters. $\mathbf{I}_p$ is an identity matrix used to normalize the $\theta_{\ell t}$s. Notice that $\mathbf{H}'\mathbf{\Theta} = \mathbf{0}$ and, therefore, pre-multiplication of (4.13) by $\mathbf{H}'$ removes the group effects:

$$\mathbf{H}'\mathbf{u}_i = \mathbf{H}'\mathbf{\Theta} + \mathbf{H}'\boldsymbol{\epsilon}_i = \mathbf{H}'\boldsymbol{\epsilon}_i \tag{4.16}$$

The μ_{it} has been removed from the right-hand side of (4.13) but its effect remains in the model through the $\theta_{\ell t}$s contained in $\mathbf{H}$. The moment conditions that are used for the estimation now take the form:

$$\mathrm{E}\left[\mathbf{H}'\boldsymbol{\epsilon}_i \odot \mathbf{z}_i\right] = \mathbf{0} \qquad \forall \mathbf{z}_i \in \Omega_t \tag{4.17}$$

where "$\odot$" denotes element-wise multiplication.

Ahn et al. (2007) propose obtaining an estimate of the μ_{it}s by projecting the residuals on the column-space of $\hat{\boldsymbol{\Theta}}$:

$$\hat{\boldsymbol{\mu}}_i = \hat{\boldsymbol{\Theta}}\left(\hat{\boldsymbol{\Theta}}'\hat{\boldsymbol{\Theta}}\right)^{-1}\hat{\boldsymbol{\Theta}}\mathbf{u}_i \tag{4.18}$$

In the structural model developed in this chapter, there exists additional information contained in the variable cost function and the input cost-share equations. Estimation can be carried out by GMM and by using the full set of equations:

$$\log E_{it} = \log C\left(\mathbf{w}_{it}, y_{it}; K_{it}, I_{it}\right) + v_{it} - \log \mathrm{CE}_{it} \tag{4.19a}$$

$$S_{it}^{j} = \frac{\partial \log C\left(\mathbf{w}_{it}, y_{it}; K_{it}, I_{it}\right)}{\partial \log w_{it}^{j}} + \eta_{it}^{j} \tag{4.19b}$$

$$u_{it} = \mu_{it} + \epsilon_{it} \tag{4.19c}$$

The same technique described above can be used to take into account and measure short-run inefficiency in the variable cost function and allocative inefficiency in the input cost-share equations.

One issue that remains to be resolved is the number of factors to be used during the estimation. This number is not a parameter to be determined by the model. Rather, different models are obtained conditional on different assumptions on the number of factors. Ahn et al. (2006) propose a sequential testing procedure for determining the number of factors in a single-equation model. The Sargan test of overidentifying restrictions can be used to test the hypothesis $p = 0$ against the alternative $p > 0$. If the null is rejected then a model with one factor is estimated and the hypothesis $p = 1$ is tested against the alternative $p > 1$. The procedure goes on until a model is not rejected.

Although this procedure is guaranteed to consistently estimate the true number of factors in a single equation model, there exists no formal proof that it will work in a multiple-equations model. In a model with many equations the order in which different combinations of factors are tested could lead to different values of p. In such a case a Bayesian information criterion could be used to infer the number of factors in each equation. Ahn et al. propose using the following criterion function:

$$f(N) = J_N|p - \alpha \log(N)\,\mathrm{DF} \tag{4.20}$$

where N is the number of firms, $J_N|p$ is the value of the objective in the GMM estimation framework given the model contains p factors, DF is the number of degrees of freedom, and α is a positive constant. This criterion function favors a model with small J-statistic and penalizes for excessive number of parameters (factors). Therefore, the model with the smallest value of the criterion function should be chosen. Different models, however, could be chosen for different values of α.

4.4 Conclusions and Further Remarks

This chapter presented a structural model of firm behavior that explicitly allows for suboptimal decision making with respect to investment. The restrictive assumption of static expectations is dropped in favor of rational expectations and estimation is proposed within the framework of the Generalized Method of Moments, using a system of equations consisting of a variable cost function, the derived variable cost-share equations and the Euler equations.

Cost minimization is assumed in the long run and the optimality of decisions with respect to investment levels can be assessed against this objective. The direct estimation of the Euler equations avoids the necessity of explicitly solving for a long-run equilibrium point. Instead efficiency is measured in a period-by-period basis, at the point where the decisions are made. Additionally the observed streams of output are used to evaluate the efficiency scores, avoiding in this way to infer what the optimal level of output should be in the path towards the long-run equilibrium.

On the other hand the use of the Euler equations imposes some restrictions on the specification of the model. The derivation of the Euler equations invokes the envelope theorem. But the envelope theorem holds only if the objective function is smooth with respect to capital and gross investment. This restriction is necessary for the model to be internally consistent.

Chapter 5

Estimation of the Parameters of the Structural Model: An Application to Mexican Food-Processing Plants

5.1 Introduction

This chapter presents an application of the structural model for dynamic efficiency measurement developed in Chapter 4 to a panel of food-manufacturing plants from Mexico. Apart from illustrating the applicability of the model, the application has its own significance. Mexico is the second largest US trade partner in the category of manufactured food products, both in terms of imports and exports[1]. Although the data used here are old, the state and dynamics of the industry prior to the NAFTA can provide insight about what led Mexico to take up such a position.

The data used for the application are described in detail in the next section. Section 5.3 discusses some specification issues, while section 5.4 presents the details and the results of the econometric estimation, along with extensive discussion of the estimated efficiency scores. Finally, section 5.5 provides some concluding comments.

5.2 Data

The dataset used for this application comes from Mexico's Annual Industrial Survey and covers the period 1984-'90. The data were provided by Mexico's Secretary of Commerce and Industrial Development and originally used in a project concerning the study of the effect that trade liberalization had on the efficiency of manufacturing industries (Tybout and Westbrook 2000). The same data were also used by Brown and Domínguez (1994) to measure productivity growth in Mexican manufacturing.

[1]According to data from the Department of Commerce, Mexico accounted for 16% of US exports and 9% of imports in the category of food products in 2008.

The dataset contains annual plant-level information on output (value added), variable input use (labor in hours, energy in KWatt hours and cost of materials), as well as the amount of capital stock (machinery and equipment, buildings, and land) in current-value replacement cost and gross investment. The cost of employment of variable inputs is also available and can be used to infer the prices for these inputs. Industry-level price indices for output and for capital goods can be used to calculate the amount of output and capital stock in real terms.

During the survey each plant was assigned a sector classification index. These indices vary from one year to the other but they are directly related to the International Standard Industrial Classification (ISIC), revision 2 coding system. Only food-manufacturing plants are used in this application[2]. The number of plants in the sample per ISIC 4-digit code is given in Table 5.1. Summary statistics for the key variables are presented in Table 5.2.

ISIC Code	Industry	# of Plants
3111	Slaughtering, preparing and preserving meat	38
3112	Manufacture of dairy products	30
3113	Canning and preserving of fruits and vegetables	25
3114	Canning, preserving and processing of fish, crustaceans and similar foods	0
3115	Manufacture of vegetable and animal oils and fats	27
3116	Grain mill products	90
3117	Manufacture of bakery products	21
3118	Sugar factories and refineries	0
3119	Manufacture of cocoa, chocolate and sugar confectionery	7
3121	Manufacture of food products not elsewhere classified	12
SUM		**250**

Table 5.1: Number of Plants in the Sample per ISIC 4-Digit Code.

What has been observed in the literature is that when microeconomic data are used, many firms appear not to invest regularly[3]. Rather, the data are characterized by

[2]The plants that are used here are classified to codes 311 (3111-3119) and 3121 in the ISIC, rev.2 system.

[3]See Cooper and Haltiwanger (2006) and Letterie et al. (2004) for examples.

Variable	Mean	Std. Dev.
Variable Cost[1]	2.965	4.426
Gross Value of Output[2]	3.897	5.676
Total Remunerations[1]	0.246	0.365
Total Material Cost[1]	2.719	4.201
Number of Emploees[3]	220.461	326.756
Share of Labor Expenses in Variable Cost	0.107	0.086
Machinery, Equipment, Construction Assets[3]	1.049	1.763
Acquisitions of New and Used Capital Minus Sales of Capital[3]	0.047	0.113

[1] Millions of Mexican pesos normalized by the price index for materials.
[2] Millions of Mexican pesos normalized by own price index.
[3] Adjusted for the number of days for which the plant is open.

Table 5.2: Summary Statistics of Key Variables.

investment spikes (high investment to capital stock ratio). This appears to be the case for this dataset as well. Figure 5.1 presents a histogram of the investment rate for the dataset (observations truncated at -0.2 and 0.6). The majority of the observations are clustered around zero investment levels, with some firms reporting large adjustments in specific years. As a relative measure of investment spikes one can use the percentage of observations that report investment rates at least as high as 2.5 times the firm's median investment rate (Power 1998). For this dataset, according to this criterion, 19.2% of the observations are characterized by investment spikes.

The period covered by the data is characterized by high and volatile inflation rates. The nominal interest rates appear to follow the inflation rates, although not very closely. Table 5.3 presents the mid-year inflation rates and the immediate interest rates for the years 1982-90. The real interest rates were derived using Fisher's formula[4].

In general, in a stable economic environment, the real interest rate would be used to calculate the discount factor, β_t. In an environment with so highly volatile interest rates, however, it would be erroneous to assume that the managers use the prevailing interest rate to discount future flows. Instead β_t will be considered here as a behavioral parameter. This assumption has no further implications for firms which own the capital they are using. For a firm that is using the financial market to obtain capital, the

[4]Real Interest Rate $= \dfrac{1 + \text{Nominal Interest Rate}}{1 + \text{Inflation Rate}} - 1$

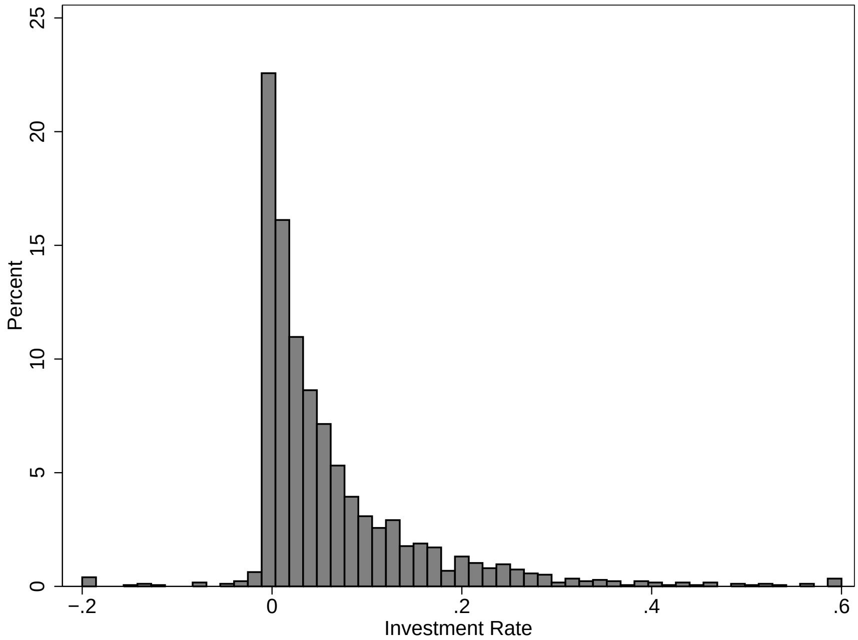

Fig. 5.1: Histogram of $\frac{I_t}{K_t}$ for the Mexican Food-Manufacturing Industry.

assumption of constant discount factor implies that either the contract between the firm and the lender is made on an interest rate that is a constant addition to inflation or, that refinancing is possible if the firm finds itself borrowing at an interest rate which is higher than the one corresponding to the intrinsic discount factor[5].

In order to impose linear homogeneity in input prices in the variable cost function, the price of one variable input will be normalized to unity. Therefore, absolute variable-input prices are not required. But the rental price of capital enters the model in absolute terms, in the form of the percentage value of capital that should be paid as rent for using it. Theoretically, this price should be equal to the sum of the depreciation rate and the real interest rate. The interest and depreciation rates used for the estimation appear to become important again[6]. However, as this price enters the model additively and only

[5]The baseline analysis in this chapter is centered on an interest rate of 5%. A complete set of results from models with discounting factors that correspond to interest rates equal to 1%, 5%, 7% and 10% is provided in Appendix B.

[6]A constant depreciation rate for capital of 8% is used throughout the application.

	Inflation Rate[1]	Immediate Interest Rate[2]	Real Interest Rate
1982	49.37	46.12	-2.18
1983	112.50	56.44	-26.38
1984	67.14	47.54	-11.73
1985	53.43	65.66	7.97
1986	83.17	95.33	6.64
1987	126.73	104.29	-9.90
1988	161.44	45.48	-44.35
1989	17.58	40.11	19.16
1990	26.11	29.23	2.47

[1] Source: Central Bank of Mexico.
[2] Source: OECD.

Table 5.3: Inflation, Nominal, and Real Interest Rates in Mexico.

through the Euler equations, it can be absorbed by the group effects in these equations. After the estimation, one can derive the rental price of capital that would rationalize the observed behavior and compare it to the theoretical price.

In an environment with such high and volatile inflation rates, some questions about the quality of the data are raised. Nominal values have to be discounted using country-wide price indices which, in general, are imprecise indicators of how the prices of inputs and outputs are moving for each firm separately. The dataset contains such price indices at the 4-digit level of the ISIC classification. In general, these indices could be considered rather accurate measures of price volatility at the firm level. Yet, some of the price changes that can not be measured exactly by the indices could obscure the results.

5.3 Specification

In the previous chapter the structural problem for dynamic efficiency measurement was developed leaving the variable cost function unspecified. For an empirical application, this function should, in general, have a flexible form, with the specification including first-order and interaction terms of all the variables. It should also allow for imposition of linear homogeneity of the variable cost function in input prices. In general terms, the specification of the variable cost function will be of the form:

$$\log C\left(\mathbf{w}_{it}, y_{it}; K_{it}, I_{it}\right) = \log g\left(\mathbf{w}_{it}, y_{it}; K_{it}\right) + \log h\left(\mathbf{w}_{it}, y_{it}; K_{it}, I_{it}\right) \tag{5.1}$$

In the last expression $g\left(w_{it}, y_{it}; K_{it}\right)$ is the variable cost function given that the level of gross investment is zero. A natural choice for this function is the translog specification. The adjustment costs are captured by the $h\left(w_{it}, y_{it}; K_{it}, I_{it}\right)$ function. Given that the effect of the adjustment cost is multiplicative on the variable cost function, h should be restricted to be unity when $I = 0$. Furthermore, the derivation of the Euler equations requires the adjustment cost function to be smooth around zero. Clearly gross investment cannot be treated as any other argument of the variable cost function in a translog specification[7].

The following specification imposes both required properties of the adjustment cost function:

$$\begin{aligned}\log C_{it} = {} & \delta_t + \beta_w \log w_{L,it} + \beta_y \log y_{it} + \beta_K \log K_{it} \\ & + \beta_{ww} \log^2 w_{L,it} + \beta_{wy} \log w_{L,it} \log y_{it} + \beta_{wK} \log w_{L,it} \log K_{it} \\ & + \beta_{yy} \log^2 y_{it} + \beta_{yK} \log y_{it} \log K_{it} + \beta_{KK} \log^2 K_{it} \\ & + \gamma_I I_{it}^2 + \gamma_y I_{it}^2 \log y_{it} + \gamma_K I_{it}^2 \log K_{it}\end{aligned} \tag{5.2}$$

The interaction terms of squared investment with output and capital can allow for larger firms being able to absorb a change in their capital stock with relatively less adjustment cost than smaller firms[8].

[7] Pindyck and Rotemberg (1983a) use a translog specification for the cost function excluding investment and an additive quadratic term for the adjustment cost function. But they estimate a system consisting only of the variable input cost shares and the Euler equations. Since they do not estimate the variable cost function, the high degree of non-linearity in the parameters when the adjustment cost function is additive on variable cost poses no problem in their application.

[8] Theoretically, the prices of variable inputs could also affect adjustment costs. In the model presented here, the cost of adjustment is measured in terms of increase in variable cost that stems from gross investment. Firms which are facing higher variable input prices could also have higher adjustment costs. To account for this, an interaction term of squared investment with variable input prices was originally included in the specification. This interaction term, however, made the parameter estimates of the adjustment cost function particularly sensitive to outliers.

With this specification, linear homogeneity in variable input prices is imposed by dividing the observed expenditure for variable inputs and the price of labor by the price index for materials. Furthermore, the cost-share equation for labor is linear in the parameters. On the other hand, with such a flexible specification as the one in (5.2) it is not possible to impose global convexity in capital and gross investment. Instead, depending on the parameters and the firm- and time-specific values of the right-hand side variables of (5.2), the curvature of the variable cost function could be different from the one hypothesized for some observations in the sample.

The specification in (5.2) treats investment and disinvestment symmetrically in the sense that adjustment costs are increased as the investment level moves away from zero in either positive or negative directions. Given that with this specification it is possible to force the adjustment cost function to go through zero and its derivative to be zero around this point, one could allow for different shapes of the function in the positive and the negative quadrant. This would come at the cost of including another set of γ parameters for the observations with negative investment levels. In the application considered here, too few observations report disinvestment for this set of additional parameters to be estimated accurately[9].

In order to be consistent with the derivation of the Euler equations, the specification of the adjustment cost function imposes a smoothing assumption on the data around zero investment levels. This smoothing assumption allowes the zero marginal adjustment cost observations to be the proxies for the zero investment episodes, as they appear in the sample. It is possible to develop models which reproduce the firm-level investment behavior suggested by Figure 5.1, and for which estimation does not rely on the Euler equations. Cooper and Haltiwanger (2006) build a model of investment decisions which combines convex and non-convex (in some cases fixed) adjustment costs, and which can explain the large proportion of zero-investment observations. However, their model is based on the stronger assumption of profit maximization and the estimation proceeds in two steps. In the first step, the parameters of a profit function, which

[9]The model was estimated using different functional forms for the adjustment cost function in the positive and negative quadrants but, again, the results are very sensitive to outliers and to the instruments used for the estimation.

is free from adjustment costs, are estimated. It is questionable whether the procedure they use can be applied to a richer specification of the profit function. Additionally, the purpose of the model developed by Cooper and Haltiwanger is to estimate the parameters through reproducing the moments of the data, whether inefficiency is present or not. As such, this model cannot measure dynamic inefficiency. The model proposed here imposes more structure on the data, but also, it is more appropriate for exploring the issues this dissertation deals with.

5.4 Estimation Details and Results

5.4.1 Instruments

The parameters are estimated using the following system of equations:

$$\log C_{it} = \log g\left(\mathbf{w}_{it}, y_{it}; K_{it}\right) + \log h\left(\mathbf{w}_{it}, y_{it}; K_{it}, I_{it}\right) + v_{it} - \log \mathrm{CE}_{it} \tag{5.3a}$$

$$S_{it}^{L} = \mu_{2,it} + 2\beta_{ww} \log w_{L,it} + \beta_{wy} \log y_{it} + \beta_{wK} \log K_{it} + \eta_{it} \tag{5.3b}$$

$$u_{it} = \mu_{3,it} + \epsilon_{it} \tag{5.3c}$$

where g and h are defined in (5.2) and u_{it} is defined in (4.11). Three possible sets of factors are included in the model, one in each equation of the system.

The set of instruments used for the first equation consists of all the regressors in (5.2). Although it would be reasonable to assume that the variables used as instruments are weakly exogenous[10], including lagged values of the regressors as instruments would result in an excessive number of moment restrictions, which is likely to lead to biased estimates in finite samples (Hahn and Hausman 2004). Therefore, only concurrent values of the regressors are used as instruments. A constant term and the regressors in (5.3b) are used as instruments in the labor cost-share equation.

For the Euler equations, the set of instruments used consists of a constant term, $\log C$, $\log y$, and $\log K$. Note that what is unknown in period t and has to be predicted

[10] A variable z is weakly exogenous if $\mathrm{E}\left[v_{it}|z_{is}\right] = 0, \ \forall s \leq t$.

by the firm's manager is:

$$\frac{\partial C_{t+1}}{\partial I_{t+1}} = C_{t+1} \cdot \left[2\gamma_I I + 2\gamma_y I \log y_{t+1} + 2\gamma_K I \log K_{t+1}\right] \tag{5.4}$$

The variables used as instruments are, therefore, important in predicting the level of future adjustment cost. Gross investment also appears frequently in the last equation. However, since investment is rather irregular, it is questionable whether past investment levels can predict future investment. Again only the first lags of the variables are used as instruments.

5.4.2 Number of Factors

The model parameters are estimated conditional on the number of factors included in each equation. Eight different models are estimated using different combinations of zero and one factor in each equation. Table 5.4 presents the p-values for the Sargan test these models. From this table it appears that the data favor the model with one factor in each equation. Table 5.5 gives the values of the Bayesian Information Criterion function for $a = 0.5$. The same model is chosen according to this criterion, although for larger values of α, the model with zero factors in the variable cost equation is favored by the data.

		zero factors in the Euler equations		**one factor in the Euler equations**	
		# of factors in the cost-share equation			
		0	**1**	**0**	**1**
# of factors in the variable cost equation	**0**	0.0000	0.0000	0.0000	0.0000
	1	0.0000	0.0003	0.0000	0.4349

Table 5.4: p-values for the Sargan Test of Overidentifying Restrictions.

5.4.3 Parameter Estimates

Table 5.6 presents the parameter estimates for the model with one set of factors in each equation. Prior to estimation the w_L, y, and K variables were normalized

		zero factors in the Euler equations		one factor in the Euler equations	
		# of factors in the cost-share equation			
		0	**1**	**0**	**1**
# of factors in the	**0**	-147.4	-135.7	-118.1	-153.9
variable cost equation	**1**	-97.7	-123.6	-68.5	-160.4

Table 5.5: Values of the Bayesian Information Criterion.

by their geometric means. However, the investment variable was not normalized and, therefore, the parameter estimates are not exactly estimates of variable-cost elasticities at the geometric mean of the data for the output and capital variables. Instead, the variable-cost elasticities with respect to these two variables evaluated at the geometric mean of w_L, y, and K are given by the formulas:

$$\frac{\partial \log C_{it}}{\partial \log y_{it}} = \beta_y + \gamma_y I_{it}^2 \tag{5.5a}$$

$$\frac{\partial \log C_{it}}{\partial \log K_{it}} = \beta_K + \gamma_K I_{it}^2 \tag{5.5b}$$

and they vary by observation. But, given that all γ_xs are less than one and that the sample mean of I^2 is 0.015, the second term in these expressions is on average very small.

The variable-cost elasticity with respect to the price of labor evaluated at the geometric mean of the data is 0.1435. As implied by Shephard's Lemma, this number is close to the average share of labor in variable cost. The variable-cost elasticity evaluated at the sample mean of the data for I^2 using (5.5a) is 0.98, indicating that the production technology is characterized by almost constant returns to scale in the short run. The elasticity with respect to capital is -0.0179. As expected, *ceteris paribus*, availability of more capital input reduces variable cost.

The γ_I parameter defines the shape of the adjustment cost function at the geometric of w_L, y and K. Using specific data points we obtain estimates of the adjustment costs for each observation. Figure 5.2 presents a histogram of the predicted adjustment costs for the observations for which the predicted value is greater than unity[11].

[11]Since the specification of the adjustment cost function is flexible, the predicted adjustment cost can turn out negative. This happens for 65 observations in the sample.

Parameter	Coeff.	Std. Error	p-value	Factor Loading[1]	Coeff.	Std. Error	p-value[2]
β_w	0.1435	0.0247	0.0000	θ_{12}	-1.0291	0.0200	0.1449
β_y	0.9841	0.0143	0.0000	θ_{13}	-1.1427	0.0188	0.0000
β_K	-0.0180	0.0053	0.0008	θ_{14}	-1.2381	0.0223	0.0000
β_{ww}	0.0147	0.0038	0.0001	θ_{15}	-1.3517	0.0264	0.0000
β_{wy}	-0.0204	0.0062	0.0010	θ_{16}	-1.1927	0.0211	0.0000
β_{wK}	0.0190	0.0035	0.0000	θ_{17}	-0.9877	0.0079	0.1199
β_{yy}	-0.0715	0.0066	0.0000	θ_{22}	-0.9072	0.0204	0.0000
β_{yK}	0.0065	0.0027	0.0166	θ_{23}	-0.9067	0.0168	0.0000
β_{KK}	-0.0011	0.0015	0.4699	θ_{24}	-0.8990	0.0159	0.0000
γ_I	0.1016	0.0115	0.0000	θ_{25}	-0.8603	0.0152	0.0000
γ_y	-0.0510	0.0048	0.0000	θ_{26}	-0.9291	0.0162	0.0000
γ_K	0.0055	0.0046	0.2339	θ_{27}	-0.9845	0.0102	0.1290
				θ_{32}	-0.9234	0.0235	0.0011
				θ_{33}	-1.0786	0.0247	0.0014
				θ_{34}	-1.0128	0.0191	0.5008
				θ_{35}	-0.9661	0.0197	0.0853
				θ_{36}	-0.9615	0.0197	0.0509

[1] The first subscript indicates a factor in the first, second, or third estimated equation. The second subscript indicates time.

[2] These p-values are for testing the hypothesis $H_0 : \theta_{\ell t} = -1$.

Table 5.6: Parameter Estimates of the Model.

For the majority of the observations the level of gross investment is close to zero. The corresponding adjustment costs are again very small and, therefore, the value of the adjustment cost function, which has a multiplicative effect on variable cost, is close to unity.

5.4.4 Efficiency Scores

The model identifies three types of possible inefficiency effects and each one of those is related to the estimated time-varying individual effects. Two of these sets of individual effects provide information about the efficiency scores in absolute terms in the sense that they do not correct for the size of the firm. Different normalizations are used here to provide estimates of the efficiency scores that are meaningful in relative terms.

For the short-run efficiency associated with the variable cost equation we can derive a measure that is consistent with the definition of cost efficiency (Definition 2.8). Following Ahn et al. (2007), the firm- and time-specific estimate of short-run efficiency

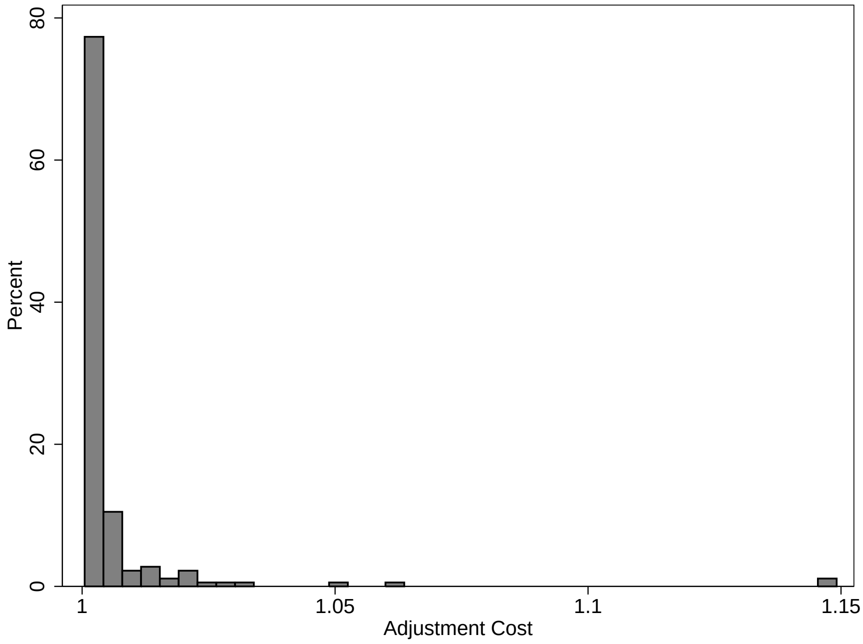

Fig. 5.2: Histogram of the Predicted Adjustment Costs.

is defined as:

$$\hat{\text{CE}}_{it} = \exp\left\{-\left(\hat{\mu}_{1,it} - \hat{\delta}_t\right)\right\} \tag{5.6}$$

where $\hat{\delta}_t = \min_i \hat{\mu}_{1,it}$ is a time-varying intercept. This measure assumes values in the interval $(0, 1]$ and can be interpreted as the percentage to which a firm's variable cost could be shrunk while still being able to produce the observed amount of output. This is a Corrected Least Squares type of measure that will force one firm in each period to be perfectly efficient.

Table 5.7 presents the estimated intercept along with the mean of the individual effects and variable-cost efficiency per year. It appears that the average variable-cost efficiency is rather low, ranging between 50 and 60%. However, this is something to be expected as the calculation of the efficiency scores forces any unobserved heterogeneity in the data to appear as inefficiency[12].

Year	Average $\hat{\mu}_{1,t}$	$\hat{\delta}_t$	Average Variable-Cost Efficiency
1984	0.4242	-0.1718	0.5632
1985	0.4711	-0.1907	0.5299
1986	0.5104	-0.2066	0.5037
1987	0.5572	-0.2256	0.4744
1988	0.4917	-0.1991	0.5160
1989	0.4072	-0.1648	0.5759
1990	0.4122	-0.1669	0.5720

Table 5.7: Individual Effects, Intercept, and Variable-Cost Efficiency per Year.

Allocative efficiency is measured in the cost-share equation for labor. Shephard's lemma implies that, in the absence of allocative inefficiency, the share of labor expenses in variable cost should be equal to the derivative of the log variable cost function with respect to labor. In the estimated model firms are allowed to be allocatively inefficient since the implied constant term in the cost-share equation (β_w) was replaced by $\mu_{2,it}$. Therefore, the difference $\hat{\beta}_w - \hat{\mu}_{2,it}$ captures the discrepancy between optimal and observed share of labor expenses in variable cost. In order to get a relative measure of allocative efficiency, the observed labor cost share is divided by the predicted optimal cost share:

$$S^*_{L,it} = \hat{\beta}_w + 2\hat{\beta}_{ww} \log w_{it} + \hat{\beta}_{wy} \log y_{it} + \hat{\beta}_{wK} \log y_{it} \tag{5.7}$$

With this measure of allocative efficiency $S_L/S^*_L > 1$ implies overuse and $S_L/S^*_L < 1$ underuse of labor compared to materials.

Table 5.8 presents the means of the individual effects from the labor cost-share equation and the implied average efficiency scores per year. As it appears from the results, the food-manufacturing industry in Mexico has been under-employing labor

[12]Other studies that report similar or moderately higher estimates of efficiency scores include Taylor et al. (1997) for the Mexican banking industry, and Choi et al. (2006) for U.S. agricultural banks.

compared to use of materials for the period under consideration. This effect, however, becomes weaker during the last years for which data are available.

Year	Average $\hat{\mu}_{2,t}$	Average Cost-Share Efficiency
1984	0.1056	0.7048
1985	0.1055	0.7361
1986	0.1046	0.7154
1987	0.1001	0.6950
1988	0.1081	0.7431
1989	0.1146	0.8055
1990	0.1164	0.8342

Table 5.8: Individual Effects and Cost-Share Efficiency per Year.

Finally, inefficiency with respect to investment is measured from the Euler equations. The estimated individual effects provide information about dynamic efficiency. Their unit of measurement is millions of pesos per unit of capital and are independent of firm size. By subtracting the effects from the rental price of capital we can obtain the implied rental price of capital that would rationalize the observed behavior.

Table 5.9 presents the sample mean of the individual effects in the Euler equations and the average implied rental price of capital. The positive sign of the sample mean of $\hat{\mu}_{3,it}$ indicates that, on average, the firms in the food-manufacturing industry in Mexico are over-investing during the period covered by the data. The effect appears to be larger in the years between 1985-87 and in 1989-90. The first period comes after the 1985 earthquake that struck Mexico City and overinvestment could be attributed in part to replacement of damaged installations. The shift in the investment behavior of the industry in the late 1980's is associated with the stabilization of the economic environment during that period in Mexico. As it appears from Table 5.3, the inflation and interest rates where extremely erratic during the period 1984-88.

An interpretation of the findings regarding the implied rental price of capital can be given from a finance perspective. According to the arbitrage pricing theory (Ross 1976), the expected return of a risky asset depends on the risk-free interest rate and

Year	Average $\hat{\mu}_{3,t}$	Implied Rental Price of Capital
1984-85	0.0877	0.0423
1985-86	0.1024	0.0276
1986-87	0.0962	0.0338
1987-88	0.0918	0.0382
1988-89	0.0913	0.0387
1989-90	0.0950	0.0350

Table 5.9: Individual Effects and Dynamic Efficiency per Year.

the premia on economy-wide factors (inflation rate, GDP, etc.). In general, the food-processing industry is expected to be less exposed to the uncertainty associated with these factors. The arbitrage pricing theory would imply that more capital is likely to flow to firms in this industry and, therefore, lower the cost of borrowing. In such an uncertain environment as the one considered in this application, the low implied price of capital is not a very extreme outcome.

The results on the efficiency score estimates should be interpreted in the context of the dataset used, taking into account its weaknesses. As the efficient variable-cost frontier is defined by a small sub-group of firms in the sample, errors of measurement in the relative quantities in this sub-group will have a large effect on the estimated efficiency scores. Additionally, given that any unobserved heterogeneity present in the data is eventually treated as inefficiency, it is not surprising that the average efficiency scores are so low.

Considering allocative efficiency, the underuse of labor compared to materials could be stemming from a delayed reaction from the firm's manager side to the faster growing prices of materials as opposed to the price of labor. Any improper estimate of how these relative prices move, implicit in the price indices used for the normalization of the data, will have an effect in the estimated allocative efficiency scores.

When moving to the dynamic efficiency measurement, the issue is a little different. The model presented here explicitly recognizes the inability to get a precise firm-specific measure of the rental price of capital. On one hand, the quality of the data plays an important role for the estimation of the model parameters and, eventually, for the implied price of capital. But on the other, the estimate of the price that rationalizes the observed behavior is free from any measurement error in the actual price of capital, as the actual price is absorbed in the firm- and time-varying effects in the Euler equations.

5.5 Conclusions and Further Remarks

In this chapter, a structural model for dynamic efficiency measurement is estimated using a panel of food-manufacturing plants from Mexico. The data cover a period of great economic instability in the country, with high and very volatile inflation and interest rates. In such an economic environment uncertainty is expected to reduce efficiency.

Three types of possible inefficiency were identified and estimated: (i) variable-cost inefficiency, (ii) allocative inefficiency with respect to labor and materials inputs, and (iii) dynamic inefficiency with respect to capital input. The results suggest that firms in the industry are on average about 53% efficient with respect to variable input use. Under-employment of labor is observed during the period of economic instability, but allocative efficiency improved as the economic environment started stabilizing. With respect to capital input, the industry is found to be overinvesting on average. The price of capital that would rationalize the observer behavior is about 3.6%; a value that does not even cover depreciation.

These findings suggest that the industry is going through a transition. Overinvestment could come as a reaction to the need for better technologies that would improve variable-cost efficiency. The very low implied price of capital supports this argument by showing that the industry is over-capitalizing during the period under consideration. Two possible explanations exist. One is related to the anticipation of NAFTA, with firms in Mexico overinvesting in preparation for the change in the economic conditions; a change that will bring new opportunities and new potential competitors. The second possible explanation is that the firms' managers are expecting the real interest rate to go up[13]. Such an expectation could justify overinvestment in the period covered by the data.

In general, the trends in the estimated efficiency scores show an improvement of the industry on average in terms of variable-cost and allocative efficiency. In the years covered by the data, the food-processing industry improved its competitiveness before the formulation the North American free trade area. With respect to capital input, no clear trend is apparent. The over-capitalization of the industry, however, could explain why food products originating from Mexico started flowing through the borders to the new US market after the NAFTA. In fact, this over-capitalization itself could be in part due to the anticipation from the firms' managers of the emergence of new market opportunities.

[13]In fact, after the relative stabilization of the economy in the late 1980s the real interest rate settled at about 7-9%

Chapter 6

Summary and Conclusions

6.1 Overview

The vast literature on efficiency measurement departs from neoclassical microeconomic theory by relaxing one basic assumption; namely, that firms are perfect decision-making units. The producers are still assumed to behave according to some rules, seeking to optimize an objective. The degree to which the optimum of the assumed objective is achieved is the main focus of this literature.

It becomes apparent that the efficiency scores that come from such a procedure will depend heavily on modeling assumptions. First, unless the assumed objective coincides with the true objective of the producers, the estimated efficiency scores would reflect the degree of optimality of decisions with respect to the researcher's opinion on how producers should behave. Entering the realm of normative economics, assuming a different objective than the true behavior could be justified on the grounds that this approach could form a valid way to asses the capability of a firm to survive in a competitive environment. But in such a case one should be cautious in interpreting the resulting efficiency scores, since they can no longer be used as indicators of managerial ability. Second, and more importantly, the restrictions under which firms operate should be modeled accurately. It would be erroneous to claim that a manager fails to optimize when in fact the observed data are generated from a process that involves restrictions in the action set that are ignored by the researcher.

In this dissertation a specific viewpoint is adopted in modeling the firm's decision problem. Special attention is given to the dynamic nature of the decision-making process at the firm level. Recognizing that it is costly to adjust some factors of production, the quasi-fixity of these inputs is used as a restriction in the action set of the firm. Naturally, the long-run objective of the firm is assumed to extend over many periods.

Considering behavioral assumptions, intertemporal cost minimization is adopted as a weaker assumption than profit maximization.

Data availability is identified as the major limitation for modeling inefficiency in a dynamic context in a way that is a direct extention of static efficiency measurement techniques. In a dynamic framework, the optimality of decisions has to be assessed with respect to the long-run objective of the firm. But, in order to evaluate the objective function, one needs to use data on the relevant variables that go far in the future or, alternatively, be willing to assume that these variables will follow specific paths beyond the point for which data are available. Clearly an approach that does not require explicit calculation of the objective function is necessary.

Two models are developed and estimated here that deal with the issue of data availability indirectly. The first one is based on a complete structural model of firm behavior. This model's implications for the evolution of the short-run efficiency scores are derived and incorporated in a typical stochastic frontier model. Only the reduced-form model is then estimated. Projections of the prevailing efficiency scores in the long-run are then available using only a finite amount of data.

The second model developed here is truly structural, in the sense that the estimated parameters are those that appear in the model itself. For this model, instead of assessing the optimality of decisions in the objective function, efficiency score estimates are derived from the implied Euler equations. This approach is consistent with a flow notion of dynamic efficiency, according to which sub-optimality is assessed at the level it occurs, i.e. in the short run. It postulates that in every period t for which data are available, it is irrelevant how efficiency evolved prior to t. What is important is the state the firm finds itself in and whether the manager makes optimal decisions conditional on that state. This notion of efficiency provides more information about when and possibly why a sub-optimal decision is made. Optimality, however, is defined with respect to the long-run objective of the firm.

Both models developed here account for uncertainty about future economic conditions. The reduced-form model does so implicitly by recognizing that inefficiency could persist if a firm's manager decides to wait before reorganizing the production process until the state of the world is revealed. In the structural model firm managers are assumed to form rational expectations. Dynamic efficiency scores are thus not inflated by the inherent uncertainty in the economic environment, as they would under an assumption of perfect foresight.

6.2 Summary of Empirical Findings

6.2.1 Reduced-Form Model

The reduced-form model is applied to two panels of dairy farms from Germany and the Netherlands. Two separate output distance functions in cow's milk and other output are specified to capture the multi-output nature of production in dairy farming. The parameter estimates, however, indicate that the production technology is very similar between the two countries.

In terms of efficiency scores, dairy farms in the Netherlands are found to be more efficient than in Germany, with average efficiency scores at 83% and 79%, respectively. In both cases inefficiency is highly persistant with 96% and 99% of the inefficiency to efficiency ratio being transfered for the Netherlands and Germany, respectively, from one period to the next. For the Netherlands the stochastic process that describes the evolution of this ratio is very close to being divergent, leading to estimated average long-run efficiency scores that approach unity. In contrast, the Germany results suggest that the stochastic process is most likely stationary and the average efficiency score that is expected to prevail in the long run is virtually the same as the one estimated for the period covered by the data.

6.2.2 Structural Model

The structural model is applied to a panel of food-processing plants from Mexico. The data used cover a period of great economic instability in the country. The assumption of rational expectations over perfect foresight is crucial in this environment.

Three types of possible inefficiency where identified and estimated: (i) variable-cost inefficiency, (ii) allocative inefficiency with respect to variable inputs, and (iii) dynamic inefficiency with respect to capital input. Firms in the food-processing industry are found to be largely inefficient on average with respect to variable input use, with the average estimated efficiency scores ranging between 47% and 58% in the years covered by the data. On the other hand, allocative efficiency is much larger and improving over time. An underuse of labor relative to material input is observed, especially during the period when the economic environment was very unstable. With respect to capital input, the industry appears to be over-investing on average, with the firms behaving as if the rental price of capital is about 3.6%. This price is too low to even cover depreciation.

6.3 Suggestions for Further Research

This dissertation contributes to the efficiency literature by developing parametric models for dynamic efficiency measurement. During the model development process certain restrictions were identified and dealt in ways that were considered appropriate. The solutions suggested here do not exhaust the set of approaches one could consider. Several extentions and modifications are worth exploring.

Considering the reduced-form model, different transformations of technical efficiency and different distributional assumptions could be used to test the hypothesis of persistent inefficiency. Departing from a state-space formulation of the autocorrelated inefficiency model, the estimation could be based on Bayesian methods. Of particular interest would be a comparison of the approach Tsionas (2006) uses, of integrating-out technical efficiency from the likelihood in one step, as opposed to the one proposed here, that consists of sequential integration.

Concerning the structural model, strong assumptions on the values of relevant variables that go beyond the available data are avoided by measuring dynamic efficiency in the Euler equations. But the derivation of the Euler equations requires smoothness of the adjustment cost function around zero investment levels. This is a rather strong restriction given that the point of zero investment is particularly interesting. Many observations appear to be clustered around this point and the decision to wait before investing in an unstable economic environment is directly related to this clustering. A different approach needs to be used if one wants to allow for a more flexible specification of the adjustment cost function.

A useful tool for achieving this flexibility is agent-based modeling. With this approach many behavioral assumptions could be relaxed even further, as the agents can be modeled as having different objectives from one another. Furthermore, the decision to invest and how much to invest could be modeled in two different steps, dealing in this way with the observations that report zero investment.

Another direction could be taken as well. The model developed by Cooper and Haltiwanger (2006) could serve as the basis upon one could build models with flexible adjustment costs, accounting for discontinuity of the adjustment cost function and irreversibility of investment decisions. The possibility of inefficiency with respect to dynamic factors could be included in the form of industry-wide parameters. Whether their model can accommodate cost-minimizing behavior (instead of profit maximizing) with richer specifications is also worth exploring.

If something can be derived from this dissertation is that dynamic models of firm behavior that allow for inefficiency can be estimated using available statistical techniques. These techniques require a lot of computing power, but are within the limits of modern computers.

Appendix A

Results of the Reduced-Form Model

Table A.1

	Germany			**The Netherlands**		
log_other	Coef.	Std. Error	p-value	Coef.	Std. Error	p-value
log_milk	0.8265	0.0020	0.000	0.9013	0.0041	0.0000
log_mm	0.0543	0.0006	0.000	0.0328	0.0038	0.0000
log_K	-0.0539	0.0036	0.000	-0.0591	0.0058	0.0000
log_L	-0.0590	0.0071	0.000	-0.0645	0.0084	0.0000
log_A	-0.0168	0.0069	0.014	-0.1559	0.0111	0.0000
log_M	-0.2193	0.0060	0.000	-0.1640	0.0088	0.0000
log_S	-0.5029	0.0089	0.000	-0.4295	0.0147	0.0000
log_F	-0.1682	0.0032	0.000	-0.2156	0.0078	0.0000
log_KK	-0.0128	0.0019	0.000	0.0000	0.0049	0.9981
log_KL	0.0119	0.0095	0.210	-0.0178	0.0161	0.2691
log_KA	0.0418	0.0092	0.000	-0.0441	0.0200	0.0273
log_KM	0.0198	0.0072	0.006	0.0368	0.0152	0.0153
log_KS	0.0006	0.0100	0.956	0.0213	0.0260	0.4122
log_KF	-0.0057	0.0028	0.042	0.0190	0.0122	0.1174
log_LL	-0.0062	0.0127	0.627	-0.0389	0.0135	0.0040
log_LA	0.0015	0.0193	0.937	-0.0146	0.0325	0.6532
log_LM	-0.0180	0.0170	0.289	-0.1154	0.0279	0.0000
log_LS	0.0368	0.0253	0.145	0.0384	0.0437	0.3789
log_LF	0.0100	0.0080	0.211	0.1142	0.0231	0.0000
log_AA	0.0825	0.0133	0.000	0.0322	0.0235	0.1697
log_AM	-0.2035	0.0167	0.000	0.0796	0.0341	0.0195
log_AS	0.0125	0.0246	0.611	-0.2069	0.0574	0.0003
log_AF	0.0238	0.0060	0.000	0.1275	0.0294	0.0000
log_MM	0.0516	0.0096	0.000	0.0121	0.0188	0.5219
log_MS	-0.0998	0.0210	0.000	0.0013	0.0442	0.9774
log_MF	0.0536	0.0049	0.000	-0.0307	0.0216	0.1538
log_SS	0.0864	0.0204	0.000	0.1557	0.0444	0.0005
log_SF	-0.0230	0.0078	0.003	-0.1535	0.0417	0.0002
log_FF	-0.0272	0.0009	0.000	-0.0021	0.0109	0.8464
log_Km	-0.0001	0.0015	0.934	-0.0083	0.0070	0.2392
log_Lm	0.0187	0.0038	0.000	-0.0039	0.0127	0.7623
log_Am	-0.0406	0.0028	0.000	0.0099	0.0145	0.4938

continued on next page

Table A.1 – continued from previous page

	Germany			The Netherlands		
log_other	Coef.	Std. Error	p-value	Coef.	Std. Error	p-value
log_Mm	0.0118	0.0022	0.000	0.0198	0.0128	0.1207
log_Sm	0.0021	0.0045	0.635	0.0087	0.0214	0.6851
log_Fm	0.0014	0.0009	0.144	-0.0042	0.0100	0.6759
trend	-0.0115	0.0008	0.000	-0.0125	0.0011	0.0000
trend2	-0.0049	0.0016	0.002	0.0075	0.0022	0.0007
milkt	0.0014	0.0003	0.000	0.0001	0.0015	0.9234
Kt	-0.0063	0.0009	0.000	0.0020	0.0019	0.2860
Lt	-0.0049	0.0020	0.016	0.0078	0.0029	0.0071
At	0.0030	0.0020	0.136	0.0106	0.0038	0.0048
Mt	0.0025	0.0019	0.191	-0.0010	0.0029	0.7326
St	0.0087	0.0026	0.001	-0.0099	0.0049	0.0431
Ft	-0.0019	0.0008	0.016	-0.0009	0.0024	0.7183
zero_milk	-0.2744	0.1000	0.006			
east_t	-0.0037	0.0024	0.129			
North	0.0524	0.0069	0.000			
West	-0.0201	0.0062	0.001			
east_t	0.0136	0.0100	0.175			
cons	-0.3517	0.0054	0.000	-0.2226	0.0047	0.0000
σ_v	0.0849	0.0011	0.000	0.0615	0.0014	0.0000
σ_w	0.2801	0.0063	0.000	0.2776	0.0104	0.0000
δ	-0.0524	0.0122	0.000	-0.0733	0.0301	0.0147
ρ	0.9574	0.0101	0.000	0.9876	0.0214	0.0000
μ_1	-1.4114	0.0316	0.000	-1.7096	0.0516	0.0000
σ^2_{w1}	0.5784	0.0362	0.000	0.5787	0.0643	0.0000

Table A.1: Estimates of the Output Distance Function Parameters

Appendix B

Complete Set of Results for the Structural Model

		zero factors in the Euler equations		**one factor in the Euler equations**	
		# of factors in the cost-share equation			
		0	**1**	**0**	**1**
				r=0.01	
# of factors in the variable cost equation	**0**	0.0000	0.0000	0.0000	0.0000
	1	0.0000	0.0008	0.0000	0.3989
				r=0.05	
	0	0.0000	0.0000	0.0000	0.0000
	1	0.0000	0.0003	0.0000	0.4349
				r=0.07	
	0	0.0000	0.0000	0.0000	0.0000
	1	0.0000	0.0004	0.0000	0.4523
				r=0.10	
	0	0.0000	0.0000	0.0000	0.0000
	1	0.0000	0.0005	0.0000	0.4759

Table B.1: p-values for the Sargan Test of Overidentifying Restrictions for Discount Factors Corresponding to Interest Rates Equal to 1%, 5%, 7%, and 10%.

	r=0.01			r=0.05		
	Coeff.	Std. Error	p-value[1]	Coeff.	Std. Error	p-value[1]
β_w	0.1080	0.0224	0.0000	0.1435	0.0247	0.0000
β_y	0.9946	0.0144	0.0000	0.9841	0.0143	0.0000
β_K	-0.0218	0.0049	0.0000	-0.0180	0.0053	0.0008
β_{ww}	0.0136	0.0037	0.0002	0.0147	0.0038	0.0001
β_{wy}	-0.0254	0.0062	0.0000	-0.0204	0.0062	0.0010
β_{wK}	0.0233	0.0031	0.0000	0.0190	0.0035	0.0000
β_{yy}	-0.0594	0.0063	0.0000	-0.0715	0.0066	0.0000
β_{yK}	0.0036	0.0026	0.1726	0.0065	0.0027	0.0166
β_{KK}	-0.0030	0.0014	0.0335	-0.0011	0.0015	0.4699
γ_I	0.0897	0.0126	0.0000	0.1016	0.0115	0.0000
γ_y	-0.0554	0.0045	0.0000	-0.0510	0.0048	0.0000
γ_K	0.0190	0.0048	0.0001	0.0055	0.0046	0.2339
θ_{12}	-1.0281	0.0191	0.1399	-1.0291	0.0200	0.1449
θ_{13}	-1.1484	0.0202	0.0000	-1.1427	0.0188	0.0000
θ_{14}	-1.2461	0.0232	0.0000	-1.2381	0.0223	0.0000
θ_{15}	-1.3639	0.0278	0.0000	-1.3517	0.0264	0.0000
θ_{16}	-1.1914	0.0211	0.0000	-1.1927	0.0211	0.0000
θ_{17}	-0.9732	0.0092	0.0037	-0.9877	0.0079	0.1199
θ_{22}	-0.8986	0.0196	0.0000	-0.9072	0.0204	0.0000
θ_{23}	-0.8881	0.0162	0.0000	-0.9067	0.0168	0.0000
θ_{24}	-0.8832	0.0153	0.0000	-0.8990	0.0159	0.0000
θ_{25}	-0.8479	0.0148	0.0000	-0.8603	0.0152	0.0000
θ_{26}	-0.9167	0.0157	0.0000	-0.9291	0.0162	0.0000
θ_{27}	-0.9861	0.0097	0.1528	-0.9845	0.0102	0.1290
θ_{32}	-0.8746	0.0367	0.0006	-0.9234	0.0235	0.0011
θ_{33}	-1.1676	0.0415	0.0001	-1.0786	0.0247	0.0014
θ_{34}	-1.0405	0.0326	0.2146	-1.0128	0.0191	0.5008
θ_{35}	-0.9446	0.0338	0.1011	-0.9661	0.0197	0.0853
θ_{36}	-0.9170	0.0353	0.0187	-0.9615	0.0197	0.0509

[1] The p-values for the factor loadings are for testing the hypothesis $H_0 : \theta_{\ell t} = -1$.

Table B.2: Estimates of the Structural Model Parameters for Discount Factors Corresponding to Interest Rates Equal to 1% and 5%.

	r=0.07			r=0.10		
	Coeff.	Std. Error	p-value[1]	Coeff.	Std. Error	p-value[1]
β_w	0.1441	0.0249	0.0000	0.1415	0.0250	0.0000
β_y	0.9842	0.0142	0.0000	0.9845	0.0141	0.0000
β_K	-0.0176	0.0057	0.0021	-0.0165	0.0062	0.0075
β_{ww}	0.0147	0.0038	0.0001	0.0145	0.0037	0.0001
β_{wy}	-0.0198	0.0062	0.0013	-0.0199	0.0061	0.0011
β_{wK}	0.0183	0.0037	0.0000	0.0178	0.0038	0.0000
β_{yy}	-0.0730	0.0066	0.0000	-0.0734	0.0067	0.0000
β_{yK}	0.0081	0.0029	0.0056	0.0094	0.0032	0.0036
β_{KK}	-0.0004	0.0016	0.7923	0.0005	0.0017	0.7884
γ_I	0.1084	0.0114	0.0000	0.1149	0.0114	0.0000
γ_y	-0.0523	0.0049	0.0000	-0.0528	0.0050	0.0000
γ_K	0.0029	0.0048	0.5489	-0.0006	0.0050	0.9036
θ_{12}	-1.0254	0.0201	0.2053	-1.0197	0.0202	0.3292
θ_{13}	-1.1422	0.0187	0.0000	-1.1422	0.0188	0.0000
θ_{14}	-1.2354	0.0223	0.0000	-1.2324	0.0225	0.0000
θ_{15}	-1.3499	0.0265	0.0000	-1.3490	0.0270	0.0000
θ_{16}	-1.1896	0.0212	0.0000	-1.1863	0.0216	0.0000
θ_{17}	-0.9836	0.0078	0.0369	-0.9776	0.0078	0.0041
θ_{22}	-0.9064	0.0204	0.0000	-0.9045	0.0204	0.0000
θ_{23}	-0.9073	0.0168	0.0000	-0.9062	0.0168	0.0000
θ_{24}	-0.8997	0.0160	0.0000	-0.8986	0.0159	0.0000
θ_{25}	-0.8606	0.0153	0.0000	-0.8598	0.0153	0.0000
θ_{26}	-0.9292	0.0162	0.0000	-0.9279	0.0162	0.0000
θ_{27}	-0.9838	0.0103	0.1161	-0.9830	0.0103	0.0997
θ_{32}	-0.9301	0.0209	0.0008	-0.9403	0.0176	0.0007
θ_{33}	-1.0580	0.0215	0.0070	-1.0397	0.0176	0.0245
θ_{34}	-1.0061	0.0168	0.7169	-1.0011	0.0140	0.9397
θ_{35}	-0.9664	0.0174	0.0529	-0.9700	0.0146	0.0400
θ_{36}	-0.9675	0.0168	0.0538	-0.9745	0.0136	0.0607

[1] The p-values for the factor loadings are for testing the hypothesis $H_0 : \theta_{\ell t} = -1$.

Table B.3: Estimates of the Structural Model Parameters for Discount Factors Corresponding to Interest Rates Equal to 7% and 10%.

Year	Average $\hat{\mu}_{1,t}$	$\hat{\delta}_t$	Average Variable-Cost Efficiency	Average $\hat{\mu}_{1,t}$	$\hat{\delta}_t$	Average Variable-Cost Efficiency
		r=0.01			**r=0.05**	
1984	0.4131	-0.1603	0.5748	0.4242	-0.1718	0.5632
1985	0.4614	-0.1791	0.5401	0.4711	-0.1907	0.5299
1986	0.5006	-0.1943	0.5136	0.5104	-0.2066	0.5037
1987	0.5480	-0.2127	0.4837	0.5572	-0.2256	0.4744
1988	0.4786	-0.1858	0.5283	0.4917	-0.1991	0.5160
1989	0.3910	-0.1518	0.5915	0.4072	-0.1648	0.5759
1990	0.4018	-0.1560	0.5833	0.4122	-0.1669	0.5720
		r=0.07			**r=0.10**	
1984	0.4224	-0.1715	0.5643	0.4181	-0.1696	0.5675
1985	0.4705	-0.1910	0.5301	0.4683	-0.1900	0.5316
1986	0.5088	-0.2066	0.5045	0.5053	-0.2050	0.5069
1987	0.5560	-0.2258	0.4749	0.5531	-0.2244	0.4768
1988	0.4900	-0.1990	0.5169	0.4864	-0.1974	0.5193
1989	0.4052	-0.1645	0.5771	0.4008	-0.1626	0.5805
1990	0.4119	-0.1672	0.5721	0.4100	-0.1664	0.5735

Table B.4: Estimates of Variable-Cost Efficiency for Discount Factors Corresponding to Interest Rates Equal to 1%, 5%, 7%, and 10%.

Year	Average $\hat{\mu}_{2,t}$	Average Cost-Share Efficiency	Average $\hat{\mu}_{2,t}$	Average Cost-Share Efficiency
	r=0.01		**r=0.05**	
1984	0.1057	0.9508	0.1056	0.7048
1985	0.1044	0.9827	0.1055	0.7361
1986	0.1038	0.9579	0.1046	0.7154
1987	0.0997	0.9348	0.1001	0.6950
1988	0.1078	1.0031	0.1081	0.7431
1989	0.1159	1.0943	0.1146	0.8055
1990	0.1176	1.1274	0.1164	0.8342
	r=0.07		**r=0.10**	
1984	0.1055	0.7016	0.1054	0.7137
1985	0.1056	0.7329	0.1056	0.7455
1986	0.1047	0.7123	0.1047	0.7244
1987	0.1002	0.6918	0.1002	0.7036
1988	0.1081	0.7395	0.1081	0.7520
1989	0.1145	0.8013	0.1145	0.8150
1990	0.1164	0.8301	0.1165	0.8444

Table B.5: Estimates of Allocative Efficiency for Discount Factors Corresponding to Interest Rates Equal to 1%, 5%, 7%, and 10%.

Year	Average $\hat{\mu}_{3,t}$	Implied Rental Price of Capital	Average $\hat{\mu}_{3,t}$	Implied Rental Price of Capital
	r=0.01		**r=0.05**	
1984-85	0.0466	0.0434	0.0877	0.0423
1985-86	0.0622	0.0278	0.1024	0.0276
1986-87	0.0554	0.0346	0.0962	0.0338
1987-88	0.0503	0.0397	0.0918	0.0382
1988-89	0.0488	0.0412	0.0913	0.0387
1989-90	0.0532	0.0368	0.0950	0.0350
	r=0.07		**r=0.10**	
1984-85	0.1062	0.0438	0.1349	0.0451
1985-86	0.1208	0.0292	0.1491	0.0309
1986-87	0.1148	0.0352	0.1436	0.0364
1987-88	0.1103	0.0397	0.1391	0.0409
1988-89	0.1104	0.0396	0.1398	0.0402
1989-90	0.1141	0.0359	0.1435	0.0365

Table B.6: Estimates of Dynamic Efficiency for Discount Factors Corresponding to Interest Rates Equal to 1%, 5%, 7%, and 10%.

Bibliography

Afriat, S. N. (1972). Efficiency estimation of production functions. *International Economic Review*, 13(3):568–598.

Ahn, S. C., Good, D. H., and Sickles, R. C. (2000). Estimation of long-run inefficiency levels: A dynamic frontier approach. *Econometric Reviews*, 19(4):461–492.

Ahn, S. C., Lee, Y. H., and Schmidt, P. (2006). Panel data models with multiple time-varying individual effects. Working Papers 0702, University of Crete, Department of Economics.

Ahn, S. C., Lee, Y. H., and Schmidt, P. (2007). Stochastic frontier models with multiple time-varying individual effects. *Journal of Productivity Analysis*, 27(1):1–12.

Aigner, D., Lovell, C. A. K., and Schmidt, P. (1977). Formulation and estimation of stochastic frontier production functions. *Journal of Econometrics*, 6(1):21–37.

Alvarez, A., Amsler, C., Orea, L., and Schmidt, P. (2006). Interpreting and testing the scaling property in models where inefficiency depends on firm characteristics. *Journal of Productivity Analysis*, 25(3):201–212.

Atkinson, S. E. and Cornwell, C. (1994). Parametric estimation of technical and allocative inefficiency with panel data. *International Economic Review*, 35(1):231–243.

Atkinson, S. E. and Halvorsen, R. (1980). A test of relative and absolute price efficiency in regulated utilities. *The Review of Economics and Statistics*, 62(1):81–88.

Banker, R. D. (1993). Maximum likelihood, consistency and data envelopment analysis: A statistical foundation. *Management Science*, 39(10):1265–1273.

Banker, R. D., Charnes, A., and Cooper, W. W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management Science*, 30(9):1078–1092.

Banker, R. D. and Maindiratta, A. (1988). Nonparametric analysis of technical and allocative efficiencies in production. *Econometrica*, 56(6):1315–1332.

Battese, G. E. (1997). A note on the estimation of Cobb-Douglas production function when some explanatory variables have zero values. *Journal of Agricultural Economics*, 48(1-3):250–252.

Battese, G. E. and Coelli, T. J. (1988). Prediction of firm level technical efficiencies with a generalized frontier production function and panel data. *Journal of Econometrics*, 38(3):387–399.

Battese, G. E. and Coelli, T. J. (1992). Frontier production functions, technical efficiency and panel data: With application to paddy farmers in India. *Journal of Productivity Analysis*, 3(1-2):153–169.

Battese, G. E. and Coelli, T. J. (1995). A model for technical inefficiency effects in a stochastic frontier production function for panel data. *Empirical Economics*, 20(2):325–332.

Brown, F. and Domínguez, L. (1994). The dynamics of productivity performance in mexican manufacturing, 1984-1990. *The Developing Economies*, 32(3):279–298.

Byrnes, P., Färe, R., Grosskopf, S., and Lovell, C. A. K. (1988). The effect of unions on productivity: U.S. surface mining of coal. *Management Science*, 34(9):1037–1053.

Charnes, A., Cooper, W. W., and Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research*, 2(6):429–444.

Chavas, J.-P. (1994). Production and investment decisions under sunk cost and temporal uncertainty. *American Journal of Agricultural Economics*, 76(1):114–127.

Choi, O., Stefanou, S. E., and Stokes, J. R. (2006). The dynamics of efficiency improving input allocation. *Journal of Productivity Analysis*, 25(1-2):159–171.

Christensen, L. R. and Greene, W. H. (1976). Economies of scale in U.S. electric power generation. *The Journal of Political Economy*, 84(4):655–676.

Cooper, R. W. and Haltiwanger, J. C. (2006). On the nature of capital adjustment costs. *The Review of Economic Studies*, 73(3):611.

Cooper, W. W., Park, K. S., and Pastor, J. T. (1999). RAM: A range adjusted measure of inefficiency for use with additive models, and relations to other models and measures in DEA. *Journal of Productivity Analysis*, 11(1):5–42.

Cornwell, C., Schmidt, P., and Sickles, R. C. (1990). Production frontiers with cross-sectional and time-series variation in efficiency levels. *Journal of Econometrics*, 46(1-2):185–200.

Debreu, G. (1951). The coefficient of resource utilization. *Econometrica*, 19(3):273–292.

Deprins, D. and Simar, L. (1989). Estimating technical inefficiencies with corrections for environmental conditions with an application to railway companies. *Annals of Public and Cooperative Economics*, 60(1):81–102.

Eisner, R. and Strotz, R. H. (1963). The determinants of business investment. In Eisner, R. and Strotz, R. H., editors, *Impacts of Monetary Policy*, Engelwood Cliffs, New Jersey. Prentice-Hall.

Epstein, L. G. (1981). Duality theory and functional forms for dynamic factor demands. *The Review of Economic Studies*, 48(1):81–95.

Epstein, L. G. and Denny, M. G. S. (1983). The multivariate flexible accelerator model: Its empirical restrictions and an application to U.S. manufacturing. *Econometrica*, 51(3):647–674.

Färe, R. and Grosskopf, S. (1990). A distance function approach to price efficiency. *Journal of Public Economics*, 43(1):123–126.

Färe, R., Grosskopf, S., and Lovell, C. A. K. (1985). *The measurement of efficiency of production*. Kluwer-Nijhoff Publishing, Hingham, Massachusetts.

Farrell, M. J. (1957). The measurement of productive efficiency. *Journal of the Royal Statistical Society*, Series **A** 120(3):253–281.

Ferrier, G. D. and Lovell, C. A. K. (1990). Measuring cost efficiency in banking: Econometric and linear programming evidence. *Journal of Econometrics*, 46(1-2):229–245.

Gardebroek, C. and Oude Lansink, A. (2004). Farm-specific adjustment costs in Dutch pig farming. *Journal of Agricultural Economics*, 55(1):3–24.

Gould, J. P. (1968). Adjustment costs in the theory of investment of the firm. *The Review of Economic Studies*, 35(1):47–55.

Greene, W. H. (1980). On the estimation of a flexible frontier production model. *Journal of Econometrics*, 13(1):101–115.

Greene, W. H. (1990). A gamma distributed stochastic frontier model. *Journal of Econometrics*, 46(1):141–164.

Hahn, J. and Hausman, J. (2004). Notes on bias in estimators for simultaneous equations models. *Economics Letters*, 75(2):237–241.

Hansen, L. P. (1982). Large sample properties of generalized method of moments estimators. *Econometrica*, 50(4):1029–1054.

Hansen, L. P. and Sargent, T. J. (1980). Formulating and estimating dynamic linear rational expectations models. *Journal of Economic Dynamics and Control*, 2(1):7–46.

Heiss, F. (2008). Sequential numerical integration in nonlinear state space models for microeconometric panel data. *Journal of Applied Econometrics*, Forthcoming.

Hsiao, C. (1986). *Analysis of Panel Data*. Cambridge University Press, Cambridge.

Jondrow, J., Lovell, C. A. K., Materov, S. I., and Schmidt, P. (1982). On the estimation of technical inefficiency in the stochastic frontier production function model. *Journal of Econometrics*, 19(2-3):223–238.

Kalirajan, K. (1981). An econometric analysis of yield variability in paddy production. *Canadian Journal of Agricultural Economics*, 29(3):283–294.

Kalman, R. E. (1960). A new approach to linear filtering and prediction problems. *Transactions of the ASME-Journal of Basic Engineering*, 82(D):35–45.

Koopmans, T. C. (1951). Analysis of production as an efficient combination of activities. In Koopmans, T. C., editor, *Activity analysis of production and allocation*, New York. Wiley.

Kumbhakar, S. C. (1990). Production frontiers, panel data, and time-varying technical inefficiency. *Journal of Econometrics*, 46(1-2):201–211.

Kumbhakar, S. C. (1997). Modeling allocative inefficiency in a translog cost function and cost share equations: An exact relationship. *Journal of Econometrics*, 76(1-2):351–356.

Kumbhakar, S. C., Ghosh, S., and McGuckin, J. T. (1991). A generalized production frontier approach for estimating determinants of inefficiency in U.S. dairy farms. *Journal of Business & Economic Statistics*, 9(3):279–286.

Kumbhakar, S. C. and Tsionas, E. G. (2005). Measuring technical and allocative inefficiency in the translog cost system: A Bayesian approach. *Journal of Econometrics*, 126(2):355–384.

Lasserre, P. and Ouellette, P. (1999). Dynamic factor demands and technology measurement under arbitrary expectations. *Journal of Productivity analysis*, 11(3):219–241.

Lau, L. J. and Yotopoulos, P. A. (1971). A test for relative efficiency and application to Indian agriculture. *The American Economic Review*, 61(1):94–109.

Lee, Y. H. and Schmidt, P. (1993). A production frontier model with flexible temporal variation in technical efficiency. In Fried, H. O., Lovell, C. A. K., and Schmidt, S., editors, *The measurement of productive efficiency: Techniques and applications.*, Oxford, New York. Oxford University Press.

Letterie, W. A., Pfann, G. A., and Polder, J. M. (2004). Factor adjustment spikes and interrelation: An empirical investigation. *Economics Letters*, 85(2):145–150.

Löthgren, M. (1998). A dynamic conditionally heteroscedastic stochastic frontier model. Working Paper 226. Department of Economic Statistics, Stockholm School of Economics.

Lovell, C. A. K. (1993). Production frontiers and productive efficiency. In Fried, H. O., Lovell, C. A. K., and Schmidt, S., editors, *The measurement of productive efficiency: Techniques and applications.*, Oxford, New York. Oxford University Press.

Lucas, R. E. (1967). Adjustment costs and the theory of supply. *The Journal of Political Economy*, 75(4):312–334.

Lucas, R. E. (1976). Econometric policy evaluation: A critique. *Carnegie-Rochester Conference Series on Public Policy*, 1:19–46.

Luh, Y.-H. and Stefanou, S. E. (1996). Estimating dynamic dual models under nonstatic expectations. *American Journal of Agricultural Economics*, 78(3):991–1003.

McLaren, K. R. and Cooper, R. J. (1980). Intertemporal duality: Application to the theory of the firm. *Econometrica*, 48(7):1755–1762.

Meeusen, W. and van den Broeck, J. (1977). Efficiency estimation from Cobb-Douglas production functions with composed error. *International Economic Review*, 18(2):435–444.

Naveau, P., Genton, M. G., and Shen, X. (2005). A skewed Kalman filter. *Journal of Multivariate Analysis*, 94(2):328–400.

Nemoto, J. and Goto, M. (1999). Dynamic data envelopment analysis: Modeling intertemporal behavior of a firm in the presence of productive inefficiencies. *Economics Letters*, 64(1):51–56.

Nemoto, J. and Goto, M. (2003). Measurement of dynamic efficiency in production: An application of data envelopment analysis to Japanese electric utilities. *Journal of Productivity Analysis*, 19(2-3):191–210.

Ouellette, P., Petit, P., and Vigeant, S. (2005). Investment and regulation: The case of Canadian air carriers. *Transportation Research Part E: Logistics and Transportation Review*, 41(2):93–113.

Ouellette, P. and Vigeant, S. (2001). Cost and production duality: The case of the regulated firm. *Journal of Productivity analysis*, 16(3):203–224.

Ouellette, P. and Vigeant, S. (2003). Technological choices and regulation: The case of the Canadian manufacturing sectors. *Canadian Journal of Economics*, 36(1):88–125.

Pietola, K. and Myers, R. J. (2000). Investment under uncertainty and dynamic adjustment in the Finnish pork industry. *American Journal of Agricultural Economics*, 82(4):956–967.

Pindyck, R. S. and Rotemberg, J. J. (1983a). Dynamic factor demands and the effects of energy price shocks. *The American Economic Review*, 73(5):1066–1079.

Pindyck, R. S. and Rotemberg, J. J. (1983b). Dynamic factor demands under rational expectations. *The Scandinavian Journal of Economics*, 85(2):223–238.

Pitt, M. M. and Lee, L. F. (1981). The measurement and sources of technical inefficiency in the Indonesian weaving industry. *Journal of Development Economics*, 9(1):43–64.

Power, L. (1998). The missing link: Technology, investment and productivity. *The Review of Economics and Statistics*, 80(2):300–313.

Reifschneider, D. and Stevenson, R. (1991). Systematic departures form the frontier: A framework for the analysis of firm inefficiency. *International Economic Review*, 32(3):715–723.

Richmond, J. (1974). Estimating the efficiency of production. *International Economic Review*, 15(2):515–521.

Rodrigez-Álvarez, A., Fernádez-Blanco, V., and Lovell, C. A. K. (2004). Allocative inefficiency and its cost: The case of Spanish public hospitals. *International Journal of Production Economics*, 92(2):99–111.

Ross, S. (1976). The arbitrage theory of capital asset pricing. *Journal of Economic Theory*, 13(3):341–360.

Rungsuriyawiboon, S. and Stefanou, S. E. (2007). Dynamic efficiency estimation: An application to U.S. electric utilities. *Journal of Business & Economic Statistics*, 25(2):226–238.

Schmidt, P. (1984). An error structure for systems of translog cost and share equations. Working Paper 8309. Department of Economics, Michigan State University.

Schmidt, P. and Lovell, C. A. K. (1979). Estimating technical and allocative inefficiency relative to production and cost frontiers. *Journal of Econometrics*, 9(3):343–366.

Schmidt, P. and Sickles, R. C. (1984). Production frontier and panel data. *Journal of Business & Economic Statistics*, 2(4):367–374.

Silva, E. and Stefanou, S. E. (2003). Nonparametric dynamic production analysis and the theory of cost. *Journal of Productivity Analysis*, 19(1):5–32.

Silva, E. and Stefanou, S. E. (2007). Dynamic efficiency measurement: Theory and application. *American Journal of Agricultural Economics*, 89(2):398–419.

Simar, L. and Wilson, P. W. (1998). Sensitivity analysis of efficiency scores: How to bootstrap in nonparametric frontier models. *Management Science*, 44(3):49–61.

Simar, L. and Wilson, P. W. (2000). Statistical inference in nonparametric frontier models: The state of the art. *Journal of Productivity Analysis*, 13(1):49–78.

Simar, L. and Wilson, P. W. (2007). Estimation and inference in two-stage, semi-parametric models of production processes. *Journal of Econometrics*, 136(1):31–64.

Stefanou, S. E. (2009). A dynamic characterization of efficiency. *Agricultural Economics Review*, Forthcoming.

Stefanou, S. E. and Saxena, S. (1988). Education, experience, and allocative efficiency: A dual approach. *American Journal of Agricultural Economics*, 70(2):338–345.

Stevenson, R. E. (1980). Likelihood functions for generalized stochastic frontier estimation. *Journal of Econometrics*, 13(1):57–66.

Stigler, G. J. (1976). The Xistence of X-efficiency. *The American Economic Review*, 66(1):213–216.

Tanizaki, H. (1999). Nonlinear and nonnormal filter using importance sampling: Antithetic Monte Carlo integration. *Communications in Statistics - Simulation and Computation*, 28(2):463–486.

Tanizaki, H. and Mariano, R. S. (1994). Prediction, filtering and smoothing in non-linear and non-normal cases using Monte Carlo integration. *Journal of Applied Econometrics*, 9(2):163–179.

Tanizaki, H. and Mariano, R. S. (1998). Nonlinear and non-Gaussian state-space modeling with Monte Carlo simulation. *Journal of Econometrics*, 83(1-2):263–290.

Taylor, W. M., Thompson, R. G., Thrall, R. M., and Dharmapala, P. S. (1997). DEA/AR efficiency and profitability of Mexican banks a total income model. *European Journal of Operational Research*, 98(2):346–363.

Toda, Y. (1976). Estimation of a cost function when the cost is not minimum: The case of Soviet manufacturing industries, 1958-1971. *The Review of Economics and Statistics*, 58(3):259–268.

Treadway, A. B. (1969). On rational entrepreneurial behaviour and the demand for investment. *The Review of Economic Studies*, 36(2):227–239.

Treadway, A. B. (1970). Adjustment costs and variable inputs in the theory of the competitive firm. *The Review of Economic Studies*, 2(4):329–347.

Tsionas, E. G. (2006). Inference in dynamic stochastic frontier models. *Journal of Applied Econometrics*, 21(5):669–676.

Tybout, J. R. and Westbrook, M. D. (2000). Trade liberalization and the dimensions of efficiency change in Mexican manufacturing industries. *Journal of International Economics*, 39(1-2):53–78.

Wan, E. A., van der Merwe, R., and Nelson, A. T. (2000). Dual estimation and the unscented transformation. In Solla, S., Leen, T., and Muller, K. R., editors, *Advances in Neural Information Processing Systems*, volume 12, pages 666–672. MIT Press.

Winsten, C. B. (1957). Discussion on Mr. Farrell's paper. *Journal of the Royal Statistical Society*, Series **A** 120(3):282–284.

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