A PRODUCTION MODEL TO MEASURE TECHNICAL EFFICIENCY IN THE REFRIGERATED WAREHOUSE INDUSTRY

A Thesis

by

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Submitted to the Office of Graduate and Professional Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

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August 2015

Major Subject: Agricultural Economics

ABSTRACT

Warehouses are a vital link in the global supply chain, and play a critical role in inventory flow by providing points of storage and coordination. While much work has been done on individual parts of the warehousing process, only a handful of studies have analyzed the technical efficiency of the warehouse as a whole. As a subset of this industry, refrigerated warehouses provide a much needed role in the distribution of agricultural, food, and pharmaceutical products. As such, they have unique parameters that set them apart from other warehousing operations. There has been little formal analysis on refrigerated warehousing. Here, a production model for refrigerated warehouses is reported, and firm-specific technical efficiency estimates obtained through stochastic frontier analysis are provided. In addition, factors affecting efficiency were identified. This study found the mean efficiency estimated for the refrigerated warehouse industry in 2012 was 0.72. Additionally, the number of inventory turns was found to correlate with increased efficiency while order error percentage and occupancy of warehouse space were correlated with inefficiency.

DEDICATION

To Marissa, Phoebe, and Colton—for your undying support and unquestionable love.

ACKNOWLEDGEMENTS

First of all, I would like to thank my committee chair, Dr. Salin, for her guidance, patience, and help in completing this project. I would also like to thank my committee members, Dr. Capps, Dr. Leatham, and Dr. Johnson for their help and feedback in completing my thesis.

Next, a special thanks to the IARW for providing the data used to conduct this research.

I want to acknowledge the faculty and staff in the Agricultural Economics Department—especially Dr. Leatham, Dr. Peacock, and Brandi Blankenship—for the help that they have provided along the way.

I also acknowledge my wife and children for their unwavering support while accomplishing this degree. Finally, I want to thank Uncle David, for planting this idea in my head in the first place.

NOMENCLATURE

DEA	Data Envelopment Analysis
IARW	International Association of Refrigerated Warehouses
MLE	Maximum likelihood estimation
SFA	Stochastic Frontier Analysis
SKU	Stock Keeping Unit

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CHAPTER I

INTRODUCTION

Warehouses are a vital link in the global supply chain; however, it is only recently that assessing warehouse performance has been addressed in the literature (Johnson and McGinnis, 2011). As a subset of the warehouse industry, refrigerated warehouses provide a much needed role in the distribution of agricultural, food, and pharmaceutical products. As such, they have unique parameters that set them apart from other warehousing operations. There is very little formal analysis on refrigerated warehousing and its specific production technology.

The purpose of this project is to assess the production frontier of the refrigerated warehousing industry and provide both industry mean and firm specific technical efficiency estimates. In addition, performance attributes that correlate with greater technical efficiency are identified, and the relationship to overall production efficiency is measured. As a result, warehouse managers will have information to assist in implementing changes to improve their overall efficiency and utility.

Justification

It is estimated that, globally, only 10% of perishable foodstuffs are properly refrigerated, and that gaps in refrigeration may account for much of the 30% post-harvest loss of total production (Coulomb, 2008). This problem comes against the backdrop of world population growth and the increasing concern and attention toward climate change and the energy required to maintain an efficient and effective cold supply chain (James and James, 2010). It is in this context that increasing refrigerated warehousing efficiency must be viewed. Although warehousing is only a component of the global supply chain, it is a key component. Warehouses play a critical role in inventory flow control and buffer stock management, and switching points for efficient transportation (Kuglin and Hood, 2009). With the growth of the global supply chain and the introduction of lean manufacturing and just-in-time production, warehouses are expected to increase efficiency. An increase in efficiency at this important control point can increase the overall efficiency of the supply chain. Estimating technical efficiency and identifying factors that contribute to efficiency will lead to greater understanding of refrigerated warehouses and will help identify best practices. Implementation of best practices can lead to increased efficiency. Increased efficiency not only benefits warehouses, but contributes to the overall efficiency of the global cold supply chain.

Thesis Organization

This thesis begins in Chapter II by presenting a brief background of warehousing and the refrigerated warehousing industry, followed by a literature review on efficiency measurement in warehousing. Chapter III presents the theory behind efficiency measurement and develops the stochastic frontier analysis model that is employed in this study. In Chapter IV, the data will be presented, and the specific methods employed in the study will be reported, including the specification of the production function and the stochastic model employed in the analysis. The results and discussion of the research findings are presented in Chapter V. The summary and concluding comments are contained in Chapter VI.

CHAPTER II

BACKGROUND AND LITERATURE REVIEW

This chapter begins by providing background information on warehousing, its place in the supply chain, and the different functions warehouses fulfill. It also outlines basic strategies employed to fulfill different warehouse functions. This section concludes by outlining the contrast between refrigerated warehousing and conventional warehousing. Following the presentation of warehouse background information, a literature review is presented that gives a very brief history of applied production economics and a more thorough review of measurement of efficiency in the warehousing industry.

Background

Warehousing is an indispensable part of the supply chain. The supply chain can be described as all the steps, resources, and operations involved in the process starting with procurement of raw materials to the delivery of final goods and services to the customer. Warehouses have traditionally been a place for the storage of goods; from the raw materials and work-in-process, to finished goods awaiting delivery to customers. Warehousing was viewed as having little or no added value, and was often considered an unwanted, but necessary cost-center (Manzini, 2012).

With the growth of the global market place, and subsequently the global supply chain, as well as improved managerial paradigms, such as just-in-time and lean production, warehousing has changed and adapted, and is now viewed as a vital hub in the supply chain. Warehouses still perform an essential storage role, but they have also become service and information centers. The roles of warehouses include: (1) raw material and component storage; (2) work-in-process storage; (3) finished goods storage; (4) distribution centers; (5) fulfillment centers; (6) local warehouses; and (7) value added service providers (Frazelle, 2002). A warehouse may have only one dedicated role, or may carry out many roles, concurrently. The number of roles depends on the specific warehouse design, location, and intended function.

The warehouse storage role, for finished goods, is vital in the supply chain because it acts as a buffer against variability in material flows resulting from seasonality and batching in production and transportation (Gu, et al., 2007). Distribution centers consolidate products from one or several firms, and combine them for shipments to common customers. Fulfillment centers function like distribution centers, but receive, consolidate, and ship small orders for individual customers. Local warehouses are widely distributed in the effort to reduce transportation distance and response time, and commonly ship single items to individual customers. Warehouses also have become centers of value-added services such as packaging, pricing, labeling, product customization, and returns processing.

The cross-docking strategy also utilizes warehouses. With cross-docking warehouses function as product coordination points (Simchi-Levi, et al., 2008). Cross-docking involves receiving goods from the manufacturer that are consolidated and shipped without the need for storage. Most products involved in cross-docking remain in the warehouse for less than 24 hours. Although employed in the 1980s, most notably by Wal-Mart, cross-docking has only recently grown in use. Cross-docking applies well to products that have a stable demand rate (e.g. grocery and perishable food items). To be effective, cross-docking requires a high degree of coordinated information between warehouses, retailers, and suppliers; a responsive transportation system; and a large distribution network with a large fleet of vehicles that are simultaneously present at the same facilities (Simchi-Levi, et al., 2008).

All warehouses handle product. How warehouses handle product varies by role. However, there are several functions common to warehouses in general. These functions can be classified into four general processes; receiving, storage, order picking, and shipping. Each process will be briefly described below.

The receiving process includes all of the activities associated with the arrival of product to the warehouse and its subsequent preparation for storage or shipment. The specific activities associated with receiving vary according to the nature of the product. For example, product may be inspected to insure correct quantity and quality are being delivered. In addition, some repackaging and reassembling may occur to increase efficiency of downstream processes. Product storage may also considered part of the receiving process. These steps are skipped when product is intended to be transshipped as part of a cross-docking strategy.

Storage may be categorized into two parts: a reserve area and a forward area. The reserve area is for bulk storage. Product may include pallet stacks or employ a system of pallet racks. The forward area is where product is stored for efficient removal by an order picker. Here, products are usually stored in smaller, more easily manageable amounts. The transfer of goods from the reserve area to the forward area is referred to as replenishment.

Order picking is the process of retrieving product from its storage location to fulfill customer orders. In general, product is received in full pallet quantities. These pallets are made up several cases, and each case will contain a specific number of SKUs. Product may be picked in pallet quantities, or broken down into full-case, or broken-case amounts (i.e. individual SKUs). Orders may contain many different items, thus individual items must be picked and consolidated before shipment. Picking strategies include pick to order, batch picking, zone picking, and wave picking.

The pick to order strategy involves the picker taking one order and retrieving items line-by-line from their storage location. This strategy requires the least amount of product handling; however, it may take the most time depending on order-items and warehouse design. Pick to order is the most frequently employed picking method.

Batch picking occurs when multiple orders are batched together to be picked simultaneously. Pickers may fill batched orders by going to the storage location to retrieve items. After picking these batches are sorted into their respective individual orders. Another variation of batch picking occurs when bulk items are brought to the sorting area where pickers fill individual orders. This batch picking method is often referred to as pick by line. The advantage of bulk picking is that it allows more lines to be picked per hour. In addition, accuracy may improve due to multiple people reviewing an order. However, bulk picking requires more handling and thus is more labor intensive.

Zone picking divides the storage/picking area into zones and assigns the picker to one or more specific zones. The picker only picks items from his/her assigned zones. When all lines from one order are picked in a zone the order is handed off to the next zone, until the order is completed. Zone picking has obvious similarities to production on an assembly line. Zone picking reduces travel and offers increased speed over the pick to order method. Generally, this method is most effective in operations with a large number of SKUs, a large number of orders, and low picks per order. In addition, it is an appropriate strategy for warehouses with different storage areas for products such as pharmaceuticals, hazardous items, and perishables (Richards, 2011).

Wave picking is when all zones are picked at once and then sorted. Orders are released at specific times, and are usually coordinated with scheduled events such as vehicle departures and shift changes. As with batch picking and zone picking, wave picking reduces travel and time, however sorting the picked items to complete individual orders requires extra labor and/or equipment.

The refrigerated warehouse presents a unique application of the principles stated above. The refrigerated warehouse fulfills many roles, such as production warehouse and distribution warehouse. In addition, many are involved with cross-docking activities and many offer value added services, such as blast freezing. While sharing many of the features of the conventional warehouse, refrigerated warehouses have several unique requirements. Facility costs are typically higher for refrigerated warehouses. It has been estimated that a freezer warehouse will typically cost two to three times as much as a conventional warehouse, and that energy costs are as much as five times greater per square foot (Ackerman, 1997).

In addition to higher energy costs, refrigerated warehouses require specialized equipment designed to withstand the low temperatures. Specialized equipment includes heavy duty batteries, enclosed lift trucks with heated contact points, and insulated clothing for workers. Another issue faced by refrigerated warehouses is the need for constant monitoring of temperature. As the majority of product handled is perishable, product expiration and spoilage must be monitored (Richards, 2011).

The warehouse is a system of many different processes that can be categorized into receiving, storage, order picking, and shipping. Analyzing the warehouse operation as a whole can be challenges because of the variety of technologies and operational procedures involved. The following section presents studies that have assessed production efficiency and how these apply to the evaluation of warehousing.

Literature Review

The study of warehouse technical efficiency falls within the interdisciplinary space between economics, engineering, food science, biotechnology, information technology, and supply chain management. However, its core is firmly rooted in applied production economics. The foundational principles of production economics can easily be found in most microeconomics texts. A brief survey of the history of applied production economics is given and the recent work that has been done in the field of warehousing technical efficiency is highlighted.

Agricultural economists did much of the early work in production economics. Henry Moore pioneered using statistical techniques in economic analysis. Around this same time, Tolley, Black, and Ezekiel (1924) developed tools to help agricultural producers make production decisions. These techniques were the first attempts to isolate technology that would allow application of the marginal productivity principle (Chambers, 1988). A short time later, Cobb and Douglas (1928) published their seminal paper and production functions became common in the economic literature. The next milestone in production economics came with the development of advanced methods for solving mathematical programming problems.

The theoretical work in production efficiency began in the 1950s. Koopmans (1951) provided a definition of technical efficiency. Debreu (1951) and Shephard (1953) independently introduced distance functions, a useful way to model multiple-input and multiple-output technologies. The work of Koopmans and Debreu was built upon by Farrell (1957) who defined cost efficiency, decomposing it into its allocative and technical components. This early work in production efficiency influenced the work of Charnes, Cooper, and Rhodes (1978) who developed the non-parametric method of data envelopment analysis (DEA). Farrell's work also influenced several others, including Aigner and Chu (1968), Afriat (1972), and Richmond (1974). These authors each presented a variation of deterministic production frontier estimation. Stochastic frontier estimation was proposed independently by Meeusen and van den Broeck (1977) and Aigner, et al. (1977). Both stochastic frontier analysis (SFA) and DEA are frequently used to address question of technical efficiency. While DEA has been used to characterize warehouse efficiency, SFA has yet to be utilized in this capacity.

Despite the importance of warehousing in the overall supply chain, the availability of performance evaluation literature is relatively limited. Of the existing literature, there are two major areas of emphasis. These are: (1) developing a structured framework to analyze warehouse design and operations problems, and (2) directly assessing performance through benchmarking. This section begins with a brief overview of the literature under this first area; a more thorough review of the benchmarking literature follows, as this topic is more relevant to the subject at hand.

Assessing the warehouse as a whole system presents challenges. Any framework built to address warehouse design and operations problems must coordinate and synthesize specific sub-problems (e.g. storage processes, order picking, etc.) into an integrated process. The work done by Rouwenhorst, et al. (2000) is a good example of this. They present a framework by which to analyze warehouse and design problems. This framework consists of three axes along which warehouses can be examined; these are processes, resources, and organization. Processes involve receiving, storage, order picking, and shipping. Warehouse design methods are then evaluated along these lines, and are further broken down at a strategic, tactical, or operational level. This framework allows classification performance evaluation against a set of well-defined criteria.

The framework presented by Rouwenhorst, et al. (2000) is mainly descriptive and does not provide a synthesis of models and/or techniques as a basis for warehouse design decisions. More recent work by Baker and Canessa (2009) sets forth a new framework that does address specific tools and techniques that can be applied to each step of the design process. This conceptual framework was established by an extensive literature review and examining the design steps employed by warehouse design companies. Thus, this framework attempts to synthesize the available models and techniques that are used in warehouse design. Although useful, the framework does not provide a comprehensive warehouse design methodology, as there is still much variability in the steps of the process and the techniques available for use at each step. The authors suggest that such a comprehensive model, if at all possible, is far from being realized.

Other work in this area is represented by Gu, et al. (2007), and Gu, et al. (2010). The first (Gu, et al., 2007) presents a framework to classify the existing research on warehouse operation and planning problems. These problems are classified by the four basic warehouse functions: receiving, storage, order picking, and shipping. The second paper (Gu, et al., 2010) expands this evaluation and classifies the research on warehouse design, performance evaluation, practical case studies and computational support tools. The authors intend that these two papers be considered together as a comprehensive review of the current research and a useful framework for classification.

These four papers represent an area of emphasis in warehouse performance assessment. They address the coordination problems that arise in warehouse design decisions. The work done in this area is largely descriptive and focuses on building frameworks to understand the decision process and options/techniques available at each step.

The second area of emphasis reported in the literature on warehouse performance evaluation is logistics benchmarking. Benchmarking is the practice of identifying best-practices within a company, industry, or across industries, and then applying those practice to improve performance. Benchmarking was popularized by Xerox Corporation in the late 1980s and has been employed by many Fortune 1000 companies to increase quality and productivity of business operations (Foster, 1992). Benchmarking can be applied internally in a company, externally across industries or competitively across the same industry (Frazelle, 2002). A goal of benchmarking studies is to identify top performers, and then identify the key practices or attributes that distinguish the top performers from others.

The work reported by Hackman, et al. (2001) may be the most important in the field of warehouse logistics benchmarking. This represents the first study to employ a production model and frontier analysis to assess overall warehouse production efficiency. Prior to this study, only Stank, Rogers, and Daugherty (1994), and Cohen, Zheng, and Agrawal (1997) report formal studies on warehouse benchmarking.

Stank, Rogers, and Daugherty (1994) conducted a survey of 154 warehousing companies to determine if, and in what areas, external benchmarking is employed. They report that a majority of warehouses did utilize benchmarking in areas of cost, customer service, productivity, quality, and warehouse operations, although specific benchmarking methods were not identified. Whether or not the use of benchmarking was correlated with increased efficiency of warehouse operations was subsequently examined. They reported that there was no correlation between benchmarking and size. However, it was found that firms that conducted benchmarking in the areas of order processing, productivity, transportation operations, and warehousing operations offered a greater variety of services than non-benchmarking counterparts. Additionally, all firms which employed benchmarking relied more heavily on computer applications than firms that did not benchmark.

Cohen, Zheng, and Agrawal (1997) directly evaluated service parts warehouses using a variety of performance metrics. Parts availability, after-sales service revenue, operating cost, inventory investment, and annual inventory turnover were found to be important internal benchmarking metrics. A cost-service analysis was performed by graphing inventory investment against level of service (represented as 24-hour parts fill rate). The authors point to the results as the efficient frontier; however, they do not support the frontier by a formal model or statistical analysis. Although this work addressed the service parts industry as a whole, it fails to provide a consistent model that can be applied to further industry analysis or to warehousing as a whole.

Traditionally, performance in the warehousing and distribution industries has focused on measures such as cost as a percentage of sales, lines or cases handled per person-hour, response time, and shipping accuracy (Forger, 1998, Hackman, et al., 2001). The study presented by Cohen, Zheng, and Agrawal (1997) used metrics that fall within these same lines. These ratio-based performance metrics are popular because they are relatively easy to calculate, use, and understand. While useful in many respects, these metrics fail to capture the warehouse as a single system. In addition, they may represent entities that are either outside the direct control of warehouse managers, or may be interrelated and depend on multiple input factors (de Koster and Balk, 2008, Hackman, et al., 2001).

Hackman, et al. (2001) address these issues by developing a model of a warehouse system based on three specific input factors and five specific output factors. The inputs into the warehouse system are labor, space, and equipment. The outputs are broken-case lines, full-case lines, pallet lines, storage, and accumulation. In developing this model the authors sought to capture the simultaneous interaction of several dimensions in a generally applicable model.

On the input side of the model are labor, space, and equipment. An index was used as a proxy for labor. This index consists of the sum of all labor hours expended in performing the necessary receiving, storing, order picking, and shipping operations. Space was accounted for by the square feet associated with receiving, storage, and shipping operations. The authors noted that it was possible to use cubic feet for this input. However, square footage was used because in warehouses vertical height is not always effectively utilized, especially in dock areas where much of the receiving and shipping operations occur. The third input, equipment, was reported as the investment in storage and material handling equipment. Equipment investment was calculated as the sum of the number of units of each type of equipment weighted by the average of the 1991 replacement cost. Replacement value was used instead of book value to eliminate differences in bookkeeping and depreciation methods. Categories included vehicles, storage systems, and conveyor systems. Rental and depreciation costs for the building were ignored. In addition, the cost of conventional storage systems (racks) was excluded, as this cost was considered insignificant.

The output side of the warehouse model includes movement, storage, and accumulation. The movement output is counted as the number of orders and the number of lines in those orders. The number of lines is further outlined as broken-case lines, full-case lines, and pallet lines and each are considered separately. Accumulation was used to measure the workload used to assemble a complete order from different product lines. Because different products are stored in various locations in the warehouse, the more varied the lines, the more labor and capital are involved to aggregate and ship the order. In contrast to the industry standard average lines per order ratio, this accumulation index was calculated as the difference between the annual lines picked and the annual orders shipped. The storage output was used to capture the storage function of the warehouse, and is intended to measure the cost to store inventory in the warehouse. This index was constructed by assigning floor space to each item handled, and then weighting the average of the square root of the broken case, pallet rack, and floor storage square footage estimations. The weights were determined by the frequency of visits made to each location.

Based on this model, efficiency was estimated using data envelopment analysis (DEA). Data for Hackman's analysis were collected between 1992 and 1996 for 57 warehouses. Warehouses included service parts, electronics assembly, health care, photographic supplies, and food items. The majority of this sample was composed of finished goods consolidation facilities that ship to the final customer. The remaining warehouses in the sample were distribution centers which collect, store, and re-ship product from manufactures to smaller warehouse facilities serving local markets.

Using DEA, an efficiency score was estimated for each warehouse. The mean efficiency for the sample was calculated as 0.70. This efficiency score was then evaluated against variables that captured warehouse design and operations decisions. In this analysis they sought to answer the following questions: (1) Do larger warehouses perform more efficiently? (2) Do capital intensive warehouses perform more efficiently? and (3) Do non-union facilities outperform their union counterparts? Based on this analysis Hackman, et al. (2001) concluded that smaller, less capital intensive warehouses are more efficient. Unionization appeared to have a neutral to slightly positive effect on efficiency.

More recent work by de Koster and Warffemius (2005) reports an international comparison of Asian, American, and European Distribution Centers (EDCs). EDCs are defined as European warehouses that have the majority of inbound goods produced in another country and that distribute goods to at least five countries in Europe, the Middle East, and Africa. The study's aims were 3-fold: (1) to determine if Asian EDCs performed better than American EDCs; (2) to determine if management differed between these two groups; and (3) to determine if third party and public warehouses performed better than own-account warehouses.

To address these aims de Koster and Warffemius (2005) collected survey data on 65 warehousing operations. The data collected were evaluated on a variety of performance and operational aspects. Performance aspects included productivity, flexibility, and quality of outbound shipments. Operational aspects included labor, value added activities, and warehouse size, number of SKUs handled, industry sector, automation, and complexity. The sample was divided into subgroups based on the regional origin of the manufacturer, own-account versus outsourced warehouses, and warehouse industry sector. Basic statistical tests were used to ascertain the differences and similarities between subgroups. Based on their analysis, the authors conclude that although some differences in operations exist between American and Asian EDCs, there are no significant differences in productivity and quality levels. In addition, outsourced warehouse operations were found to have better accuracy and flexibility.

The study by (de Koster and Warffemius, 2005) was built on and expanded by de Koster and Balk (2008). The authors were able to update information on 39 of the 65 warehouses surveyed in the previous study. An input-output model was formulated and used to estimate the efficiency and efficiency change using DEA. Both cross-sectional and time-series analyses were conducted to compare efficiency between American, Asian, and European EDCs.

The input-output model differs from that of Hackman, et al. (2001), although there are some similarities as both models include labor and size for inputs. Labor was proxied as number of full-time equivalents (FTEs), and size was measured in square meters. De Koster and Balk did not use an equipment input, but instead chose automation and number of different SKUs, as these correlated better with outputs in their model. Automation was measured on a 5-point ordinal scale: (1) being very low—

meaning minimal automation, such as using a computer—to (5) very high—including WMS, barcoding, automated guided vehicle, miniloaders, sorters, and/or robots. Product mix was reported as number of SKUs handled on average in the facility. An ordinal scale was also employed with the scale ranging from 1 to 8, with (1) being less than 500 and (8) being greater than 100,000 SKUs.

On the output side of the model, five factors were selected. These include, number of daily order lines picked, level of value added logistics (VAL) carried out on a regular basis, the number of special processes carried out to optimize warehouse performance, error-free orders shipped, and order flexibility. Of the above, the first, daily order lines picked, is fairly self-explanatory. VAL activities were reported on using a 3-point ordinal scale, low to high. Examples of low end VAL included adding labels or kit assembly. High end VAL included repair, sterilization, and final product assembly. The next output factor, special processes carried out to optimize warehouse performance, included cross-docking, cycle counting, item repacking, return handling, and quality inspection on inbound products. The rationale given for using this metric was that these processes directly or indirectly contribute to the long term performance and customer service success. The next output factor considered, error-free orders, was measured as a percentage of orders shipped.

The last output factor, order flexibility, may require some explanation. Each respondent was presented with three external and three internal changes and asked if they could cope with these changes worse (0), equal (1), or better (2) than his/her competitors. The sum of each response was then analyzed on a 6-point ordinal scale.

Although a highly subjective measure, the authors report that this output provided meaningful results. This metric had been included in the previous study by de Koster and Warffemius (2005), and the authors report that these responses have a high degree of objectivity. They concluded that due to the open culture and high turnover of managers in the industry, respondents tend to have a fairly accurate view of how they compare to their competitors.

In this warehouse model there are several variables measured on an ordinal, not ratio scale. The authors gave the reasoning that this was to improve the speed and accuracy of responses. Typically, managers do not know exact numbers, such as the size of the warehouse in square meters. However, they do usually know in which category their warehouse falls.

Based on the analysis of the model, mean efficiency for all warehouses was calculated as 0.76. In addition, European warehouses were found to be more efficient in both 2000 and 2004 than both Asian and American warehouses, and outsourced warehouses, especially public warehouses, were more efficient than own-account warehouses. The results of the longitudinal study showed a decline in efficiency of 6%, and a corresponding 3% decline in productivity. This decline in efficiency came at the same time as a 3% increase in technological progress. The authors suggested that this decline may have been the result of economic decline, increased government regulation, and/or a deterioration of the work environment.

Most recently, Johnson and McGinnis (2011) extended the model presented by Hackman, et al. (2001) and tested for the statistical significance of each input and output.

Johnson and McGinnis estimated technical efficiency for a group of 216 warehouses across many industries. DEA was used to solve the linear program and obtain the efficiency estimates. In addition, the technical efficiency estimate was used to identify operational policy, design characteristics, and attributes of a warehouse that correlate with greater efficiency.

To specify the most parsimonious model, Johnson and McGinnis (2011) used the model specification test of Pastor, Ruiz, and Sirvent (2002). In brief, a linear program is solved for the most detailed proposed model. Next, a second linear program is solved with fewer inputs/output. Statistical analysis is then conducted to determine the impact of the data lost. If performance distribution is not statistically significant, then the simplified model is selected.

The initial model proposed by Johnson and McGinnis included labor, space, equipment, and inventory as inputs. For outputs they proposed broken-case lines, full-case lines, pallet lines, returns, storage, accumulation, and value added services. The linear program was solved using the model specification test. Based on the results of their analysis, the proposed model was simplified to contain labor, space, and investment as input and broken-case, full-case, and pallet lines as output. Technical efficiency for the warehouse sample was estimated at 0.66, with 23% operating at 100%.

In addition to the efficiency estimates, Johnson and McGinnis identified several warehouse practices or attributes that correlated with the efficiency estimates. The input-oriented technical efficiency estimation was regressed against several warehouse practices and attributes to identify correlation between these and warehouse efficiency estimates. Seasonality, SKU churn/span, inventory cost and temporary labor were found to be negatively correlated with efficiency. Cross-docking and inventory turns were positively correlated with efficiency.

Despite its importance in the supply chain, relatively few studies that have proposed models to describe the warehouse operation as a whole. A few notable exceptions are studies by Hackman et al. (2001), de Koster and Balk (2008), and Johnson and McGinnis (2009). These studies are summarized in TABLE 2.1.

Table 2.1 Summary of Previous Warehousing Efficiency Studies.

	Hackman	Johnson/McGinnis	de Koster/Balk
Model			
Input Variables			
	Labor	Labor	Labor
	Space	Space	Size
	Equipment	Equipment	Automation
			Number of SKUs
Output			
	Movement	Broken-case lines	Daily order lines picked
	Storage	Full-case lines	Level of value-added logistics
	Accumulation	Pallet lines	Number of Special Processes
			Error-free order percent
			Order Flexibility
Method			
	DEA	DEA	DEA
Mean Efficiency Estimate			
	0.7	0.66	0.76

Each study presents a unique input-output model used to estimate technical efficiency using DEA. These studies represent warehouses and distribution centers from various industries in several countries across the globe. Although these studies have been helpful in describing the warehousing industry as a whole, little work has focused specifically on the refrigerated warehousing industry. In addition, no reported warehouse studies have employed the econometric estimation of a production frontier and corresponding technical efficiency estimates. The present study addresses both of these issues and provides information regarding this industry and the methods used in this analysis.

CHAPTER III

THEORY

The purpose of this study is to develop a production model that effectively characterizes the technical efficiency of the refrigerated warehouse industry. The measurement of efficiency is based on the ability to estimate a production frontier and then specific producer's performance is measured with respect to that frontier. This chapter presents the theory that defines technical efficiency measurement and develops the stochastic frontier model used in this analysis.

Representing Technology with Sets

We assume that a producer uses a nonnegative vector of *N* inputs, denoted $x = (x, \ldots, \mathrm{x}_N) \in R_+^N$, to produce a nonnegative vector of *M* outputs. This output vector is denoted $y = (y, \ldots, y_M) \in R_+^M$. Thus, the technology set, or the collection of all feasible input and output vectors, is defined as

$$T = \{(y, x) : x \text{ can produce } y\} \in R_+^{M+N} \tag{3.1}$$

The production technology in the single-input, single-output case is illustrated in Figure 3.1. The following assumptions are made regarding the technology set:

1) $(0, x) \in T$ and $(y, 0) \in T \Rightarrow y = 0$.
2) It is a closed set.
3) *T* is bounded for each $x \in R_+^N$.

4) $\left(y, x\right) \in T \Rightarrow \left(\lambda y, x\right) \in T$ for $0 \leq \lambda \leq 1$.

5) $\left(y, x\right) \in T \Rightarrow \left(y, \lambda x\right) \in T$ for $\lambda \geq 1$.

6) $\left(y, x\right) \in T \Rightarrow \left(y', x'\right) \in T \;\; \forall \left(y', -x'\right) \leq \left(y, -x\right)$.

7) *T* is a convex set.

The first assumption states that producing nothing from a given set of inputs is possible, and that no output is possible without any input. The second assumption ensures the existence of technically efficient input and output vectors. The third property ensures that finite input cannot produce infinite output. Assumptions four and five are weak monotonicity (weak disposability) properties that ensure both radial contractions and radial expansions are possible. These two assumptions are often replaced by strong disposability property. Any increase of inputs and any decrease in output is not limited to only radial movement. The convexity assumption is not generally required, but if included commodities must be continuously divisible.

The production technology also can be represented using output or input sets. The technology defined by set *T* can be equivalently defined using the output set. For each input vector *x*, *P*(*x*) is defined as the set of feasible outputs. P(*x*) is expressed formally as,

$$P\left(x\right) = \left\{y : x \text{ can produce } y\right\} = \left\{y : \left(y, x\right) \in T\right\} \in R_{+}^{N} \tag{3.2}$$

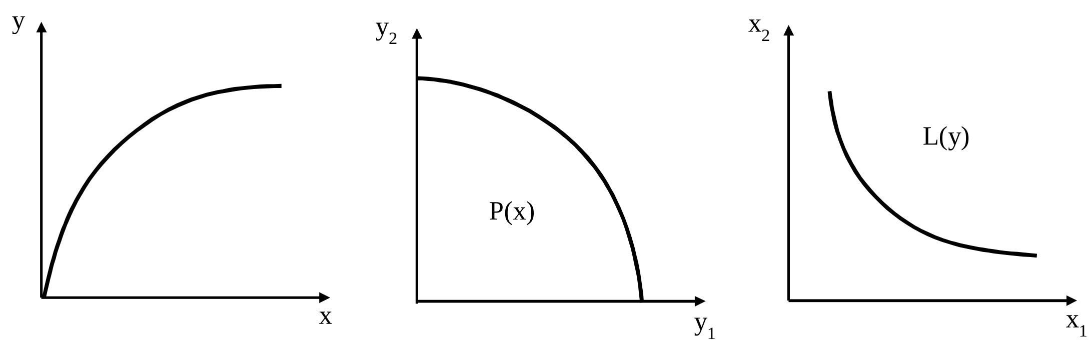
The output sets *P*(*x*) are defined in terms of *T*, and since *T* is assumed to satisfy certain properties, it follows that *P*(*x*) can satisfy corresponding properties. Similar properties as *T* are assumed for P(*x*). The reader is referred to Färe, Grosskopf, and Lovell (1994) or

Kumbhakar and Lovell (2000) for a more thorough presentation of these assumptions. The output set *P*(*x*) is illustrated in Figure 3.1.

A third characterization of the technology can be defined by the input set, *L*(*y*). L(*y*) is represented as,

$$L(y) = \{x : x \text{ can produce } y\} = \{y : (y, x) \in T\} \in R_{+}^{M}. \tag{3.3}$$

This input set consists of all input vectors x that can produce a given output vector, y. As with *P*(*x*), *L*(*y*) is assumed to satisfy similar properties corresponding to *T*. Figure 3.1 represents the input set L(*y*).



(a) Production technology (b) Output Set (M = 2) (c) Input Set (N = 2)

Figure 3.1 Representing Technology with Sets. Based on figures presented in Färe, Grosskopf, and Lovell (1994).

Production Frontiers

The single-output case of the production technology is useful in illustrating a production function. The single-output specification can be used to describe a technology that only produces a single output, or the more likely event that multiple outputs are produced and then aggregated into a single composite output

$y = g\left(y_1, \ldots, y_{M.}\right)$. Definitions 3.2 and 3.3 can be used to obtain the following

definition:

$$f\left(x\right)\max\left\{y : y \in P\left(x\right)\right\} = \max\left\{y : x \in L\left(y\right)\right\}, \tag{3.4}$$

where x is a vector of inputs and y is a scalar quantity. The production frontier $f(x)$ describes the maximum output that can be produced with any given input vector, and as such, describes the upper boundary of the possible output. Producers operate at or below this boundary. The measurement of the distance from the input-output combination of each producer to the production frontier characterizes the central problem in measuring technical efficiency. Two approaches to measuring this distance are distance functions and cost, revenue, and profit frontiers. Distance functions will be presented below.

Before moving on to the discussion of distance functions, it is important to mention the case where multiple-inputs are used to produce multiple-outputs. In this case a joint production frontier, or production possibilities frontier, is used to describe the upper boundary of feasible production. This frontier involves defining the efficient subset of both the input and output vectors in which are at an un-scalable maximum and minimum, respectively. Joint production frontiers are seldom used in empirical analysis because the upper boundary of the production function in the multiple-input and multiple-output case is more easily obtained using distance functions.

Distance Functions

Distance functions are a useful way to describe technology when multiple inputs are used to produce multiple outputs. Introduced independently by Malmquist (1953) and Shephard (1953), distance functions are related to production frontiers and characterize the structure of the production technology. In general, distance functions allow the characterization of a production technology through radial expansions and contractions depending on the input-output orientation. The input distance function looks to characterize the production technology maximize the contracting of the input vector and still remain feasible for the output vector. The output distance function characterizes the maximum proportional expansion of the output vector, given the input vector. Formal definitions of input and output distance functions will be provided below.

An input distance function involves the scaling of the input vector to measure distance from the producer to the boundary of production possibilities. The input distance function can be defined based on the input set $L(y)$ as follows:

$$D_I\left(x, y\right) = \max\left\{\rho : x/\rho \in L\left(y\right)\right\}. \tag{3.5}$$

Since $L(y)$ satisfies certain properties, the input distance function will satisfy a corresponding set of properties. The input distance function is illustrated in Figure 3.2 for two inputs, x_1 and x_2, that are used to produce one output, y. The isoquant line, Iso-L(y), represents the minimum combinations of inputs, x_1 and x_2, feasible to produce the given output vector, and forms the lower bound for the input set, L(y). Point A in Figure 3.2 represents the production point where a firm, firm A, uses x_{1A} and x_{2A} to produce the output vector **y**. The value of the distance function at point A is defined as the ratio ρ = OA/OB.

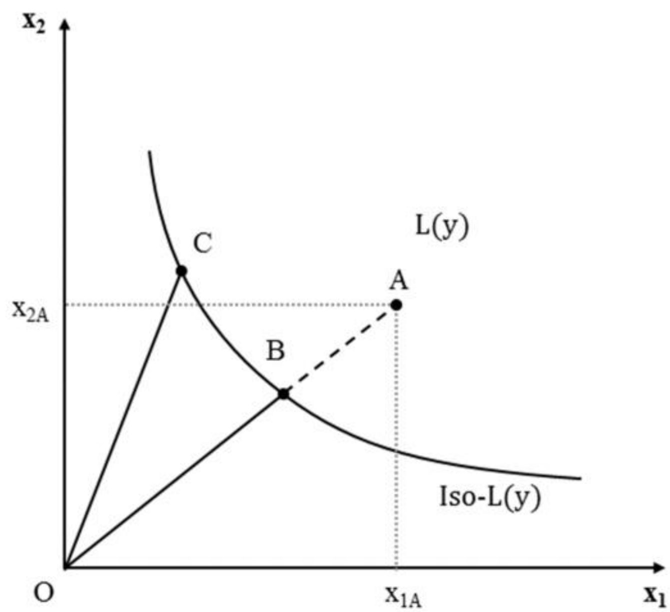


Figure 3.2 Input Distance Function. Adapted from a figure presented in Coelli, et al. (2005).

Conversely, the output distance function is based on the maximal proportional expansion of the output given the input vector. The output distance function can be defined based on the output set P(*x*) as follows:

$$D_0(x, y) = \min\{\delta : y/\delta \in P(x)\}, \tag{3.6}$$

where δ = OA/OB as represented in Figure 3.3. This ratio equals the value of the distance function for firm A, at Point A, where **x** input is used to produce the outputs y_{1A}

and y_{2A}. The production possibility frontier is denoted in Figure 3.3 by PPF-P(x), and represents the upper boundary of feasible production for the technology represented by the set, P(x).

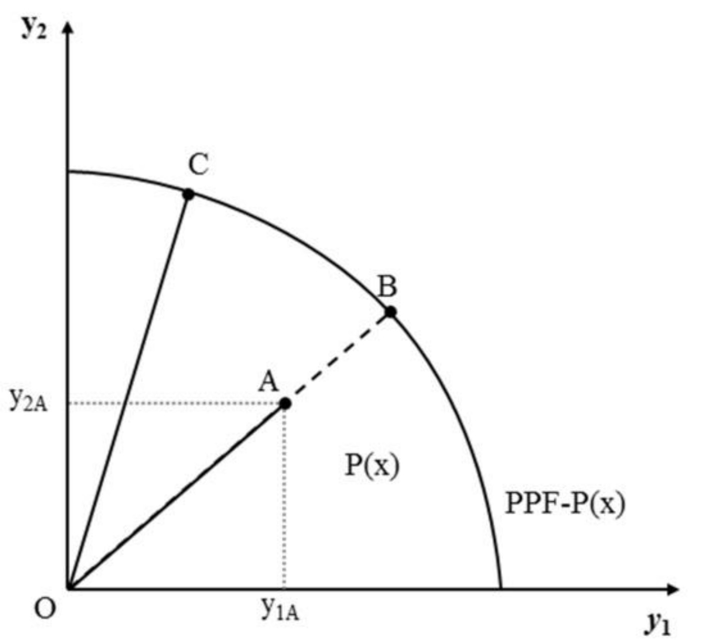


Figure 3.3 Output Distance Function. Adapted from a figure presented in Coelli, et al. (2005).

The use of distance functions has gained popularity in empirical use as it is not necessary to specify a behavioral objective (such as profit-maximization) to describe the technology. In addition, distance functions play a major rule in duality theory. The input distance function is dual to a cost frontier and the output distance function is dual to a revenue frontier.

Technical Efficiency

Koopmans (1951) provided a definition of technical efficiency for a multiple-input and multiple-output case: A producer is technically efficient if an increase in any output is possible only by decreasing at least one other output or increasing at least one input. Conversely, a reduction in any input is possible only by reducing at least one output, or by increasing at least one other input. Based on this definition, a technically inefficient producer could improve efficiency by using less of at least one input to produce the same level of output, or could use the same inputs to produce more of at least one output.

Koopmans' definition of technical efficiency provides a way to differentiate between efficient and inefficient production states. It does not, however, provide a measure of the degree of inefficiency or the tools for comparison between inefficient and efficient vectors. Debreu (1951) presented a radial measure of technical efficiency that addressed these issues. Radial measures are convenient as they focus on the maximum feasible equiproportionate reduction of variable inputs, or the converse maximum feasible expansion of all outputs. Radial measures are also useful as they are independent of a unit of measurement. There is, however, one major drawback to using radial measures of efficiency. Technical efficiency as measured by radial contraction of the input vector or expansion of the output vector may understate the degree of inefficiency present given the technology due to slack in inputs or outputs. In other words, it fails to take into account the reallocation of one input for another. Thus, a producer may be efficient based on Debreu's measure, but can be inefficient based on the definition of Koopmans.

Farrell (1957) expanded on the work of Debreu by proposing that efficiency is made up of two components; technical efficiency and allocative, or price, efficiency. Technical efficiency refers to the producer being able to achieve maximum output from a given set of inputs. Allocative efficiency refers to the producer being able to select the appropriate proportion of inputs based on price of those inputs and the available technology. Note that implicit in the measure of allocative efficiency is a behavioral assumption. Farrell's work uses the assumption of cost minimization in a competitive market. The product of these two efficiency terms gives a measure of overall, or economic, efficiency.

A simple example based on Farrell (1957) illustrates this concept of technical and allocative efficiency in the constant returns to scale case. The input-orientated two input (x_1 and x_2) one output (y) case is illustrated in Figure 3.4. The efficient isoquant is represented by SS'. Point P represents the two inputs per unit of output a given firm is observed to utilize. Point Q represents an efficient firm using the same ratio of inputs as P. Thus, the technical efficiency (TE) of firm P can be measured by the ratio

$$TE = OQ/OP \tag{2.7}$$

where the perfectly efficient firm has the value of one. This allows technical efficiency to be measured on a scale of zero to one, and allows it to be calculated as one minus QP/OP.

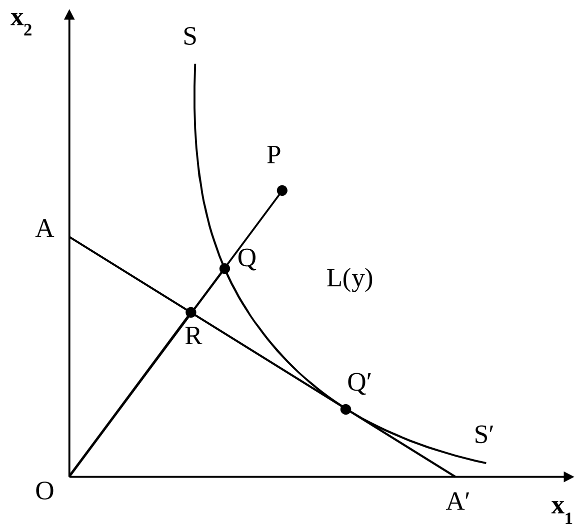


Figure 3.4 Input Oriented Technical and Allocative Efficiency.
Based on Farrell (1957).

If the input price ratio is known, it can be represented by the isocost line *AA′* and allocative efficiency can be calculated. Points *Q* and *Q′* have a technical efficiency of 1. However, the costs of production at *Q′* will be a fraction *OR/OQ* of those at *Q*. Thus, allocative efficiency (*AE*) can be measured by the ratio

$$AE = OR/OQ. \tag{2.8}$$

The distance *RQ* can be interpreted as the cost reduction that occurs when the producer moves to the point of allocative and technical efficiency, *Q′*, from *Q*.

If both technical efficiency and allocative efficiency can be measured, overall cost efficiency, or economic efficiency (EE) can be determined. It is simply the product of technical efficiency and allocative efficiency:

$$EE = TE \cdot AE = (OQ/OP) \cdot (OR/OQ) = (OR/OP). \tag{2.9}$$

As seen above, economic efficiency can also be defined as the ratio of *OR/OP*.

It may also be convenient to measure the technical efficiency of the firm in terms of the input-distance function, $D_I(x,y)$, defined above in equation (2.5). Technical efficiency can be expressed as

$$TE = 1/\ D_I(x,y) \qquad (2.10)$$

where the fully efficient firm operates on the production frontier, and technical efficiency is unity.

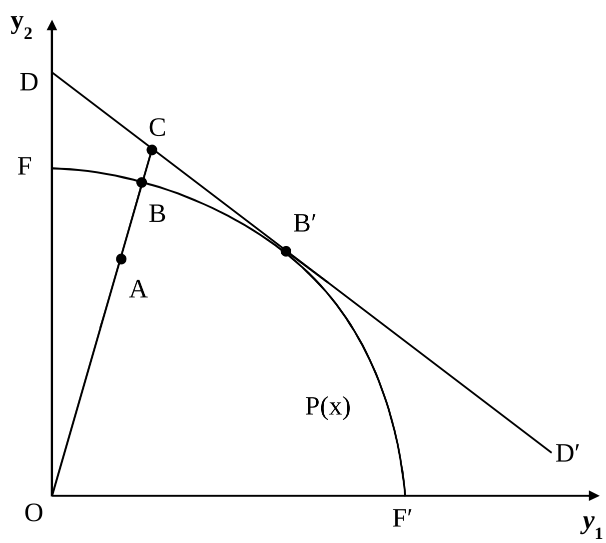


Figure 3.5 Output Oriented Technical and Allocative Efficiency.
Based on Farrell (1957).

This simple example of the input-oriented efficiency measure can be adapted to illustrate the output-oriented measure. The two output (y_1 and y_2) and single input (x) case is depicted in Figure 3.5. The curve FF' represents the efficient production frontier. Point A represents the inefficient firm as it lies below the efficient boundary. Technical inefficiency is represented by the distance AB. Thus, the firm producing at point A could increase output to point B without requiring any additional input. The technical efficiency is measured by the ratio

$$TE = OA/OB. \tag{2.11}$$

This is the ratio as described by the output distance function $D_O(x, y)$ in equation (2.6).

In the output-oriented case, it is assumed that the firm's behavioral goal is to maximize revenue. Price information is represented by the isorevenue line DD'. The distance BC can be interpreted as the increase of revenue when moving from point B to B', and this can be used to define allocative efficiency. This is given as

$$AE = OB/OC. \tag{2.12}$$

With both technical and allocative efficiency measured, economic efficiency can be calculated as

$$EE = TE \cdot AE = (OA/OB) \cdot (OB/OC) = (OA/OC). \tag{2.13}$$

Note that the product of technical efficiency and allocative efficiency is the ratio OA/OC.

These two examples show the radial input-oriented and output-oriented efficiency measurements introduced by Farrell. In the constant returns to scale case these measures are equivalent. However, in the decreasing and increasing returns to scale cases, the orientation must be selected based on the technology employed. In these examples the production technology is known and the efficient isoquant is identified. However, in practice the production frontier may be difficult to identify. The following section will review the two major methods of efficiency measurement that are currently employed.

Methods of Efficiency Measurement

Measurement of productive efficiency requires the empirical approximation of the true production frontier. Once the frontier has been estimated, the measurement of efficiency based on distance from the frontier is straight-forward. The challenge lies in estimating the frontier. Two major contrasting techniques have been frequently employed to estimate production frontiers; one based on mathematical programming and the other based on econometrics.

Data envelopment analysis (DEA) is a mathematical programming approach that seeks to define a piecewise linear, quasi-convex hull over the data. To be technically efficient, production must occur on the frontier. In the case of DEA, the frontier is defined by best practice based on comparison of observed producers. Each producer's inputs and outputs are weighted, and the program is solved to minimize the weighted input-output ratio subject to the constraint that all weights are non-negative and that the weighted sample is bounded below by one. The first DEA model was presented by Charnes, Cooper, and Rhodes (1978), and is frequently referred to as the CCR model. This model takes an input orientation and assumes constant returns to scale. A variable returns to scale model, referred to as the BCC model, was popularized by Banker, et al. (1984). DEA is popular among practitioners because it does not require the specification of a functional form for the production technology or make behavioral assumptions for the producer. In addition, if prices are known, economic efficiency can be estimated and decomposed into its technical and allocative components. The basic DEA model is deterministic; however, more advanced models incorporate stochastic characteristics.

The econometric approach, typified by stochastic frontier analysis (SFA), seeks to estimate the production frontier, and to distinguish the effects of noise from inefficiency. This form requires the specification of a production function and estimation of the distributional form of the inefficiency term. In a simple multiple input and single output case, the functional relationship is given as $y_i = f(x_i, \beta) + \varepsilon_i$, where y_i is the scalar output of the producer, i is the producer being evaluated, and β is a vector of parameters to be estimated. The residual ε_i is decomposed into a random error component v_i and an inefficiency component u_i. This approach allows the estimation of the production frontier. In addition, if price data are available a cost frontier can be estimated. An advantage of this approach is that it allows conventional statistical tests to be used in data analysis.

The programming and econometric approaches to measure technical efficiency each have strengths and weaknesses. The programming approach is non-stochastic, and does not distinguish between noise and inefficiency; the econometric approach is stochastic, and attempts to distinguish between noise and inefficiency. Conversely, the programming approach is nonparametric and is thus able to avoid the confounding effects caused by the misspecification of the functional form. While both methods have advantages and disadvantages, both have proven to be robust in efficiency estimation as well, and there appears to be some consistency in analyzing the same data using both methods (Fried, et al., 2008). Since the econometric approach is employed in this study, the following section will present a more in depth review of SFA. For a more comprehensive treatment of DEA, the reader is referred to Färe, et al. (1994) and Charnes, et al. (1994).

Stochastic Frontier Analysis

This section sets forth basic theory behind the econometric estimation of technical efficiency and develops the basic SFA model. In this section it is assumed that the producers are confined to a single output—either due to the constraints of the production technology—or that multiple inputs have been aggregated into a single-output index. It is also assumed that cross-sectional data are used for the analysis. The discussion is limited to estimating a stochastic production function, so no price or behavioral assumptions are set forth. The panel data and cost function model can be easily adapted from this basic model. However, these will not be presented here due to the scope of the research involved. If interested in these topics, the reader is referred to Kumbhakar and Lovell (2000).

The presentation in this section follows Kumbhakar and Lovell (2000). As stated above we assume access to cross-sectional data on quantities of K inputs used to produce a single output for each N producer. Without any stochastic elements, a production frontier model can be written as

$$y_i = f(x_i; \beta) \cdot TE_i \tag{3.14}$$

where y_i is the scaler output of producer i, $i = 1,\ldots N$, x_i is a vector of K inputs used by the producer, β is a vector of technology parameters to be estimated, $f(x_i; \beta)$ is the production frontier, and TE_i is the output-oriented technical efficiency of producer i.

We can rewrite equation (3.14) to express technical efficiency as the ratio of observed output to the maximum feasible output. Thus,

$$TE_i = \frac{y_i}{f(x_i;\beta)} \tag{3.15}$$

where y_i reaches it maximal value of $f(x_i; \beta)$ if, and only if, $TE_i = 1$. The amount by which $TE_i < 1$ describes the firm's inefficiency.

Thus far, the case we described in equation (3.14) the production frontier $f(x_i; \beta)$ is a deterministic frontier. A deterministic frontier is defined by the way that inefficiency is defined. As seen in equation (3.15) the entire gap that exists between y_i and the observed frontier $f(x_i; \beta)$ is attributed to technical efficiency. Thus, in this case the econometrically determined deterministic frontier is not unlike the frontier assed by DEA. Such specifications do not account for the fact that output can be affected by factors outside the control of the producer. These may include uncertainties in the market, equipment breakdown, or natural disasters.   The stochastic production frontier takes this into account by introducing a producer specific part that captures the effect of random shocks on each producer. Thus, we rewrite equation (3.14) as

$$y_i = f(x_i;\beta)\cdot\exp\{v_i\}\cdot TE_i \tag{3.16}$$

where $\left[f(x_i;\beta)\cdot\exp\{v_i\}\right]$ represents the stochastic production frontier. The deterministic part, common to all producers, is $f(x_i;\beta)$, and the producer specific part $\exp\{v_i\}$, which captures the random shocks to the producer. With the production frontier now being specified as stochastic, technical efficiency as defined in equation (3.15) can be redefined as

$$TE_i = \frac{y_i}{f\left(x_i;\beta\right)\cdot\exp\left\{v_i\right\}}, \tag{3.17}$$

where the ratio of observed output to maximum feasible output is characterized by $\exp\left\{v_i\right\}$. Again, TE_i = 1 when y_i is produced at $\left[f\left(x_i;\beta\right)\cdot\exp\left\{v_i\right\}\right]$, otherwise technical inefficiency is present, represented by TE_i < 1, which can vary by $\exp\left\{v_i\right\}$.

Technical efficiency can be estimated using either the deterministic production frontier or by the stochastic production frontier. The stochastic model is preferred as it can account for random shocks on the production environment. We will now consider the stochastic frontier model.

The stochastic production frontier model was introduced simultaneously by Aigner, Lovell, and Schmidt (1977) and Meeusen and van den Broeck (1977). If we assume that the production technology takes the log-linear Cobb-Douglas form, the stochastic model given in equation (3.16) is given as

$$\ln y_i = \beta_0 + \sum_n \beta_n \ln x_{ni} + \varepsilon_i, \tag{3.18}$$

where $\varepsilon_i = v_i - u_i$. Thus, the error term is decomposed into v_i, which represents symmetric disturbance, or noise, and u_i which accounts for technical inefficiency. The noise component v_i is assumed to be independently and identically distributed (iid) as $N\left(0,\sigma_v^2\right)$, and independent of u_i. The inefficiency component u_i is restricted to be a positive number, so that $u_i \geq 0$, and the error term $\varepsilon_i = v_i - u_i$ is asymmetric. Assuming that v_i and u_i are distributed independently of x_i, estimation of equation (3.18) by OLS provides consistent estimates of all the parameters except β_0. This result is due to the fact that $E(\varepsilon_i) = -E(u_i) \leq 0$. In addition, OLS fails to provide producer-specific estimates of technical efficiency. As producer-specific estimates of technical efficiency are desired—and OLS does not provide them—different estimation techniques are required. Maximum likelihood estimation (MLE) provides a robust method to estimate both the intercept and the inefficiency term.

The concept of MLE is founded on the idea that a given sample of observations is more likely to favor certain distributions over others. The maximum likelihood estimate of an unknown parameter is often defined as the value of the parameter that increases the probability of randomly drawing a particular sample of observations. Thus, the estimation of the likelihood function requires that we make certain assumptions about the distribution of the error. The next section presents methods for the estimation of MLE for two stochastic models and the distributional assumptions made.

Distributional Assumptions

To use the maximum likelihood principle to estimate the parameters of a stochastic model, we have to make assumptions concerning the distributions of the error terms. Typically, the noise term is assumed to be normally distributed. The inefficiency term has been evaluated using differing distributions including half-normal, exponential, truncated normal, and gamma. The section will present the half normal model, as this model is frequently used in practice. In addition, due to its use in this analysis, the truncated normal model will be presented.

The Normal-Half Normal Model

Given the stochastic frontier production model given is equation (3.18) we begin with three assumptions. First, the noise error component is normally distributed as $v_i \sim \text{idd } N\left(0,\sigma_v^2\right)$. Second, the inefficiency term is distributed as nonnegative half normal, $u_i \sim \text{iid } N^+\left(0,\sigma_u^2\right)$. Third, both error components are distributed independently of each other and the regressors.

We now must construct the joint density function for the error terms. The density function for $u_i \geq 0$ is given as

$$f\left(u\right)=\frac{2}{\sigma_u\sqrt{2\pi}}\cdot\exp\left\{-\frac{u^2}{2\sigma_u^2}\right\} , \tag{3.19}$$

and the density function given for *v* is given as

$$f\left(v\right)=\frac{2}{\sigma_v\sqrt{2\pi}}\cdot\exp\left\{-\frac{v^2}{2\sigma_v^2}\right\} . \tag{3.20}$$

Since $\varepsilon = v - u$, we can calculate the joint density function for *u* and ε as

$$f\left(u,\varepsilon\right)=\frac{2}{2\pi\sigma_u\sigma_v}\cdot\exp\left\{-\frac{u^2}{\sigma_u^2}-\frac{\left(\varepsilon+u\right)^2}{\sigma_v^2}\right\} . \tag{3.21}$$

We can now obtain the marginal density function of ε by integrating *u* out of $f\left(u,\varepsilon\right)$, which yields

$$
\begin{aligned}
f(\varepsilon) &= \int_0^{\infty} f(u,\varepsilon)\,du \\
&= \frac{2}{\sigma\sqrt{2\pi}}\cdot\left[1-\Phi\frac{\varepsilon\lambda}{\sigma}\right]\cdot\exp\left\{-\frac{\varepsilon^2}{2\sigma^2}\right\} \\
&= \frac{2}{\sigma}\cdot\phi\left(\frac{\varepsilon}{\sigma}\right)\cdot\Phi\left(-\frac{\varepsilon\lambda}{\sigma}\right),
\end{aligned}
\tag{3.22}
$$

where $\sigma = \left(\sigma_u^2 + \sigma_v^2\right)^{1/2}$, $\lambda = \sigma_u / \sigma_v$, $\Phi(\cdot)$ is the standard normal cumulative distribution (cdf), and $\phi(\cdot)$ is the standard normal probability density function (pdf). Figure 3.6 shows three different normal-half normal distributions for three different combinations of σ_u and σ_v. Since $\sigma_u > 0$, all three distributions are negatively skewed, with negative modes and means.

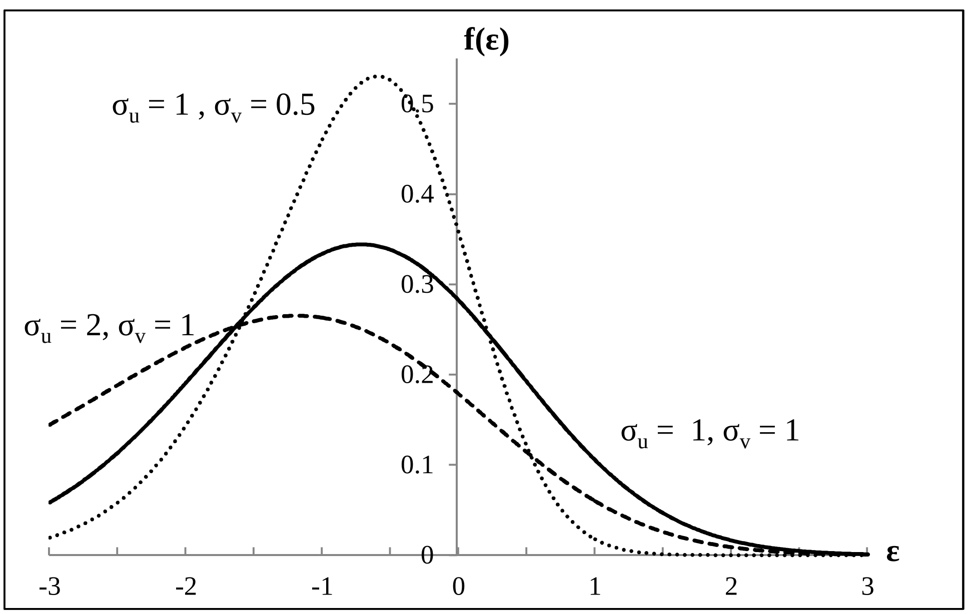


Figure 3.6 The Normal-Half Normal Model. Based on distributions shown in Kumbhakar and Lovell (2000).

The log likelihood function based on equation (3.22) for a sample of N producers is calculated as

$$\ln L = -\frac{N}{2}\ln\left(\frac{\circledR\sigma^2}{2}\right) + \sum_{i=1}^{N}\ln\Phi\left(-\frac{\varepsilon_i\lambda}{\sigma}\right) - \frac{1}{2\sigma^2}\sum_{i=1}^{N}\varepsilon_i^2. \tag{3.23}$$

We can maximize the log likelihood equation with respect to the parameters to obtain maximum likelihood estimates of each.

The firm-specific technical efficiency estimate depends on u_i. Based on Jondrow, et al. (1982), if $u_i \sim N^+\left(0,\sigma_u^2\right)$, the conditional distribution of u given ε is calculated as

$$f\left(u \mid \varepsilon\right) = \frac{1}{\sigma_*\sqrt{2\circledR}}\cdot\exp\left\{-\frac{\left(u-\mu_*\right)^2}{2\sigma_*^2}\right\}\cdot\left[1-\Phi\left(-\frac{\mu_*}{\sigma_*}\right)\right]^{-1}, \tag{3.24}$$

where $\mu_* = -\varepsilon\sigma_u^2/\sigma^2$ and $\sigma_*^2 = \sigma_u^2\sigma_v^2/\sigma^2$. Since $f\left(u \mid \varepsilon\right)$ is distributed as $N^+\left(\mu_{*,}\sigma_*^2\right)$, the mean of this distribution is a convenient point estimator for u_i. This is given as

$$E\left(u_i \mid \varepsilon_i\right) = \mu_{*i} + \sigma_*\left[\frac{\phi\left(-\mu_{*i}/\sigma_*\right)}{1-\Phi\left(-\mu_{*i}/\sigma_*\right)}\right]. \tag{3.25}$$

Thus, firm specific estimates of technical efficiency can now be obtained by

$$TE_i = \exp\left\{-\hat{u}_i\right\}, \tag{3.26}$$

where $-\hat{u}_i$ is $E\left(u_i \mid \varepsilon_i\right)$. However, Battese and Coelli (1988) have proposed the following alternative estimator for TE_i:

$$T\hat{E}_i = E\left(\exp\left\{-u_i\right\} \mid \varepsilon_i\right) = \left[\frac{1-\Phi\left(\sigma_* - \mu_{*i}/\sigma_*\right)}{1-\Phi\left(-\mu_{*i}/\sigma_*\right)}\right]\cdot\exp\left\{\frac{\sigma_*^2}{2} - \mu_{*i}\right\}. \tag{3.27}$$

This predictor can be shown to be optimal in that it minimizes the mean square prediction error.

To this point the normal-half normal model has been presented. It is widely employed in empirical work. However, other distributional assumptions are frequently used. The following section sets forth the analysis of the stochastic production frontier based on the assumption of a truncated normal distribution for u_i.

Normal-Truncated Normal Model

The normal-truncated normal model is a generalization of the normal-half normal model. In this model u_i is assumed to fit a normal distribution, truncated below at zero, with a non-zero mode. Thus, the truncated normal distribution adds an additional parameter μ that represents the mode. This parameter is estimated along with the other parameters of the model and provides more flexibility in representing patterns in the data.

We will now derive the marginal density function for this distributional model, beginning with the density function of $u > 0$ for the truncated normal distribution. This is given as

$$f(u) = \frac{1}{\sigma_u \sqrt{2\pi} \cdot \Phi(-\mu/\sigma_u)} \cdot \exp\left\{-\frac{(u-\mu)^2}{2\sigma_u^2}\right\} \tag{3.28}$$

where μ is the mode of the normal distribution truncated below zero, and $\Phi(\cdot)$ is the standard normal cdf. Because $f(u)$ is the normal density function truncated at zero, if

$\mu = 0$ then the density function given in equation (3.28) becomes the half normal density function discussed in the previous section.

The density function for $f(v)$ is the same used for the normal-half normal model and is given by equation (3.20). We can multiply the individual density functions of *u* and *v* to arrive at the joint density function given by

$$f(u,v) = \frac{1}{2{\circledR}\sigma_u\sigma_v \cdot \Phi(-\mu/\sigma_u)} \cdot \exp\left\{ -\frac{(u-\mu_i)^2}{2\sigma_u^2} - \frac{v^2}{2\sigma_v^2} \right\}. \tag{3.29}$$

This can be easily adapted to derive the joint density function of *u* and ε, which is given as

$$f(u,\varepsilon) = \frac{1}{2{\circledR}\sigma_u\sigma_v \cdot \Phi(-\mu/\sigma_u)} \cdot \exp\left\{ -\frac{(u-\mu_i)^2}{2\sigma_u^2} - \frac{(\varepsilon+u)^2}{2\sigma_v^2} \right\}. \tag{3.30}$$

The marginal density of ε can be derived as

$$\begin{aligned} f(\varepsilon) &= \int_0^\infty f(u,\varepsilon) \\ &= \frac{1}{\sigma\sqrt{2{\circledR}} \cdot \Phi(-\mu/\sigma_u)} \cdot \Phi\left(\frac{\mu}{\sigma\lambda} - \frac{\varepsilon\lambda}{\sigma} \right) \cdot \exp\left\{ -\frac{(\varepsilon+\mu)^2}{2\sigma^2} \right\} \\ &= \frac{1}{\sigma} \cdot \phi\left(\frac{\varepsilon+\mu}{\sigma} \right) \cdot \Phi\left(\frac{\mu}{\sigma\lambda} - \frac{\varepsilon\lambda}{\sigma} \right) \cdot \left[\Phi\left(-\frac{\mu}{\sigma_u} \right) \right]^{-1}, \end{aligned} \tag{3.31}$$

where $\sigma = (\sigma_u + \sigma_v)^{1/2}$ and $\lambda = \sigma_u / \sigma_v$ as given in the half normal model, Φ(·) is the standard normal cdf, and ϕ(·) is the standard normal pdf.

The normal-truncated normal distribution has three parameters; μ, a placement parameter, and two spread parameters σ_u and σ_v. Figure 3.7 provides a graph of three different distributions with the placement μ parameter negative, positive, or zero. Note that all three distributions are negatively skewed and have a negative mean.

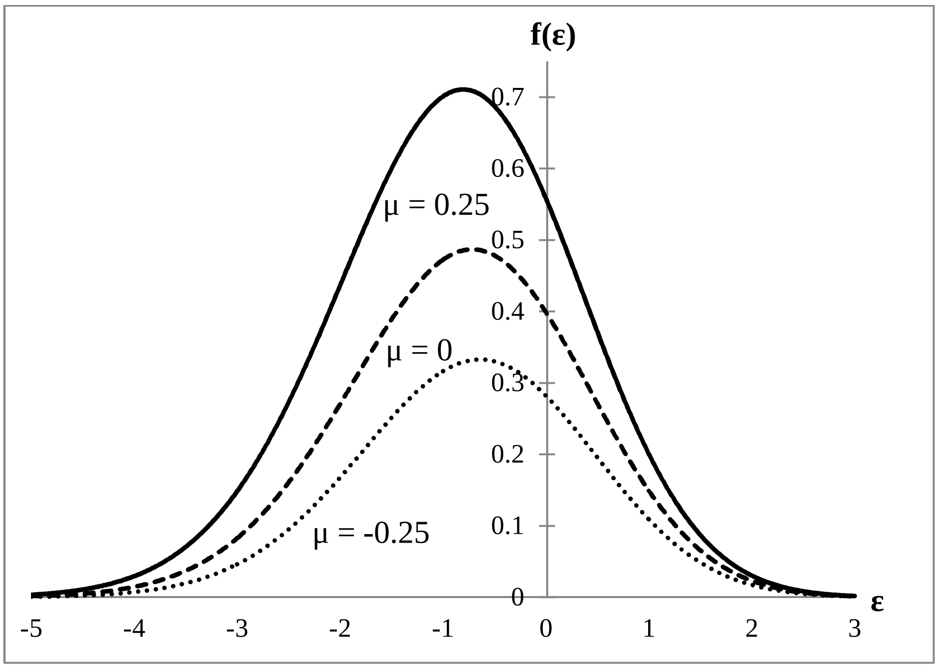


Figure 3.7 The Normal-Truncated Normal Model. Based on distributions shown in Kumbhakar and Lovell (2000).

With the marginal density function for ε defined we can now give the log likelihood function. The log likelihood function for a sample of N producers is

$$\begin{aligned}\ln L = -N\left[\ln\sigma + \frac{1}{2}\ln 2\text{®} + \ln\Phi\left(\frac{\mu}{\sigma_u}\right)\right] \\ +\sum_{i=1}^{N}\left[\ln\Phi\left(\frac{\mu}{\sigma\lambda} - \frac{\varepsilon_i\lambda}{\sigma}\right) - \frac{1}{2}\left(\frac{\varepsilon_i+\mu}{\sigma}\right)^2\right],\end{aligned} \qquad (3.32)$$

where $\sigma_u = \lambda\sigma \Big/ \sqrt{1+\lambda^2}$. This log likelihood function can be maximized to obtain estimates of all the parameters in the stochastic frontier function.

The conditional distribution of $f\left(u \mid \varepsilon\right)$ is given by

$$f\left(u \mid \varepsilon\right) = \frac{1}{\sigma_* \sqrt{2\circledR} \cdot \left[1-\Phi\left(-\tilde{\mu}/\sigma_*\right)\right]} \cdot \exp\left\{-\frac{\left(u-\tilde{\mu}\right)^2}{2\sigma_*^2}\right\}. \tag{3.33}$$

This is distributed as $N^+\left(\tilde{\mu}_i, \sigma_*^2\right)$, where $\tilde{\mu}_i = \left(-\sigma_u^2\varepsilon_i + \mu\sigma_v^2\right)/\sigma^2$ and $\sigma_*^2 = \sigma_u^2\sigma_v^2/\sigma^2$. The mean of $f\left(u \mid \varepsilon\right)$ can be used to estimate the technical efficiency of each producer. The mean is found as

$$E\left(u_i \mid \varepsilon_i\right) = \sigma_* \left[\frac{\tilde{\mu}_i}{\sigma_*} + \frac{\phi\left(\tilde{\mu}_i/\sigma_*\right)}{1-\Phi\left(\tilde{\mu}_i/\sigma_*\right)}\right]. \tag{3.34}$$

Point estimates of the technical efficiency can be obtained as follows:

$$T\hat{E}_i = E\left(\exp\left\{-u_i\right\} \mid \varepsilon_i\right) = \frac{1-\Phi\left[\sigma_* - \left(\tilde{\mu}_i/\sigma_*\right)\right]}{1-\Phi\left(\tilde{\mu}_i/\sigma_*\right)} \cdot \exp\left\{-\tilde{\mu}_i + \frac{1}{2}\sigma_*^2\right\}, \tag{3.35}$$

which becomes the $T\hat{E}_i$ estimator of Battese and Coelli (1988) when $\mu = 0$.

This chapter has provided an overview of the theory underpinning the measurement of technical efficiency. It began with how technology is defined using sets, moved on through the use of sets to define a production frontier, and demonstrated how frontiers can be used to estimate efficiency through distance functions. We then defined efficiency and its component parts. Methods of efficiency measurements were introduced, and the stochastic frontier model was given as a way to estimate the production frontier and firm specific efficiency estimates. Lastly, two different distributional assumptions were explored to see how efficiency estimates can vary as we change distributional assumptions for the inefficiency error term. This chapter also concludes the introductory and background material that provides the context for the current analysis. The following chapters will present the model employed and associated analysis in the evaluation of the refrigerated warehousing industry.

CHAPTER IV

DATA AND METHODOLOGY

This chapter marks the beginning of the empirical analysis for this study. It begins with a description of the data and the variables utilized in the production model. It then sets forth the production model to be utilized. Finally, it outlines the one-step maximum likelihood estimation (MLE) method employed for analyzing the proposed model. The results of the MLE, including the industry technical efficiency estimate, are reported in the following chapter.

Data

Data used for this study are kindly provided by the International Association of Refrigerated Warehouses (IARW). This trade association is a partner in the Global Cold Chain Alliance (GCCA) which currently represents 1,300 member companies in over 65 countries (www.gcca.org). The IARW represents the global temperature-controlled third party warehousing and logistics industry and promotes best practices through research, and industry benchmarking (www.gcca.org/partners/iarw). As part of its benchmarking function, the IARW conducts a bi-nnual Productivity and Benchmarking Survey. Surveys are made available to members to be used in conjunction with their annual evaluation processes.

The data collected include information on company size and financial results, as well as warehouse operating statistics, labor, and wage and benefit information.

Completed surveys are collected by and analyzed by an independent CPA firm. Basic ratio and financial benchmarking analyses are conducted with these data, and are made available to members of the association. Part of the motivation for this study is to develop more effective benchmarking tools and results for the industry.

Currently, we have access to the 2012 Productivity and Benchmarking Survey. These data include responses to 69 surveys, covering 198 warehouses throughout the United States and Canada. Twenty-six surveys include aggregated data on more than one warehouse. These observations are divided by the number of warehouses in the financial statement to get average data per warehouse. Observations with missing values were discarded leaving N=39.

Methodology

This section reports the methodology employed to conduct the current efficiency analysis. The stochastic frontier method employed is based on the early models of Aigner, et al. (1977) and Meeusen and van den Broeck (1977). These early models depended on a one-sided error term that was assumed to be identically and independently distributed. More recently, models have allowed the error component to be heterogeneous and depend on different firm characteristics (Battese and Coelli, 1995, Wang and Schmidt, 2002). These one-step models allow the estimation of firm-specific technical efficiency and identify factors outside the production function that affect these efficiency estimates. A one-step technical efficiency effects model will be employed for this analysis of the refrigerated warehouse industry.

The following subsections outline the proposed production model, beginning with specifying variables in the production frontier. Next, contextual variables affecting efficiency are identified, following which the proposed production function will be presented. The section concludes with presenting the maximum likelihood estimation method used to estimate efficiency and efficiency effects.

Variables in the Production Frontier

For the production frontier part of the model, the output variable is pounds handled per year, and the inputs are direct labor hours, investment in equipment, and space in cubic feet. Previous warehouse efficiency studies have used broken case, full case, and pallet lines as output variable in a multiple output model (Hackman, et al., 2001, Johnson and McGinnis, 2011). The refrigerated warehouse industry's output is largely pallet orders, although some full case and broken case shipping does occur. The output variable, pounds handled per year (*pounds*), is an aggregate that attempts to standardize output into one variable accounting for the differences in size of broken case, full case, and pallet lines shipped.

On the input side, direct labor hours (*labor*) are measured as labor hours expended in direct inventory processing per year. This value is obtained by multiplying direct labor hours per week by 52. The next input, investment in equipment (*invest*), is proxied as fixed assets at cost. This variable is meant to capture the amount invested in material handling equipment and storage systems. It is used in place of directly reported cost of handling equipment, as fixed assists performs better in the proposed model, and it attempts to account for storage systems in addition to handling equipment.

Space is also included as an input variable. Warehouse space was used as an input in previous warehouse models (de Koster and Balk, 2008, Hackman, et al., 2001, Johnson and McGinnis, 2011). In these studies space was proxied by floor space, and did not include height. The rationale being, vertical height is not always used—especially in dock areas (Hackman, et al., 2001). Information provided in the warehousing survey is reported in cubic feet, and as vertical heights are not available, warehouse space (*space*) is applied in cubic feet. Table 4.1 presents the summary of variables included in the frontier production function.

Table 4.1 Descriptive Statistics of Variables Included in Production Function.

	POUNDS (per year)	LABOR (hours/year)	INVEST ($)	SPACE (cu. ft.)
Mean	364,736,168	54,777	18,791,274	4,999,583
Std. Dev.	277,818,920	35,919	28,652,299	2,760,890
Min.	37,442,062	4,992	168,670	734,847
Max.	1,109,600,385	158,860	141,516,105	12,584,199

Contextual Factors Affecting Efficiency

Inventory turns has been identified as being highly correlated with warehouse efficiency (Johnson and McGinnis, 2011). This is most likely due to a reduction in the amount of storage space required. The smaller the storage space, the less space, labor and equipment is required, thus reducing the amount of inputs required. In this analysis inventory turnover is labeled as turns per year (*turns*), and is calculated as the number of pounds handled during the year divided by two times the average pounds stored.

The percentage of error-free orders has been used as an output variable (de Koster and Balk, 2008). However, orders with errors percentage is included as a contextual factor in the present analysis. Errors may be caused by poorly designed production technologies or operational procedures. Additionally, errors may be caused by inefficient implementation of sound technologies and operational procedures. The percentage of orders with errors (*errors*) is given as a fraction of error-free order percentage over 100.

In the warehouse, as utilization of storage spaces approach 90 percent productivity falls off dramatically (Frazelle, 2002). This is due, in large part, to the lack of flexibility available for efficient put away and retrieval of goods. Storage space utilization is reported as the amount storage space occupied (*occupancy*). It is given as a fraction over 100. Table 4.2 presents the summary statistics for contextual factors applied in this study.

Table 4.2 Descriptive Statistics of Variables Included in Contextual Factors.

	turns (per year)	*Errors (%)*	*Occupancy (%)*
Mean	9.62	0.98861	0.76
Std. Dev.	4.46	0.01251	0.15
Min.	3.59	0.95	0.38
Max.	21.26	1	0.97

Production Function

The stochastic frontier model first requires the estimation of a production function. The specification of the functional form is of great import, as it can have significant impact on the results. A number of functional forms are used in the literature; however, the Cobb-Douglas and translog forms are by far the most common as both can be made linear in parameters and be estimated using least squares methods. In general, it is preferred that the functional form chosen for analysis be second-order flexible. This is to prevent general restrictions, such as constant production and substitution elasticities, that are present with first-order flexible forms such as Cobb-Douglas (Coelli, et al., 2005). The translog function is a generalization of the Cobb-Douglas function and provides the flexibility of a second order approximation. This increased flexibility, however, comes with a price; it is more difficult to interpret and can suffer from curvature violations. The translog function can be converted to Cobb-Douglas by setting the second-order parameters to zero. The flexible translog production function is

$$\begin{aligned}\ln\left(pounds_i\right) = \beta_0 &+ \beta_1 \ln\left(labor_i\right) + \beta_3 \ln\left(invest_i\right) + \beta_4 \ln\left(space_i\right) \\ &+ \frac{1}{2}\beta_{11} \ln\left(labor_i\right)^2 + \frac{1}{2}\beta_{22} \ln\left(invest_i\right)^2 + \frac{1}{2}\beta_{33} \ln\left(space_i\right)^2 \\ &+ \beta_{12} \ln\left(labor_i\right)\cdot\ln\left(invest_i\right) + \beta_{13} \ln\left(labor_i\right)\cdot\ln\left(space_i\right) \\ &+ \beta_{23} \ln\left(invest_i\right)\cdot\ln\left(space_i\right) + v_i - u_i\,,\end{aligned} \tag{4.1}$$

where restriction of the second order terms yields

$$\ln\left(pounds_i\right) = \beta_0 + \beta_1 \ln\left(labor_i\right) + \beta_3 \ln\left(invest_i\right) + \beta_4 \ln\left(space_i\right) + v_i - u_i. \tag{4.2}$$

This is easily recognizable as the log-linear Cobb-Douglas functional form. This functional relationship makes it possible to choose between these two models using the likelihood ratio (LR) test[1]. Both Cobb-Douglas and translog functional forms will be estimated and the most parsimonious model will be chosen for this analysis. For the sake of simplicity, the Cobb-Douglas representation will be used in the following section.

Log-likelihood Model Specification

A frequently used method for empirical analysis utilizes two steps. In the first step, the stochastic frontier model and the firm specific efficiency levels are estimated. These efficiency estimates are then used to regress against contextual variables ($z_i s$) that may account for observed differences between firms in the industry. This two-step approach has long been recognized to be problematic. In the first stage the inefficiency effects are assumed to be identically distributed, but then this assumption is contradicted in the second stage as estimated efficiencies are assumed to have a functional relationship with z_i.

An alternative methodology was introduced by Kumbhakar, et al. (1991) and Reifschneider and Stevenson (1991). They each propose stochastic frontier models in which the inefficiency component of the error term u_i is expressed as an explicit function of specific variables and random error. These models take the general from

$$y_i = x_i\beta + v_i - u_i\left(z_i', \delta\right), \tag{4.3}$$

where z' is a vector of contextual variables that may affect the efficiency of the firm, and δ is a vector of variables to be estimated. It is usually assumed u_i is distributed as

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[1] The LR test statistic, $\lambda = -2\left\{\log\left[likelihood\left(H_0\right)\right] - \log\left[likelihood\left(H_1\right)\right]\right\}$, has approximately χ^2 distribution with degrees of freedom equal to the number of restricted parameters in H_0, if H_0 is true.

$N\left(u_i,\sigma_i^2\right)^+$ with differing specification for u_i and σ_i^2. The frontier function and the inefficiency part are generally estimated in one step using MLE.

Battese and Coelli (1995) propose a one-step maximum likelihood model based on this general form. This model assumes a truncated normal distribution. This model differs from Kumbhakar, et al. (1991) in that it is amenable to panel data. The technical inefficiency effect can be defined as

$$u_i = z_i\delta + \mathrm{w}_i, \tag{4.4}$$

where the error term w_i is assumed to be a normal distribution truncated at $-z_i\delta$. Technical efficiency of production for the *i*-th firm can be estimated as

$$TE_i = \exp\{-U_i\} = \exp\{-z_i\delta - W\}. \tag{4.5}$$

In this model σ_v and σ_u are replaced with $\sigma^2 = \sigma_v^2 + \sigma_u^2$. The parameter $\gamma = \sigma_u^2 \big/ \left(\sigma_v^2 + \sigma_u^2\right)$ is introduced in the model and allows for evaluation of the inefficiency term u_i by testing for its significance. If we fail to reject the null hypothesis, H_0: $\gamma = 0$, this indicates that σ_u^2 is zero, and that there are inefficiency effects present in the model.

Under the technical efficiency effects model proposed byBattese and Coelli (1995), the stochastic production function to be estimated for the current study is given in equation (4.3), and the technical inefficiency effects are assumed to be defined by

$$u_i = \delta_o + \delta_1 turns_i + \delta_2 errors_i + \delta_3 occupancy_1 + w_i. \tag{4.6}$$

MLE is employed to simultaneously estimate the stochastic production frontier and the technical inefficiency effects.

The MLE estimation of the proposed model is conduction in the software program FRONTIER 4.1 kindly provided by Tim Coelli[2]. The program follows a three-step procedure for estimating the maximum likelihood estimates and parameters of the stochastic production frontier. These three steps are as follows:

1) Ordinary Least Squares (OLS) estimates are calculated for the production function. All β estimators with the exception of the intercept are unbiased.
2) A two phase grid search is conducted across the parameter space of γ. Values of γ from 0.1 to 0.9 in increments of size 0.1 are considered. The search is conducted for β parameters (excepting β_0) at their OLS values and β_0 and σ^2 parameters adjusted according to the corrected least squares formula in Coelli (1995). Other parameters (e.g. μ and δ) are set to zero in this search.
3) The values derived in the grid search are then used as starting values in an iterative Davidon-Fletcher-Powell Quasi-Newton procedure to obtain the final maximum likelihood estimates. Standard errors are approximated from the direction matrix used in the final iteration of the Davidon-Fletcher-Powell procedure.

For more information on this computer program the user is referred to Coelli (1996).

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[2] Available for free downloads from the Center for Efficiency and Productivity Analysis (CEPA) website: www.uq.edu.au/economics/cepa.

This concludes this chapter on data used and the methods employed in the present analysis. A stochastic frontier production model was set forth and the methods of the maximum likelihood estimation procedure outlined. The following chapter reports the results of this analysis.

CHAPTER V

RESULTS AND DISCUSSION

We have presented a model to assess the technical efficiency in the refrigerated warehousing industry. This chapter presents the results of the analysis of the stochastic frontier production model set forth in the previous chapter. The results are then discussed in the following section along with suggestions for future work.

Results

The first step in the analysis was to identify the most parsimonious production function. The results of the OLS estimation of the stochastic production frontier model are provided in Table 5.1. The likelihood ratio test indicates that we fail to reject the null hypothesis, $H_0 : \beta_{11} = \beta_{22} = \ldots = \beta_{23} = 0$. Thus, we conclude that the Cobb-Douglas model is the most parsimonious, implying the assumption that constant elasticities holds for this technology. A Breusch-Pagan-Godfrey test confirmed the absence of heteroscedasticity.

The next part of the analysis was to estimate the complete Cobb-Douglas stochastic production model taking into account inefficiency effects. These estimates are reported in Table 5.2, along with the standard errors of the maximum-likelihood estimators.

The estimated coefficients for the production model are all positive, with the coefficients of *labor* and *space*, 0.444 and 0.399 respectively, being highly significant.

Table 5.1 Results OLS Estimation. Dependent variable: ln(*pounds*).

Variables	Cobb-Douglas			Translog		
	Coefficient	Standard Error	T-ratio	Coefficient	Standard Error	T-ratio
β intercept	6.931	2.000	3.4655	-4.1757	50.0807	-0.0834
ln(labor)	0.533	0.148	3.6142	1.8244	5.4992	0.3318
ln(invest)	0.059	0.072	0.8186	0.5947	1.9884	0.2991
ln(space)	0.384	0.194	1.9875	0.2515	9.2436	0.0272
$\ln(labor)^2$				-0.4726	0.5451	-0.8669
$\ln(invest)^2$				0.0152	0.0750	0.2021
$\ln(space)^2$				0.6819	0.9597	0.7105
ln(labor)· ln(invest)				0.5380	0.2924	1.8430
ln(labor)· ln(space)				-0.3164	0.5530	-0.5721
ln(invest)· ln(space)				-0.4264	0.2839	-1.5020
R^2		0.663			0.7013	
σ^2		0.2471			0.2643	
log-likelihood		-25.9652			-23.6097	

The coefficient on invest, 0.146, is small and moderately significant. The coefficients of the log-linear Cobb-Douglas model can be interpreted as the elasticities of substitution for the production inputs. These coefficients sum to 0.99 implying that the technology represents constant returns to scale.

The estimated coefficients for the efficiency model for *turns* and *occupancy* are both significant. The negative sign on *turns,* as expected, indicates that the number of turns is negatively correlated with inefficiency. This result is similar to what has been reported previously (Johnson and McGinnis, 2011). The estimated coefficient for *errors* has a positive sign, implying that warehouses with a higher percentage of errors have greater inefficiency; however, this relationship is very weak.

Table 5.2 Results Log-likelihood Estimation. Dependent Variable: ln(pounds).

Variables	Coefficient	Standard Error	T-ratio
β intercept	6.686	1.115	5.997
ln(labor)	0.444	0.111	4.012
ln(invest)	0.146	0.060	2.417
ln(space)	0.399	0.116	3.424
δ intercept	1.142	0.823	1.387
TURNS	-0.280	0.042	-6.644
ERRORS	0.121	1.001	0.121
OCCUPANCY	1.346	0.724	1.859
σ^2	0.266	0.147	1.813
γ	0.694	0.115	6.051
log-likelihood	-13.326		

The estimate of γ, which can be interpreted as the ratio of the variance of technical efficiency to the total variance of output, is 0.694, indicating the presence of inefficiency in the model. This would mean that roughly 70 percent of the variation in warehouse output is due to technical efficiency. Likelihood ratio tests[3] were used to evaluate the significance of inefficiency in the model and are presented in Table 5.3. The first test is to see if inefficiency effects are present in the model. The null hypothesis that no inefficiency effects are present is strongly rejected. Thus, we concluded that a stochastic frontier model is justified. We next test to see if the joint effects of the contextual variables effects efficiency. The null hypothesis that inefficiency effects are not a linear function of age is also strongly rejected. Thus, we concluded that the

[3] The likelihood ratio test statistic has been shown to have a mixed χ^2 distribution (Coelli, 1995) and test statistics are taken from Table 1 in Kodde and Palm (1986).

combination of these three variables do effect efficiency. However, the individual effects of these variables cannot be determined.

Table 5.3 Tests of Inefficiency Parameters in the Stochastic Production Model.

#	Null Hypothesis	Log(Likelihood)	$\chi^2_{0.99}$-value	Test statistic
1	H_0: $\gamma = \sigma_u^2 = 0$	-25.965	14.325	25.279
2	H_0: $\delta_1 = \delta_2 = \delta_3 = 0$	-25.708	10.501	24.765

Now that it has been determined that technical inefficiency effects are present in the model, we examine the technical efficiency estimates generated by the model. The average technical efficiency for the sample is 0.72. Summary statistics for the firm specific technical efficiency estimates are given in Table 5.4. These efficiency results are similar to those obtained in previous warehouse efficiency studies (de Koster and Balk, 2008, Hackman, et al., 2001, Johnson and McGinnis, 2011).

Table 5.4 Summary Statistics for Individual Technical Efficiency Estimates.

	Mean	Median	Standard Deviation	Minimum	Maximum
TE_i	0.715	0.753	0.210	0.214	0.960

While the average technical efficiency estimate for the group is 0.72, there is a wide distribution. The TE_i estimation for each warehouse in the sample was ordered and the distribution frequency is shown in Figure 5.1. The warehouses in the sample cluster into three distinct groups. These three groups may relate to the role each warehouse fulfills, such as distribution center in contrast to a storage provider.

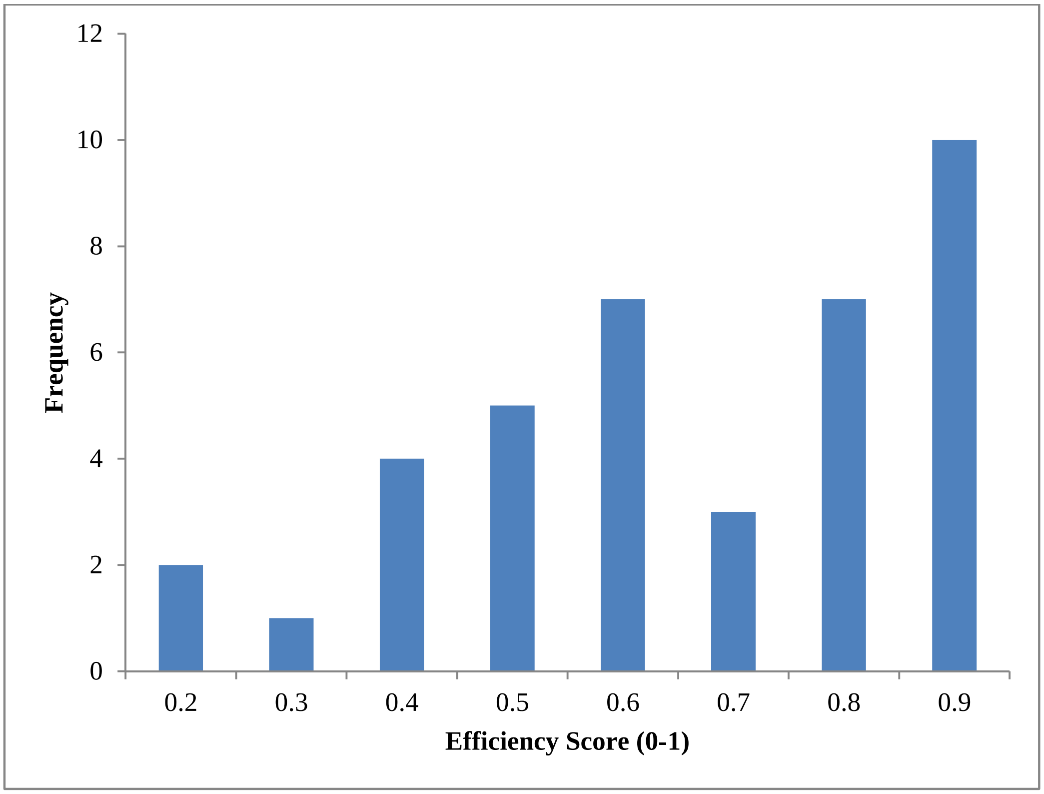

Figure 5.1 Frequency of Efficiency Estimates.

Discussion

To our knowledge, this is the first study to employ stochastic frontier analysis in measuring technical efficiency in the warehousing industry. The choice of SFA was motivated by several reasons. First, survey data are prone to reporting error, and econometric estimation takes account of some of this error in the noise component of the error term v_i. In addition, the model specifications are easily amenable to modeling cost efficiency and panel data if these become available. Finally, no studies in the current literature employ a stochastic approach to estimating efficiency for the warehousing industry. SFA requires the specification of a production function. By specifying a production technology, this study has provided further insights into the functional relationships between inputs and outputs in the refrigerated warehouse industry. The mean technical efficiency for the refrigerated industry was estimated by SFA at 0.72. This is in line with the previous warehousing studies using DEA to survey the industry as a whole (see Table 2.1). That the technical efficiency estimates from this study line up with efficiency estimates from those other studies, it suggests that SFA is similarly robust to DEA in addressing efficiency questions within the warehousing industry.

This study employs the Cobb-Douglas production function to model technology in the industry. The production technology described by the model is characterized by constant elasticities and constant returns to scale. Using a production function in efficiency estimation allows for functional relationships to be explored. The inputs associated with pounds handled are positive and labor and size are strongly significant. Investment in equipment is small, and appears to have modest significance.

It is interesting to note that warehouse size appears to have a greater impact on output than does investment in equipment. This could be for several reasons. Available space is important to the efficient operation of a warehouse. This study found that occupancy percent of total positions filled was positively correlated with inefficiency. As the amount of total storage positions decrease it often requires more effort for storage and retrieval of items. In addition, less space implies higher storage density and narrower aisles requiring more time and labor for item put away and retrieval.

Another reason that warehouse space appears to be more important than equipment is based on the choice of proxy used for handling equipment. Using a financial proxy for warehouse handling equipment may be problematic because it cannot capture the actual value of the equipment, and value reporting techniques may vary from warehouse to warehouse. In addition, it also fails to take into account age of equipment or depreciation. Reporting book value of equipment may also be confounded by the cost versus benefit effects of that equipment. A forklift and a movable storage rack not only have differing book value, but each has a unique role, and thus may affect the movement of product differently. This difficulty is compounded by the fact that we may not reflect the true value of the equipment; we cannot distinguish the effects of different equipment on either the productivity or the efficiency of the warehouse.

Going forward, we suggest that dividing equipment into respective categories would improve this study. For instance, categories could include item such as lift trucks, racks, conveyors, and robotics. Ideally, numbers of each type of equipment in selected categories would be used. However, aggregating numbers within categories would suffice. Price information could be estimated by aggregating the current replacement cost for each of the items in the categories. These could then be included as terms in the production function, similar to the investment variable of Hackman, et al. (2001). Thus, it would more closely reflect the differences in production technologies, and provide a more accurate measure for the effects of equipment on warehouse productivity and efficiency. A recommendation will be given to include this strategy in the IARW benchmarking surveys.

This study also examined the effects that specific variables have on firm efficiency. It was reported that both number of inventory turns and percent occupancy were significant. The percentage of errors appears to have a negative effect on efficiency, albeit an insignificant one. It was suggested that this variable may reflect bad technology or inefficient process. In other words, it may be a structural problem, or it may be simply an application issue. Based on the results of the analysis, the insignificance of this effect suggests the latter. If errors are a structural problem we would expect them to occur more often, and be more influential in the efficiency estimate. This may prove to be a fruitful area for further research.

An area of active research in the productivity community is the point of impact for these efficiency effects. Do they influence technical efficiency, the production function, or both? For this study, it was assumed that the contextual variables influenced the technical efficiency; however, further work in this area is encouraged. In addition, recent work has been done in identifying the best model to fit industry data (Alvarez, et al., 2006), and in measuring the amount of sample variation that is attributed to firm specific characteristics (Liu and Myers, 2009). Further work on the present model in these areas is recommended.

An obvious concern about this analysis is the small sample size. With small sample sizes much of the utilized methods lose robustness, such as statistical testing of the β parameters. In addition, there is the risk of model misspecification. Another issue is measuring skewness in the OLS residuals. The residuals may not show any skewness in small samples, however this does not mean that inefficiency effects are not present

(Greene, 2008). This is evidenced in the present study, as the OLS residuals showed no significant negative skewness, yet the estimated model showed significant effects compared to the restricted model (where $\gamma = 0$). Only with a larger sample would these issues be able to be resolved.

There are several variables of interest that could not be included in either the production or the inefficiency model because the available data set is missing values. Kilowatt hours used per warehouse, information technology expense, and pounds blast frozen are examples of these variables with missing observations. Adding kilowatt hours used to the warehouse production function would enable us to evaluate energy used as an input. As contextual variables, information technology and blast freezing would provide information on the effects of technology and value added services, respectively.

Having a larger sample size would help resolve some of the issues discussed herein. An ideal solution would be to obtain existing panel data from the last several years. This would not only allow for aggregation of variables in a cross section to obtain better parameter estimates, but would allow us to explore how technology and efficiency changes with time. In addition, going forward, obtaining cost information would allow us to test a cost model which would shed further light on the refrigerated warehousing industry. These suggestions will be made to the IARW for implementation in future benchmarking surveys.

Calculating a productivity frontier and *TEi* allows us to conduct benchmarking analysis. Individual *TEi* estimates allow identification of where each warehouse falls on the efficiency spectrum. In addition, we can evaluate warehouse efficiency compared to the industry as a whole. When evaluating the distribution of *TEi* in this study there are three distinct groupings. These grouping may correspond with the primary role of each particular warehouse. For instance, the three warehouses that group on the low end of the efficiency scale may be primarily storage warehouses, while those on the opposite side of the spectrum may be distribution centers. This clustering may indicate the relationship between efficiency and the flow of goods in and out of the warehouse. We suggest that the *TEi* of each individual warehouse may reflect the primary role that each plays, and as such, there may be strong association between technical efficiency and pounds in and out. This association warrants additional investigation in this area.

CHAPTER VI

CONCLUSION

In conclusion, this thesis presents a production model for the refrigerated warehouse industry and estimates a stochastic frontier used to generate technical efficiency estimates for the individual firms and the industry as a whole. This study is the first of its kind to address the refrigerated warehouse industry specifically. It is also the first study to use stochastic frontier analysis to evaluate technical efficiency in the warehousing industry in general. We found that the mean efficiency for the refrigerated warehouse industry is 0.72, which falls within the same range as other warehouse efficiency studies, and as such, recommend this method as a valid approach to address efficiency questions in this industry. In addition, three attributes related to production were included in the analysis to see what effect they had on efficiency. Number of turns was found to correlate with increased efficiency, and order error percentage and occupancy of warehouse space correlated with inefficiency.

Going forward, we suggest that this model be applied to a larger data set. This will help verify the conclusions presented herein. This data may be aggregated from past Benchmarking Surveys conducted by the IARW. Additionally, the model can easily be adjusted for panel data. We also suggested that future survey by the IARW collect data on categories and numbers of equipment information. Analyzing these data would allow us to explore the interaction of equipment on warehouse output and to analyze cost models of the technology.

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