ESSAYS IN EMPIRICAL ECONOMICS:

WHEAT GLUTEN IMPORTS, PEAR MARKETING AND BANKING INEFFICIENCY

By

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To the Faculty of Washington State University:

The members of the Committee appointed to examine the dissertation of CAIPING ZHANG find it satisfactory and recommend that it be accepted.

Chair

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Abstract

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This dissertation consists of three manuscripts. The goal of the first manuscript is to empirically examine how U.S. domestic wheat markets respond to wheat gluten imports from the EU, Australia, and other exporter nations. Two demand systems, factor demand and inverse demand, are specified and derived. A non-nested generalized likelihood test is applied for model selection to determine whether prices are adjusting to quantities or in reverse in U.S. wheat markets. The key results of this study suggest that gluten imports generally have significant influences on U.S. domestic wheat prices. However, specific influence depends on wheat class and the origin of the gluten imports.

The objective of the second manuscript is to assess the impacts of the new advertising strategy on the effectiveness of promotional efforts and to examine the significance and magnitude of the effect that promotional efforts have had on demand for D'Anjou pears in major U.S. retail markets. Nonparametric regression procedure is used to estimate domestic demand equations for D'Anjou pears across four regions. Results show that: 1) under the new advertising

management system, promotional activities achieved significantly higher effectiveness than did the previous system; 2) shipment demand for D'Anjou pears was significantly impacted by own price, patterns of seasonal availability of other pears, patterns of habit formation, and pear imports to the U.S.; and 3) the Ad Buy and Demo promotional efforts, as expected, impacted the demand for D'Anjou pears significantly and positively, with noticeable differences across regions.

In the third manuscript, we apply a recently proposed Bayesian approach to infer the incidence of inefficiency in U.S. commercial banks from 1990 to 2000. To overcome misspecification problem of the estimated DEA efficiency scores, uniform ignorance Bayesian prior is used to infer an appropriate posterior distribution for the latent incidence of inefficiency. Results imply that the inferred latent incidence of banking inefficiency from the Bayesian method could be more accurate than the DEA method when the sample size used in the study is limited.

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CHAPTER ONE

INTRODUCTION

This dissertation consists of three separate papers. The first study is discussed in Chapter 2, focusing on investigating how domestic wheat markets respond to wheat gluten imports. Chapter 3 will discuss the second study, analyzing the effectiveness of advertising and promotional activities conducted by the Pear Bureau Northwest on D'Anjou pears. The last chapter is the third study, inferring the latent proportional incidence of the inefficiency of U.S. commercial banks by applying a recently proposed Bayesian approach.

First study

Wheat gluten imports to the U.S. market have increased rapidly over the period of 1990 through 2004. Researchers have argued that the quickly growing gluten imports to the U.S. might be because gluten suppliers in the EU have obtained government support by subsidizing wheat starch processing and starch-based industry (Balzer and Stiegert, 1999).The increase of wheat gluten imported into the U.S. has been charged with contributing to a decline in capacity utilization in the U.S. starch-gluten process and to serious injuries for domestic industries, leading to trade disputes (USITC, 1998). In 1998, based on a petition filed by the Wheat Gluten Industry Council (WGIC), the U.S. International Trade Commission (USITC) charged the EU with dumping wheat gluten on the U.S. market. As a result of the USITC ruling, a three-year quota was approved on wheat gluten imports from the EU, Australia, and all other non-excluded countries on June 1, 1998. The economic impact associated with increasing gluten imports could also spill over to domestic wheat markets because of wheat gluten's specific role in the milling and baking industry (Balzer and Stiegert, 1999).

The objective of the first study is to investigate how domestic wheat markets respond to wheat gluten imports from the EU, Australia, and other exporter nations. Using quarterly wheat food use by class price and quantity data, we conceptualized and specified two demand systems, factor demand and inverse demand. A non-nested generalized likelihood test was applied for model selection to determine whether the data were consistent with quantity formation or price formation. Test results rejected the factor demand system in favor of the inverse demand system. Endogeniety of wheat quantities and wheat gluten imports were tested and rejected in the inverse demand model. Concavity conditions, symmetry and residual autocorrelation were tested and imposed in the inverse demand model.

The key results of this study suggest that gluten imports generally have significant influence on U.S. domestic wheat prices. However, specific influence depends on wheat class and the origin of the gluten imports. In general, the prices of three hard wheat classes (hard red winter, hard red spring, and durum) were negatively responsive to gluten imports from the EU and Australia, while the prices of two soft wheat classes (soft red winter and soft white wheat) showed contrary results to all gluten imports. The prices of hard red winter and hard red spring positively responded to gluten imports from other countries. The influences of gluten imports from the EU and Australia on price of each of five wheat classes were consistent. The European gluten imports significantly affected only the prices of hard red winter, soft red winter and durum wheat; the Australian gluten imports significantly affected prices of durum and soft red winter wheats. Meanwhile, the price flexibilities of durum and soft white wheats with respect to gluten imports were observably greater than those of hard red winter and hard red spring wheats. The reason might be that market shares of DUR and SWW in U.S. total food wheat use are smaller than those of HRW and HRS. Finally, the results from this study also show that wheat prices in U.S. domestic markets are significantly related to their own quantities, and they display seasonal fluctuations.

Second study

Advertising plays an important role in market creation and development. The Fresh Pear Committee is a federal marketing order that has authority to collect revenues from pear producers in Northwest. All marketing and promotional responsibilities of the Fresh Pear Committee are contracted to the Pear Bureau Northwest (PBN), which for many years has engaged in various forms of advertising and promotion activities on pears that are grown primarily in the Washington, California and Oregon (Cook, 2002). Evaluating the effectiveness of these promotional activities and researching more effective advertising approaches are always at the center of attention for the Fresh Pear Committee, the Pear Bureau Northwest, as well as pear producers. The results from this study are expected to provide important empirical evidence for the pear industry to evaluate the effectiveness of advertising expenditures and to draw implications to make plans for future marketing efforts to assure the effective use of pear producers' funds.

In this study, we were interested in empirically analyzing the effectiveness of promotional spending on D'Anjou pears conducted by the PBN over a period from the seasons of 1998/99 through 2004/05. In particular, we investigated a new advertising management system which was placed into effect by the PBN in the 2002/03 season. Two types of major marketing promotional activities, Ad buy and Demo, were investigated in four regional markets in the U.S. To reach these objectives, we started with an individual demand function to derive a regional demand function for D'Anjou pears. Nonparametric technique was applied for regional demand estimation. Based on the estimated model results, marginal net returns to D'Anjou growers were derived.

The key results of this study show a predominately positive and significant role of advertising expenditures in promoting D'Anjou demand and in gaining positive marginal net returns to pear growers. But the advertising effectiveness varies across regions and promotional types. Ad buys performed significantly better in marginal net returns to pear growers than did Demos. As a particular interest of this study, the new advertising management system, which has been in effect since the 2002/03 marketing season, has been found to produce greater returns for pear growers than the old system did in most regions. In addition, this study also found that domestic demand for D'Anjou pears in the U.S. continental states is significantly related to a number of other factors. In nearly all cases, pear demand was significantly impacted by the price of pears, the price of apples, patterns of seasonal availability of pears, as well as patterns of habit formation. The total quantity of imported pears was significantly and positively associated with demand for domestic D'Anjou pears in every region except for the East.

Third study

An issue of considerable interest to banking analysts and economists alike is whether the intensified competitive pressure, generated by banking deregulation and notable financial innovations, enhances banking efficiency. During the 1990s, much research attention has centered on investigating efficiency changes associated with consolidation over the period from 1985 through 1997. Banking efficiency estimates can help bank managers, market analysts, and researchers to identify opportunities for reducing costs or increasing revenues, to predict bank failures, merger activity, and to examine the effects of technological innovations and regulatory changes.

Data envelopment analysis (DEA) is one of the most popular tools to investigate banking efficiency. However, in practice, DEA often suffers from two drawbacks. First, the incidence of inefficient banks in DEA could be undercounted because of its nature of sample-based procedure that could lead to a truly inefficient firm or a decision-making unit (DMU) being treated as efficient (Friesner et al., 2006), heretofore referred to as mismeasurement. Second, DEA generally assumes that there is no random error, and this easily causes misspecifying the distribution of DEA scores when economic effects are studied (Schmidt 1985).

In this study, we apply a recently proposed method by Friesner et al. (2006) to infer the incidence of inefficiency for U.S. commercial banks from 1990 to 2000. In this approach, the incidence of inefficiency of banking within a DEA sample was shown to be a latent variable, which consists of the "observed" inefficient banks in DEA estimates and a noisy sample-based categorization of inefficiency. To avoid misspecification of the estimated DEA scores, a Bayesian approach was involved to infer an appropriate posterior distribution for the latent incidence of inefficiency.

Our results imply that the inferred latent incidence of inefficiency from the Bayesian method could be more accurate than the DEA method when the sample size used in the study is limited. Banks' efficiency has been shown to increase over time; however, the estimated DEA scores could be significantly greater than what they should be in reality. In addition, this study has also proven that the DEA estimation results are quite sensitive to sample size. Finally, the increasing banking efficiency over the studying period and the decreasing proportion of efficient banks in the industry may reflect the consequence of banking consolidation in the 1990s.

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CHAPTER TWO

IMPACTS OF GLUTEN IMPORTS ON U.S. FOOD WHEAT USE

Summary

We examined the impact of wheat gluten on the markets for wheat food use in the U.S. Using quarterly wheat food use by class price and quantity data, we conceptualized and specified an inverse demand system and factor demand system for five classes of wheat. A non-nested generalized likelihood ratio test suggests that prices were adjusting to quantities over the sample period. Endogeniety of wheat quantities and wheat gluten imports were tested and rejected in the inverse demand model.

The key results of this study suggest that gluten imports generally have significant influence on U.S. domestic wheat prices. However, specific influence depends on wheat class and the origin of the gluten imports. In general, the prices of three hard wheat classes (hard red winter, hard red spring, and durum wheat) were negatively responsive to gluten imports from the EU and Australia, while the prices of two soft wheat classes (soft red winter and soft white wheat) showed contrary results to all gluten imports. The prices of hard red winter and hard red spring positively response to gluten imports from other countries. European gluten imports significantly affected only the prices of hard red winter, soft red winter and durum wheats; Australian gluten imports significantly affected the prices of durum and soft red winter wheat. Meanwhile, the price flexibilities of durum and soft white wheats with respect to gluten imports were observably greater than those of hard red winter and hard red spring wheats.

Introduction

The increase of wheat gluten imported into the U.S. has been charged with contributing to the decline in capacity utilization in U.S. starch-gluten processing and to serious injuries for domestic industries, leading to trade disputes (USITC, 1998). Various subsidies by European governments on starch processing and starch industrial users are blamed for distorting gluten markets (Ortalo-Magne and Goodwin, 1992; Balzer and Stiegert, 1999). The economic impact associated with the increasing gluten imports could also spill over to domestic wheat markets because of wheat gluten's specific role in the milling and baking industry (Balzer and Stiegert, 1999)[1]. In this study, we were interested in investigating how domestic wheat markets respond

[1] Wheat gluten plays important roles in both milling and baking industries because of its properties of being easily extractable from wheat flour and being able to add back to flour. Wheat gluten is a composite of the proteins *gliadin* and *gultenin*. These proteins exist conjointly with starch in wheat endosperms and comprise about 80% of the protein contained in wheat seed. Being insoluble in water, wheat gluten can be purified by washing away the associated starch, then drying and powdering. In the milling industry, the powdered wheat gluten is often added back to wheat flours to increase their protein content. About 1.55 pounds of dry gluten is needed to increase the protein level of 100 pounds of wheat flour by 1 percent (Milling & Baking News). This extractable and back-to-flour property of wheat gluten makes the protein content controllable for the milling industry. This advantage is especially important during crop years when wheat protein levels are low because of weather or other reasons (Magne and Goodwin, 1992; Boland *et al*. 2000 and 2005). In the baking industry, in order to produce the high protein level required for some flour-based products (e.g., bagels, health breads, multigrain breads, etc.), bakeries often use the extracted wheat gluten as an additive to dough to improve rising and the products' structural stability and chewiness. In this manner, wheat gluten allows manufacturers of pan breads to manage the consistency of their end products.

to wheat gluten imports.

Several specific research questions included: Do gluten imports to the U.S. have significant impacts on domestic wheat markets? If so, are these impacts on wheat price or wheat demand quantity or both? Do these gluten imports effects vary across wheat classes and/or by origin of gluten import? Finding the empirical answers to these questions plays an important role in U.S. agricultural trade disputes and negotiation, and in justifying related trade policies (Boland *et al.,* 2000).

Ortalo-Magne and Goodwin (1992) and Stiegert and Balzer (2001), in separated studies, have that found gluten imports to the U.S. are statistically influenced by domestic wheat demand and protein premium in wheat. In contrast, this study focuses on investigating how the U.S. domestic wheat markets respond to gluten imports. To do so, we specified two demand systems, factor demand and inverse factor demand, for wheat by class. A non-nested test was applied for model selection to determine whether the data were consistent with quantity formation or price formation (i.e., to determine whether prices adjust to quantities or quantities adjust to prices in the U.S. wheat market). In both systems, wheat gluten imports were treated as an important shifter. We distinguished gluten imports by major origins, including the EU, Australia, and residual countries to justify the related trade policies. In addition, this study employed a latest database, which has never been used in previous studies. This database consists of quarterly statistics covering the period of 1990.1 through 2004.3. Five classes of U.S. wheat, i.e., hard red winter (HRW), hard red spring (HRS), soft red wheat (SRW), soft white wheat (SWW), and durum wheat (DUR) were analyzed.

Background

Wheat gluten imports to the U.S. market increased rapidly over the period of 1990 through 2004. Researchers have argued that the quickly growing gluten imports to the U.S. might be because the gluten suppliers in EU have obtained government support by subsidizing wheat starch processing and starch-based industry (Balzer and Stiegert, 1999). Because wheat gluten is a co-product with a fixed proportional nature with starch in the process, the subsidizing protection on starch parallel transmits on gluten, resulting in overproduction of gluten and driving the world market price lower, which, in turn, strengthens the competitive power of the EU's gluten relative to the rest of the world. In addition, the subsidy to European industrial users of wheat starch and to export for wheat starch also increases gluten production and lowers the world price for wheat gluten.

In 1998, based on a petition filed by the Wheat Gluten Industry Council (WGIC), the U.S. International Trade Commission (USITC) charged the EU with dumping wheat gluten on the U.S. market. According to the WGIC, the price of EU gluten during the period from 1993 to 1996 was about $0.04 per pound lower than that of domestic gluten, which produced a negative impact on the U.S. gluten industry. In addition, a report issued by the USITC (1998) indicated that the EU's share of U.S. total gluten imports was two percent in 1985, but it had increased to 51 percent by 1997. As a result of the USITC ruling, a three-year quota was approved on wheat gluten imports from the EU, Australia, and all other non-excluded countries[2] on June 1, 1998. The quota was immediately put into effect. Canada was the only excluded country with significant exports of gluten to world markets, and usually ranks as the third largest exporter to U.S. markets.

While the quota limited gluten imports from all nonexcluded countries in the first 12 months to 126.8 million pounds (or 2.11 million bushels) and allowed a 6 percent increase annually for the duration of the three years relief period, its actual restrictions for major exporters were diverse. In the first quota year, the imports from the EU was limited to 54.041 million pounds (or 0.9 million bushels), 62.425 million pounds (or 1.04 million bushels) from Australia, and 10.346 million pounds (or 0.172 million bushels) from the "other" nonexcluded countries (USTR, 1998). Compared to the level a year earlier, the quota was about 46% and 32% less for the EU and the "other" countries, respectively, but actually 18% greater for Australia. Given that the market share of gluten from the "other" countries is usually very small in U.S. markets, the real restriction was only effective for gluten imports from the EU. As the only excluded country with significant exports of gluten, Canada was able to capitalize on the quota (Balzer and Stiegert, 1999).

The remainder of this paper is organized in the following manner. First, we review the previous studies. Second, we present our conceptual methodology. Third, data description and estimation issues are presented. Fourth, we provide a discussion of results. Finally, we finish

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[2] The excluded countries were Canada, Mexico, Israel, beneficiary countries under the Caribbean Basin Recovery Act, and developing countries that have not exported gluten. Canada is the only excluded country with significant exports of gluten to world markets.

with some concluding remarks.

Literature Review

There are a number of studies regarding estimation of wheat demand. Chai (1972) estimated linear equation-by-equation OLS demand models for wheat by class over the period from 1929 to 1963. Five classes of wheat, HRW, HRS, SRW, SWW, and DUR were estimated. The estimated price elasticities in this study suggest that hard classes of wheat are more elastic than soft classes. Barnes and Shields (1998) also estimated demand for five classes of wheat by employing both double-log demand system and equation-by-equation OLS models. While inelastic own-price elasticities were reported for each of the five wheat classes, their results are qualitatively consistent with Chai's. Using a dynamic AIDS model, Mohanty and Peterson (1997) estimated demand for wheat differentiated by classes for the United States and the European Union. They concluded that imported wheat is more price-elastic than domestic wheat in the U.S.

Technically, the above studies were mainly based on consumer demand theories. However, production approaches are more consistent with economic theory than utility-based demand approaches for wheat demand analysis. This is because wheat is not considered to be a consumer-ready food product, but is processed into flour before consumption (Koo *et al.*, 2001; Marsh, 2005), and it is used as input in the processing industry, the same as other agricultural commodities (Davis and Jensen, 1994). Consumers respond to retail level prices of flour and flour-based products, while in the processing sector, flour millers respond to farm level wheat prices in the input market and flour prices in the output market (Marsh, 2005).

Based on production theories, several studies on wheat demand have been conducted.

Koo et al. (2001), based on a multiple output and multiple input translog cost function, analyzed import demand for wheat differentiated by class and country of origin in the Japanese wheat flour milling industry. Their results indicated that Japanese demand for food wheat is highly elastic, and that U.S. soft wheat faces strong competition with Japanese domestic wheat, while U.S. hard and semi-hard classes of wheat face Canadian competition in the Japanese market. Marsh and Featherstone (2003) applied a normalized quadratic input distance system to estimate inverse demand relationships for wheat by class. Among five categories of wheat (HRW, HRS, SRW, SWW, and DUR), DUR was found to be the most price-flexible in this study. By comparing the estimated price flexibilities for each class of wheat from a semi-nonparametric estimator with fixed effects for input inefficiency and a Bayesian estimator with random effects for input inefficiency, their results are also supportive of government programs that no longer assume wheat to be a homogenous product. More recently, Marsh (2005), conceptualized wheat for food use as an input into flour production. Economic substitution cross wheat class in U.S. was estimated. The main conclusion indicated that hard red winter and spring wheat varieties are much more responsive to their own price than soft wheat and durum wheat varieties. In addition, the estimated substitution elasticities showed that hard red winter and hard red spring wheat are economic substitutes for milling purposes.

There are few studies focused on gluten (import) demand. Ortalo-Magne and Goodwin (1992) developed a structure import demand model to estimate the demand elasticity of gluten. Their study showed that global gluten market is price inelastic. Another important finding from that study is that U.S. demand for imported wheat gluten is influenced by the price of gluten, the price of flour, and a measure of industrial income. Stiegert and Balzer (2001) modeled the demand and supply conditions for wheat gluten and intrinsic wheat protein. Their main conclusions suggested a strong influence of HRW on the wheat gluten market, but in another way, wheat gluten markets were claimed to have considerable impact on HRS protein premiums and less influence on HRW protein premiums.

Methodology

The methodology section proceeds in the following manner. An indirect profit function is specified from which to derive a factor demand system for wheat food use in the milling industry[3]. Next, an input distance function is specified to derive an inverse demand system, with which to examine price formation across wheat classes. Then, we discuss an approach to performing a non-nested test for model selection, to determine whether prices are adjusting to quantities or quantities are adjusting to prices in U.S. wheat food use markets. In both models, wheat gluten imports from the EU, Australia, and other countries are specified as shifters.

Profit Function Approach:

Following Marsh (2005), consider an indirect industry profit function of the flour milling industry specified as:

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[3] The reasons we derived the demand function for wheat use in the milling industry instead of in the baking industry are: (1) outputs in the baking industry are very diverse and extremely hard to collect; and (2) in reality, despite that wheat gluten is mostly used in the baking industry, wheat flour use in the baking industry can be equivalently transformed to wheat use in the milling industry.

(1) $$\Pi^l(\mathbf{p},\mathbf{w}) = \Pi^l(\mathbf{y}^l(\mathbf{p},\mathbf{w}),\mathbf{x}^l(\mathbf{p},\mathbf{w})) = \max_{\mathbf{y}^l,\mathbf{x}^l}\{\mathbf{w}'\mathbf{y}^l - \mathbf{p}'\mathbf{x}^l : \mathbf{y}^l = f^l(\mathbf{x}^l)\}$$

where $\Pi^l(\bullet)$ and $f^l(\bullet)$ represent the l^{th} firm's profit and production technology respectively, $\mathbf{p} = (p_1,..., p_m)'$ and $\mathbf{w} = (w_1,..., w_n)'$ are prices of *m* inputs and *n* outputs respectively, $\mathbf{y}^l = (y_1^l,..., y_n^l)$ is a $n \times 1$ vector of the l^{th} firm output quantities, and $\mathbf{x}^l = (x_1^l,..., x_m^l)$ represents a $m \times 1$ vector of its input quantities. Assuming that all existing milling firms are price-takers in both input and output markets, then industry profit function is

(2) $$\Pi(\mathbf{p},\mathbf{w}) = \sum_{l=1}^{L} \Pi^l(\mathbf{p},\mathbf{w})$$

where *L* is the total number of flour milling firms in the industry. Similarly, the industry input and output quantities can be derived respectively as:

$$\mathbf{x} = (x_1,..., x_m : x_i = \sum_{l=1}^{L} x_i^l, i = 1,..., m) \text{ and } \mathbf{y} = (y_1,..., y_n : y_j = \sum_{l=1}^{L} y_j^l, j = 1,..., n)$$

Assuming weak separability, we separate inputs into two subgroups of wheat and other inputs.[4] Hence, the industry profit function is

(3) $$\Pi = \Pi(\mathbf{p},\mathbf{w}) = \Pi(\pi^1(\mathbf{p}^1,\mathbf{w}), \pi^2(\mathbf{p}^2,\mathbf{w}), \mathbf{w})$$

where π^1 and π^2 are micro-function, $\mathbf{p}^1 = (p_1,..., p_k)'$ is a vector of input prices representing the different classes of wheat, and $\mathbf{p}^2 = (p_{k+1},..., p_m)'$ is a vector of prices for remaining inputs such as labor and energy. By applying Hotelling's Lemma to function π^1, factor demand for wheat by class can be derived as,

[4] This assumption imposes symmetric factor demand elasticities between two groups of inputs (Chambers, 1998).

(4) $$-\mathbf{x}^1(\mathbf{p}^1,\mathbf{w}) = \frac{\partial \pi^1}{\partial \mathbf{p}^1}$$

This system of factor demand equations represents the flour miller's demand for wheat by class from the producer supplier.

Empirically, we specify a normalized quadratic profit function

(5) $$\begin{aligned}\Pi^*(\tilde{\mathbf{p}}\ ,G) &= a_0 + \sum_{i=1}^{k} c_i \tilde{p}_i + .5\sum_{i=1}^{k}\sum_{j=1}^{k} b_{ij}\tilde{p}_i\tilde{p}_j + t_0 T + \sum_{i=1}^{k} t_i \tilde{p}_i T + .5 t_{00} T^2 \\ &+ \sum_{j=1}^{3} d_j D_j + \sum_{i=1}^{k}\sum_{j=1}^{3} d_{ij}\tilde{p}_i D_j + .5\sum_{j=1}^{3} d_{jj} D_j^2 \\ &+ \sum_{j=1}^{3} g_j G_j + \sum_{i=1}^{k}\sum_{j=1}^{3} g_{ij}\tilde{p}_i G_j + .5\sum_{j=1}^{3} g_{jj} G_j^2\end{aligned}$$

where $\Pi^*(\bullet)$ represents normalized profit, which is obtained by dividing profit $\Pi(\bullet)$ by a weighted average flour price $\overline{w} = \sum_{i=1}^{n} s_{ij} w_i$, where s_{ij} is the quantity of output type *i* relative to total production in the j^{th} quarter[5], $s_{ij} = \dfrac{x_{ij}}{\sum_{j=1}^{5} x_{ij}}$; $\tilde{p}_i = p_i / \overline{w}$ is a vector of input prices normalized by output price; $D_j\ (j = 1,2,3)$ are quarterly dummy variables (the 4th quarter is used as reference); *T* is a time trend that is used to capture technology progress and other changes over time; and $G_j,\ j = 1,2,3$, represents gluten imports into the U.S. from the EU, Australia, and other countries. Here, $c_i, b_{ij}, t, d_{ij}, g_{ij}$ are parameters to be estimated. By equation (4), the demand equation for each class of wheat is then

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[5] A practical assumption for calculating the weighted flour price is that the outputs produced by per unit input for five classes of wheat are the same. This is mainly because of the limited flour data.

(6) $$-x_i = c_i + \sum_{j=1}^{k} b_{ij}\tilde{p}_j + t_i T + \sum_{j=1}^{3} d_{ij} D_j + \sum_{j=1}^{3} g_{ij} G_j + \omega_i \quad for\ i = 1, \ldots, m$$

with error term ω_i.

Distance Function Approach

A direct input distance function for the flour milling sector is defined, from which we derive an inverse factor demand system. Classical duality theory suggests that the distance function approach is consistent with the cost minimization assumption or profit function approach. The standard properties of a distance function are that it is homogenous of degree one, non-decreasing, and concave in input quantities and non-increasing in outputs (Shepherd 1970). Define the distance function as:

(7) $$\begin{aligned} D(\mathbf{x}, \mathbf{y}) &= \max_{\delta} \delta \\ s.t.\ f(\mathbf{x}/\delta) &= \mathbf{y} \end{aligned}$$

where $\mathbf{y}$ and $\mathbf{x}$ are defined above, and $\delta \geq 1$ is the distance function representing a rescaling of all the input levels consistent with a target output level. Intuitively, δ is the maximum value by which one could divide $\mathbf{x}$ and still produce $\mathbf{y}$ [6]. Normalizing the price vector of inputs by total cost yields $p_i^* = p_i / \sum_{j=1}^{m} p_j x_j$. Applying Gorman's Lemma, inverse factor demand functions are

(8) $$p_i^*(\mathbf{x}, \mathbf{y}) = \frac{\partial D(\mathbf{x}, \mathbf{y})}{\partial x_i}$$

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[6] In the specification of the distance function and the econometric system, we did not differentiate the type of flour produced, instead assuming the flour output is homogeneous for the limited quantity data for flour.

Following Marsh and Featherstone (2003), the input distance function in (7) can be specified as a normalized quadratic

(9)

$$
\begin{aligned}
&D(\mathrm{x,y}) = \\
&b_0 + \sum_{i=1}^{m} b_i x_i + \sum_{i=m+1}^{m+n} b_i y_i + .5((\sum_{k=1}^{m} \alpha_k x_k)^{-1} \sum_{i=1}^{m}\sum_{j=1}^{m} b_{ij} x_i x_j + \sum_{i=m+1}^{m+n}\sum_{j=m+1}^{m+n} b_{ij} y_i y_j) + \sum_{i=1}^{m}\sum_{j=m+1}^{m+n} b_{ij} x_i y_j \\
&+ t_0 T + \sum_{i=1}^{m} t_i x_i T + .5 t_{00} T^2 \\
&+ \sum_{j=1}^{3} d_j D_j + \sum_{i=1}^{m}\sum_{j=1}^{3} d_{ij} x_i D_j + .5 \sum_{j=1}^{3} d_{jj} D_j^2 \\
&+ \sum_{j=1}^{3} g_j G_j + \sum_{i=1}^{m}\sum_{j=1}^{3} g_{ij} x_i G_j + .5 \sum_{j=1}^{3} g_{jj} G_j^2
\end{aligned}
$$

with *m* inputs and *n* outputs; $G_j \ (j = 1,2,3)$, $D_j \ (j = 1,2,3)$, and T have the same definitions as above; the $b's$, $g's$, $d's$, and $t's$ are parameters to be estimated; and α_i are predetermined positive constants that dictate the form of normalization. Symmetry is imposed by restriction $b_{ij} = b_{ji}$ [7]. Using the Gorman's Lemma, the conditional inverse factor demand functions can be given by

(10)

$$
\begin{aligned}
p_i^* = b_i + (\sum_{k=1}^{m} \alpha_k x_k)^{-1} \sum_{j=1}^{m} b_{ij} x_j + \alpha_i (\sum_{k=1}^{m} \alpha_k x_k)^{-2} \sum_{i=1}^{m}\sum_{j=1}^{m} b_{ij} x_i x_j) + \sum_{j=m+1}^{m+n} b_{ij} y_j \\
+ t_i T + \sum_{j=1}^{3} d_{ij} D_j + \sum_{j=1}^{3} g_{ij} G_j + \eta_i
\end{aligned}
$$

with error term η_i

Homogeneity of degree zero in inputs in the inverse factor demand equation implies

[7] Validities of symmetry and curvature restrictions are tested and presented in Appendix B.2.

that $\sum_{j=1}^{m} b_{ij} = 0$, while the normalization restriction requires that $\sum_{k=1}^{m} \alpha_k x_k = 1$ at a reference vector. Normalizing quantities by their mean values yields $x^* = (1,...,1)' = l_m$, which can be used as a reference bundle. At a reference vector x^*, the demand restrictions become

(11) $$\sum_{k=1}^{m} \alpha_k x_k^* = \sum_{k=1}^{m} \alpha_k = 1, \alpha_k \geq 0, \forall k, \text{ and } \sum_{j=1}^{m} x_j^* b_{ij} = \sum_{j=1}^{m} b_{ij} = 0$$

To impose these restrictions, we normalized factor demand quantities by the k^{th} input as $x_s^* = x_s / x_k \ \forall s = 1,...,m$, and predetermined constants as $\alpha = (0,...,0,\alpha_k,0,...,0) \ni \alpha_k = 1$ such that $\sum_{s=1}^{m} \alpha_s x_s^* = 1$. Hence, the input demand functions in (10) become

(12) $$p_i^* = b_i^* + \sum_{j=1}^{m-1} b_{ij}^* x_j^* + \sum_{j=m+1}^{m+n} b_{ij}^* y_j + t_i^* T + \sum_{j=1}^{3} d_{ij}^* D_j + \sum_{j=1}^{3} g_{ij}^* G_j + \eta_i \quad \text{for } i = 1,...,m-1$$

Model Selection Test

To select between the two dual competing models discussed above, we applied a non-nested test proposed by Vuong (1989). In specifying the non-nested test, we derived share equations as alternatives to the demand system in (6) and to the inverse demand system in (12)[8]. First, we constructed share equations for the factor demand system. Multiplying both sides of the

[8] Part of the motivation for specifying the share equation is that in preliminary analysis we applied standard single equation non-nested tests between the competing models. However, these tests were inconclusive, and we then applied the generalized likelihood ratio test.

equation (6) by normalized price $p_i^* = p_i / \sum_{i=1}^{k} p_i x_i$, we got the share equations

$$(13) \qquad -w_i = -p_i^* x_i = p_i^* c_i + p_i^* \sum_{j=1}^{k} b_{ij} \tilde{p}_j + p_i^* t_i T + p_i^* \sum_{j=1}^{3} d_{ij} D_j + p_i^* \sum_{j=1}^{3} g_{ij} G_j + \omega_i$$

Second, we derived the share equations for the inverse factor demand system from equation (12) by multiplying both sides of the equation by the corresponding input quantity x_i

$$(14) \qquad w_i = x_i p_i^* = x_i b_i^* + x_i \sum_{j=1}^{m-1} b_{ij}^* x_j^* + x_i \sum_{j=m+1}^{m+n} b_{ij}^* y_j + x_i t_i^* T + x_i \sum_{j=1}^{3} d_{ij}^* D_j + x_i \sum_{j=1}^{3} g_{ij}^* G_j + \eta_i$$

Using the two systems of share equations, we followed the proposed non-nested normalized likelihood ratio (LR) test by Vuong (1989) to determine a preferred model in pairwise evaluation. The test is based on the generalized likelihood ratio principle and is designed to test the null hypothesis that two dual models adjust to the data equally well versus the alternative hypothesis that one model fits better. The calculated likelihood ratio statistic is normalized by

$$(15) \qquad n^{\frac{1}{2}} \hat{w}_n = \frac{1}{2} \left[\sum_{t=1}^{n} (\hat{\boldsymbol{\mu}}_{it}^{'} \textstyle\sum_{i}^{-1} \hat{\boldsymbol{\mu}}_{it} - \hat{\boldsymbol{\mu}}_{dt}^{'} \textstyle\sum_{d}^{-1} \hat{\boldsymbol{\mu}}_{dt})^2 \right]^{\frac{1}{2}}$$

where $\boldsymbol{\mu}_s$ are the estimated residuals and $\sum_s$ are the estimated covariance matrix for model M_s, $s = i, d$. i stands for inverse demand system, d stands for factor demand system. The resulting normalized statistic is asymptotically normally distributed under the null hypothesis of equal fit. When the absolute value of the normalized LR statistic is smaller than the critical value, then the data cannot identify a superior model. If the normalized LR statistic is smaller than the negative critical value, then we can conclude that the factor demand model is preferred; and if it is greater than the critical value, then we can conclude that the inverse model is preferred.

Econometric Estimation Issues

The Likelihood Ratio test was used to test for the first-order residual autocorrelation, i.e. AR(1). To do so, both systems, with and without AR(1) imposed, were estimated. The method to impose AR(1) is from Berndt and Savin (1975). The basic idea is

$$Y_t = X_t\beta + v_t \Rightarrow \hat{v}_t = Y_t - X_t\hat{\beta} \quad (*)$$

$$v_t = \rho v_{t-1} + \varepsilon_t \Rightarrow \hat{\varepsilon}_t = \hat{v}_t - \rho\hat{v}_{t-1} \quad (**)$$

plug (*) into (**) to get $\hat{\varepsilon}_t = Y_t - X_t\hat{\beta} - \rho\hat{v}_{t-1}$, where ρ is one more parameter to be estimated than the system without AR(1) imposed[9], v_t represents ω_t in system (6) and η_t in system (12), and *t* denotes observation number. The subscript *i* representing equation number in systems (6) and (12) is dropped here for simplicity. The null hypothesis of unadjusted the Likelihood Ratio test is that there is no AR(1) presence.

The exogeneity of gluten imports in specification for both demand systems was tested by the Wu-Hausman test, which consists of an asymptotically distributed chi-square with one degree of freedom (Hausman 1978). The null hypothesis of the test is that the imported gluten is exogenous. The procedure works as follows. First, a regression with gluten imports as dependent variable and partial or full of other explanatory variables in the original functions plus several instrumental variables as explanatory variables is estimated with an ordinary least squares (OLS)

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[9] If AR(1) is not imposed, $\hat{\varepsilon}_t = Y_t - X_t\hat{\beta}$.

technique[10]. The predicted OLS residuals are then included as extra regressors in the original functions. If the estimates for those regessors are significant, then we reject the null hypothesis. Following a similar procedure, the exogeneity of wheat quantities in the inverse demand system were also tested.

In the inverse demand system, the concavity condition was imposed by Choleskey decomposition approach. This method for the normalized quadratic only requires reparameterization of the Hession matrix. In this case, concavity was imposed by decomposing the Antonelli matrix into a negative semidefinite matrix, i.e. **A= -BB'** where **B** is a lower triangular matrix (Lau 1978). By running both with and without concavity condition imposed systems, we can test the hypothesis that a curvature condition holds by using the Adjusted Likelihood Ratio test[11].

Data Description

Five major classes of wheat are grown in the U.S. for food consumption, including hard red winter (*HRW*), hard red spring (*HRS*), soft red winter (*SRW*), soft white (*SWW*), and durum

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[10] Appendix B.3 and B.4 provide endogeneity test results for gluten imports and wheat quantities in inverse demand system. The results of endogeneity tests for gluten imports and wheat prices in demand system are available upon request.

[11] The null hypothesis is Ho: no concavity. The Adjusted Likelihood Ratio Statistic is given by:

$\lambda = LR[mn - 0.5(Ku - Kr) - 0.5m(m+1)]/(mn) \sim \chi^2(J)$, where $LR = 2[\ln(Lu) - \ln(Lr)]$ is unadjusted Likelihood Ratio Statistic, *Lu* and *Lr* are likelihood values for unrestricted and restricted models, respectively; *m* is the number of equations in system; *n* is the observation numbers in each equation; *Ku* and *Kr* are the number of parameters in unrestricted and restricted model respectively; *J* is the number of restrictions, in this case, *J*=m(m+1)/2=10.

(*DUR*) wheat. Quarterly prices and quantities from USDA-ERS were used for empirical analysis. The data period ranges from the first quarter of 1990 to the third quarter of 2004. Table 1 reports the descriptive statistics for quarterly prices and quantities. Total flour production reached nearly 400 million cwt in 2003 from 343 million cwt in1990, averaging 392 million cwt. In same period, total wheat for food use increased from 749 million bushels to 918 million bushels. Of five classes of wheat, the food uses of HRW and HRS rapidly increased, but three other classes, SRW, SWW and DUR have only slightly shifted up (Figure 4). On average, hard wheat (HRW and HRS) accounts for 76 per cent out of total food wheat use, while the percentages for SRW, SWW and DUR are 18.1 per cent, 7.69 per cent and 7.92 per cent, respectively.

Quarterly imports of wheat gluten used in this study were collected from World Trade Atlas. The wheat gluten imports to the U.S. market display a rapid and sustained upward trend from 1990 through 2004, despite its historically limited use. The EU and Australia are the top two exporters to the U.S. gluten market (See Figure 1). In 1990, gluten imports from the EU and Australia were 0.55 million bushels and 0.75 million bushels, respectively. In 1996, the EU exceeded Australia to become the largest wheat gluten exporter to the U.S. market. Since then European gluten exports have skyrocketed to 2.20 million bushels in 2003, and reached a record high at 3.44 million bushels in the first three quarters of 2004. During the same period, imports from Australia experienced a moderate increase at first, and then decreased to 1 million bushels in 2004, while residual countries have generally kept gluten imports steady at around 0.5 million bushels annually. These changes in market structure are particularly observable in Figures 2 and

3, which break down the import market in 1990 and in 2004[12], respectively. Meanwhile, quarterly gluten import data also show significant seasonal variation, particularly during the three-year quota duration beginning on June 1, 1998.

Wheat quantity and price data used in this paper were from Economic Research Service, the U.S. Department of Agriculture (ERS, USDA). The original price data for classes of wheat were from four major markets. HRW price is represented by Kansas City, No.1 (13% protein); HRS price and DUR price are represented by Minneapolis, dark No.1 spring (14% protein) and No.1 hard amber durum, respectively; SRW price by Chicago, No.2; and SWW price by Portland No.1. Figure 5 shows these price trends over our study period. At the beginning of the 1990s, they were quiet close, but gradually, year after year, these prices grew far away from each other. By the end of our study period, the price of DUR was about one and half that of SRW.

Empirical Results

Based on test results, a variety of necessary conditions were imposed into two systems (see next paragraph for details). The non-nested test was then applied for model selection. The normalized LR statistics from formula (21) is 390.51, which is greater than any relevant critical values from the standard normal distribution, i.e. *p-value* closes to zero. In all, this test provides strong evidence that the inverse system is preferred to the factor demand system, given the data and model specifications. This test result suggests that in the U.S. wheat market, prices are more likely to adjust to quantities changes rather than the reverse. For simplification, we only present results for the inverse demand system in this section. The estimated results from factor demand

[12] Wheat imports to the U.S. in 2004 only contain the first three quarters.

system and associated econometric test results are attached in Appendix A for further reference (See Appendix A.1-A.4).

Table 2 presents the estimated results for the inverse demand system in (12) using iterative seemingly unrelated regression (SUR) estimator. It is important to point out the following: (1) based on the results from various tests, the AR(1) autocorrelation correction, concavity condition, and symmetry were imposed into the estimation (See Appendix B.1 and B.2 for associated test statistics), gluten imports from the three sources (the EU, Australia, and other countries) and wheat quantities were tested for endogenous problems (See Appendix B.3 and B.4 for associated test statistics), and the Kolmogorov-Smirnov-Lilliefors test result shows that we failed to reject the null hypothesis of normal residuals in inverse demand system (See Appendix B.5); (2) to avoid potential intractable estimation of parameters and to gain robust results, the bootstrap resampling procedure was applied[13]. The bootstrap confidence intervals, which were constructed based on the percentile method, were used for hypothesis testing; and (3) in order to avoid singular problems, the SWW equation was dropped from the system. The dummy variable for the fourth marketing quarter (March to May) was also dropped to prevent perfect

[13] Bootstrap resampling simulation was obtained by (a) resampling the residuals of the models, (b) predicting prices of wheat in the system, and (c) then re-estimating the system with predicted values to get parameter estimates and calculate price flexibilities. The process was repeated 200 times to generate distributions of parameter estimates and price flexibilities. The 90% confidence intervals for each parameter and flexibility were constructed based on the percentile method, which requires ordering the estimated parameters and flexibilities and then selecting outcome 10(0.05*200) for the lower critical value and outcome 290 (0.95*200) for the upper critical value.

multicollinearity.

More than half of the estimated coefficients in Table 2 are statistically significant at the 10% level. The R-square values for equations HRS, HRW, SRW, and DUR were 0.91, 0.81, 0.90, and 0.64 respectively, indicating a very high explanation of price of wheat food use for each class. These estimated results show that wheat prices in the U.S. market are significantly related to a number of variables. First, the estimated coefficients for the own-quantity demand were negative and significant for each wheat class, suggesting that for each class wheat price is negatively associated with their own quantity. Second, wheat prices, except for durum, were also found to be negatively and significantly related to quantity of flour, the primary product of milling industry. Besides, wheat prices showed seasonal changes, as we saw in Figure 5, but the estimated results only indicate that prices in the second quarter, the harvest season for most wheat production areas in the U.S., are significantly lower than those in the fourth quarter, the holiday season.

As the center interest of this study, the estimated results clearly show that most wheat prices are significantly related to gluten imports. But the responsive signs and magnitudes depend on wheat class and the origin of gluten imports[14]. This can be clearly seen in Table 3, where price flexibilities with respect to gluten imports are presented[15].

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[14] Test result for effects of individual origin of gluten imports on wheat prices is presented in Appendix B.6.

[15] Using estimated parameters, the compensated price flexibilities can be derived by

$f_{ij}^{*} = \dfrac{\partial \ln p_i}{\partial \ln x_j} = \dfrac{b_{ij} x_j}{p_i}$ for $i, j = 1, ..., m$, where b_{ij} the estimated parameters and p_i is predicted wheat price.

Generally speaking, the prices of three high protein wheat classes (HRW, HRS, and DUR) are negatively responsive to gluten imports from the EU and Australia, while the prices of two low protein content wheats (SRW and SWW) are positively related to gluten imports from all origins. This finding is consistent with what we expected, because domestic flour millers and bakers often blend wheat gluten with lower protein wheats to increase protein content in the resulting flour or flour-based products that can be produced by using high protein content wheats[16]. This blending increases demand for low protein wheats but decreases demand for high protein content wheats, thus leading to their prices moving up and down, respectively. As a result, the price of low protein wheats moves in the same direction as the quantity of imported gluten engaged in the blending. At the same time, the prices of high protein wheats move in the opposite direction.

However, the prices of two high protein wheats (HRW and HRS) display contrary relationships with gluten imports from other exporter countries as they do for the European and Australian gluten imports. An explanation for this inconsistency may be rooted in different incentives that cause domestic millers and bakers to blend imported gluten with low protein content wheats, and the different driving forces behind gluten imports. Millers and bakers are

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Similarly, the price flexibilities with respect to gluten import quantity can be given by

$$\xi_i = \frac{\partial \ln p_i}{\partial \ln G_j} = \frac{g_i G_j}{p_i} \quad \text{for } i = 1, ..., m;\ j = 1, 2, 3 .$$

[16] About 1.55 pounds of dry gluten is needed to increase the protein level of 100 lbs. of wheat flour by 1 percent, slightly varying by the current protein level (Milling & Baking News).

more likely to blend low protein wheats with gluten to produce high-protein required products when: (1) wheat protein levels are low because of weather or other reasons in some crop years (Boland *et al*. 2000 and 2005); and (2) more gluten with relatively low price is available. These two incentives for firms actually reflect two major driving forces behind gluten imports. In the first scenario, gluten import may largely be driven by domestic demand for protein premium. However, in the second example, more competitive prices could play an important role in gluten import since for millers and bakers blending relatively cheap gluten with low protein wheats could be more profitable than using high protein wheat alone for producing the same products. As discussed earlier, gluten imports from the EU and Australia, especially those from the EU, are more price competitive than those from other countries in U..S markets. Therefore, the European and Australian gluten imports are more likely driven by their cheap prices, while the gluten imports from other countries are more likely driven by the U.S. domestic demand. This may be the key reason to explain the opposite estimates for HRW and HRS but consistent for SRW and SWW.

In terms of magnitude, the estimated price flexibilities with respect to gluten imports also vary across wheat classes and by import origin. SWW and DUR generally have relatively high price-flexibilities with respect to gluten imports than do HRW and HRS. This may be because both SWW and DUR have smaller market shares relative to HRW and HRS. In addition, Table 3 shows that three classes of wheats (HRW, SRW, and DUR) are significantly related to European gluten imports, both classes (DUR and SWW) are significantly related to gluten imports from Australia, and all wheat classes other than SRW are significantly related to gluten imports from other countries.

Table 4 presents the price flexibilities with respect to quantities of wheat for food uses[17,18]. The 90% confidence intervals for the flexibilities were obtained using the bootstrap method. As expected, all five own-flexibilities were found to be significantly negative as required with the imposition of concavity condition for each wheat class. In magnitude, although none of the five classes of wheat showed price flexibility, the price of hard red winter wheat was observably less responsive to own-quantity changes than the remained four classes. This finding might be related to the largest share that HRW accounts for in the U.S. wheat food use.

Meanwhile, the cross-price flexibilities showed that the price of durum is significantly and negatively related to the quantity of HRS, but is positively related to other three wheat classes. This is not surprising when considering that both HRS and DUR are grown primarily in the Northern Plain states (mainly North Dakota, Montana, Minnesota and South Dakota) and that they are relatively high-protein wheat classes which are suitable for production of specially breads and pasta. Because of the imposition of symmetric condition, prices of all wheat classes other than durum were significantly related to quantity of durum for food use (Table 4). Other cross-price flexibilities were not statistically significant, except those between SWW and HRS.

Conclusion

This study examined the impact of wheat gluten imports on the wheat market in the U.S. Using quarterly wheat food use by class price and quantity data, we conceptualized and specified an inverse demand system and factor demand system where gluten imports from the EU,

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[17] See footnote 11 for price flexibility calculation.
[18] The price flexibilities for SWW were calculated using the recovered parameters by the imposed restrictions.

Australia, and other countries were treated as important shifting variables. With a non-nested generalized likelihood ratio test, we rejected the factor demand system in favor of the inverse demand system, suggesting that prices were more likely adjusting to quantities over the sample period. Endogeneity of wheat gluten imports to the U.S. and wheat quantities were tested and rejected.

The key results of this study suggest that gluten imports generally have significant influences on U.S. domestic wheat prices. However, specific influence depends on wheat class and the origin of the gluten imports. In general, the prices of three hard wheat classes (hard red winter, hard red spring, and durum) were negatively responsive to gluten imports from the EU and Australia, while the prices of two soft wheat classes (soft red winter and soft white wheat) showed contrary results to all gluten imports. Interestingly, the prices of hard red winter and hard red spring positively responded to gluten imports from other countries.

Appropriate explanation about these results may be rooted in two situations in which U.S. mills and bakeries often tend to blend gluten with low protein wheats to produce high-protein products. First, domestic wheats cannot provide enough protein. Second, blending imported gluten with low protein wheats to produce high-protein products is more profitable for milling and baking firms than using high-protein wheat alone for production. These two situations actually represent two major driving forces behind gluten imports. While in the first situation gluten import might be driven by domestic demand, it is more likely driven by competitive prices in the second situation. The increasing gluten imports from the EU are more likely because of its dumpling price in the U.S. market.

While the influence of gluten imports from the EU and Australia on the price of each of the five wheat classes is consistent, European gluten imports only significantly affect the prices of hard red winter, soft red winter and durum; Australian gluten imports significantly affect the prices of durum and soft red winter. Meanwhile, the price flexibilities of durum and soft white wheats with respect to gluten imports are observably greater than those of hard red winter and hard red spring wheats. The reason might be that market shares of DUR and SWW in the U.S. total food wheat use are smaller than those of HRW and HRS.

These findings provide empirical evidence that economic impact associated with increasing gluten imports to the U.S. market could spill over from the starch-gluten processing industry to domestic wheat markets through gluten's specific role in the milling and baking industry. Meanwhile, these findings also to some extent justify the three-year quota policy since June of 1998 on wheat gluten imports from the EU, Australia, and all other non-excluded countries.

In addition to answering our central question about how domestic wheat markets respond to increasing gluten imports, the results from this study also show that wheat prices in the U.S. domestic market are significantly related to their own quantities and quantity of flour; and they display seasonal fluctuations.

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Table 1. Descriptive Statistics for Price and Quantity Data from 1990.1-2004.3

Variables	Mean	St. Dev.	Min	Max
Annual Quantity of Flour (1000 cwt)	392,040	18,490	354,350	421,270
Quarterly Quantity of Flour (1000 cwt)	98,078	5,832	85,692	112,236
Price of Flour ($/cwt)	10.38	1.56	7.53	15.18
Price of Hard Red Winter Wheat ($/bu)	3.98	0.73	2.86	6.51
Price of Hard Red Spring Wheat ($/bu)	4.19	0.74	2.83	6.49
Price of Soft Red Wheat ($/bu)	3.23	0.73	2.02	5.40
Price of Soft White Wheat ($/bu)	3.80	0.69	2.77	5.68
Price of Durum Wheat ($/bu)	4.97	1.08	3.10	7.08
Quantity of Hard Red Winter Wheat (million bu)	90.58	7.93	75.65	106.60
Quantity of Hard Red Spring Wheat (million bu)	55.87	7.07	40.00	70.00
Quantity of Soft Red Wheat (million bu)	37.78	2.48	33.00	44.93
Quantity of Soft White Wheat (million bu)	18.02	2.59	12.00	23.60
Quantity of Durum Wheat (million bu)	18.71	1.70	14.83	21.70
Quantity of Imported Australia Gluten (million bu)	0.25	0.06	0.12	0.38
Quantity of Imported EU Gluten (million bu)	0.32	0.26	0.06	1.28
Quantity of Imported Other Countries Gluten (million bu)	0.11	0.04	0.05	0.23

Table 2. Estimated Results from Bootstrap Resampling Procedure

	HRW	HRS	SRW	DUR
Constant	0.008782*	0.007308*	0.012386*	0.010434*
	0.000650	0.000930	0.001390	0.002404
HRW	-0.000035*	0.000042	-0.000030	0.000093*
	0.902206	3.399784	5.456541	5.552592
HRS		-0.000177*	0.000089	-0.000196*
		0.812222	1.636430	1.923400
SRW			-0.000198*	0.000240*
			1.616397	4.151677
DUR				-0.000528*
				1.615752
Flour	-0.004155*	-0.002079*	-0.008764*	-0.003068
	0.000646	0.000921	0.001361	0.002347
1st quarter	-0.000010	0.000011	0.000034	-0.000206
	0.000044	0.000059	0.000050	0.000062
2nd quarter	-0.000025	-0.000231*	0.000357*	-0.000192
	0.000081	0.000072	0.000090	0.000120
3rd quarter	0.000026	-0.000016	-0.000094	0.000078
	0.000102	0.000163	0.000208	0.000183
EU gluten	-0.000096*	-0.000103	0.000323*	-0.000385*
	0.000085	0.000122	0.000219	0.000246
Australia gluten	-0.000323	-0.000037	-0.000006	-0.001969*
	0.000354	0.000505	0.000906	0.000357
Other gluten	0.000934*	0.001319*	0.000238	-0.007811*
	0.000499	0.000723	0.001291	0.000442
Time trend	-0.000004	-0.000009*	-0.000012*	0.000048*
	0.000003	0.000005	0.000007	0.000012
ρ	0.221122*			
	0.000073			

* 90% confidence interval does not contain zero.

Table 3. Price Flexibilities with Respect to Gluten Imports

Wheat Prices by Class	Gluten Imports	90% Confidence Intervals	
	From EU		
HRW	-0.01319*	-0.02318	-0.00213
HRS	-0.01342	-0.03212	0.00282
SRW	0.05454*	0.02536	0.08441
DUR	-0.04239*	-0.07541	-0.01117
SWW	0.03737	-0.00551	0.07908
	From Australia		
HRW	-0.03556	-0.07170	0.00067
HRS	-0.00388	-0.05527	0.04580
SRW	0.00079	-0.10123	0.10717
DUR	-0.17380*	-0.27545	-0.05627
SWW	0.26724*	0.11359	0.39483
	From Other Countries		
HRW	0.04574*	0.02130	0.06868
HRS	0.06132*	0.02721	0.09536
SRW	0.01438	-0.05097	0.08389
DUR	-0.30696*	-0.37123	-0.24142
SWW	0.27108*	0.16726	0.35510

* 90% confidence interval does not contain zero.

Table 4. Price Flexibilities for Wheat Food Use by Class and Confidence Intervals

Price \ Quantity	HRW	HRS	SRW	SWW	DUR
HRW	-0.03925*	0.02875	-0.01411	-0.01529	0.02154*
HRS	0.04457	-0.11556*	0.03958	0.05071*	-0.04335*
SRW	-0.04168	0.07552	-0.11435*	-0.02751	0.06883*
SWW	-0.08125	0.17385*	-0.04947	-0.10624*	0.09478*
DUR	0.08362*	-0.10864*	0.09047*	0.06928*	-0.09858*
		90% confidence Intervals-Lower			
HRW	-0.08234	-0.00063	-0.03591	0.00213	-0.03414
HRS	-0.00098	-0.18169	-0.00832	-0.07763	0.02084
SRW	-0.10578	-0.01580	-0.27697	0.00674	-0.07802
SWW	-0.18217	0.07115	-0.14091	0.01788	-0.20429
DUR	0.00818	-0.19292	0.00893	-0.21138	0.01322
		90% confidence Intervals-Upper			
HRW	-0.00893	0.05327	0.01418	0.04321	0.00208
HRS	0.08261	-0.05800	0.09216	-0.00920	0.08360
SRW	0.04215	0.17545	-0.01748	0.13648	0.03016
SWW	0.01106	0.28548	0.05423	0.20049	-0.02957
DUR	0.16670	-0.02296	0.18121	-0.02900	0.14703

* 90% confidence interval does not contain zero.

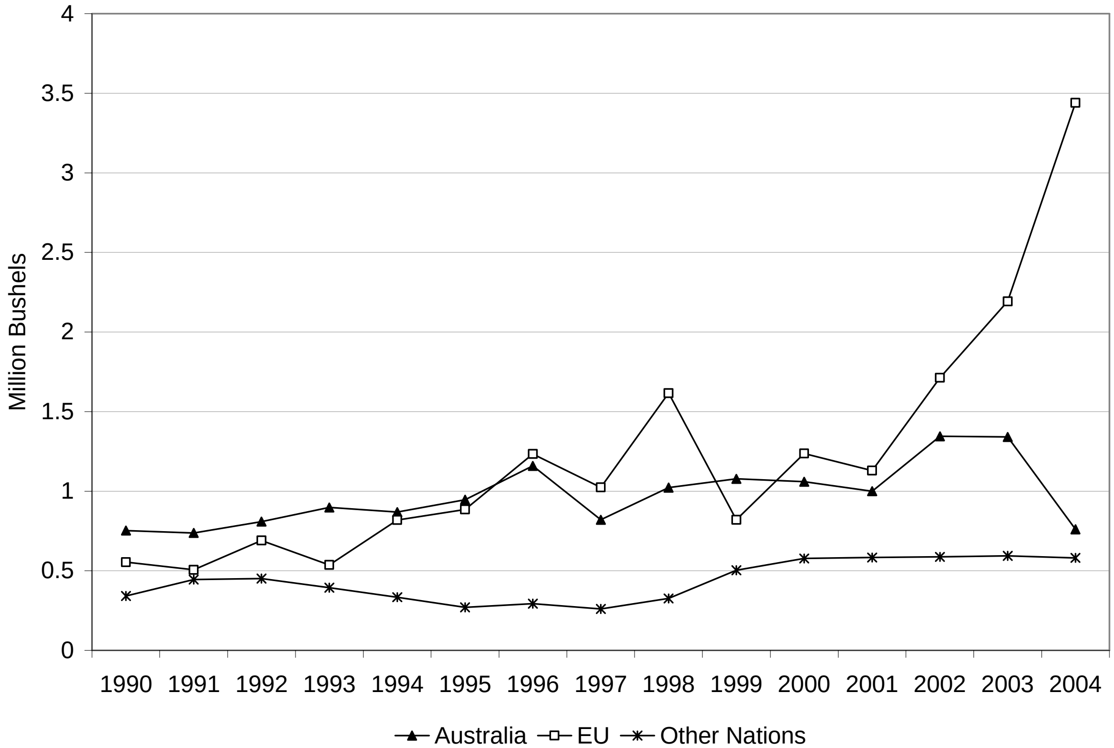

Figure 1. Wheat Gluten Imports to the U.S. by Origin*

*The gluten import data in 2004 does not include the 4th quarter.

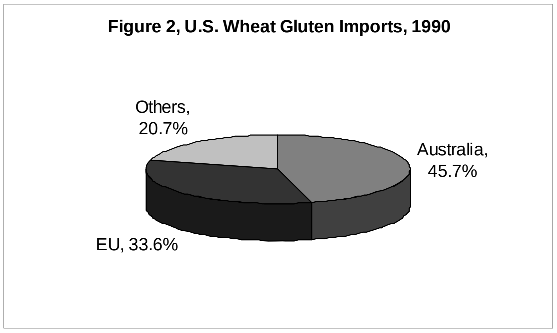
Figure 2, U.S. Wheat Gluten Imports, 1990
Others, 20.7%
Australia, 45.7%
EU, 33.6%

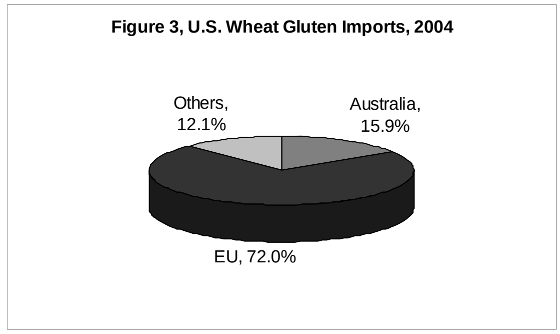
Figure 3, U.S. Wheat Gluten Imports, 2004
Others, 12.1%
Australia, 15.9%
EU, 72.0%

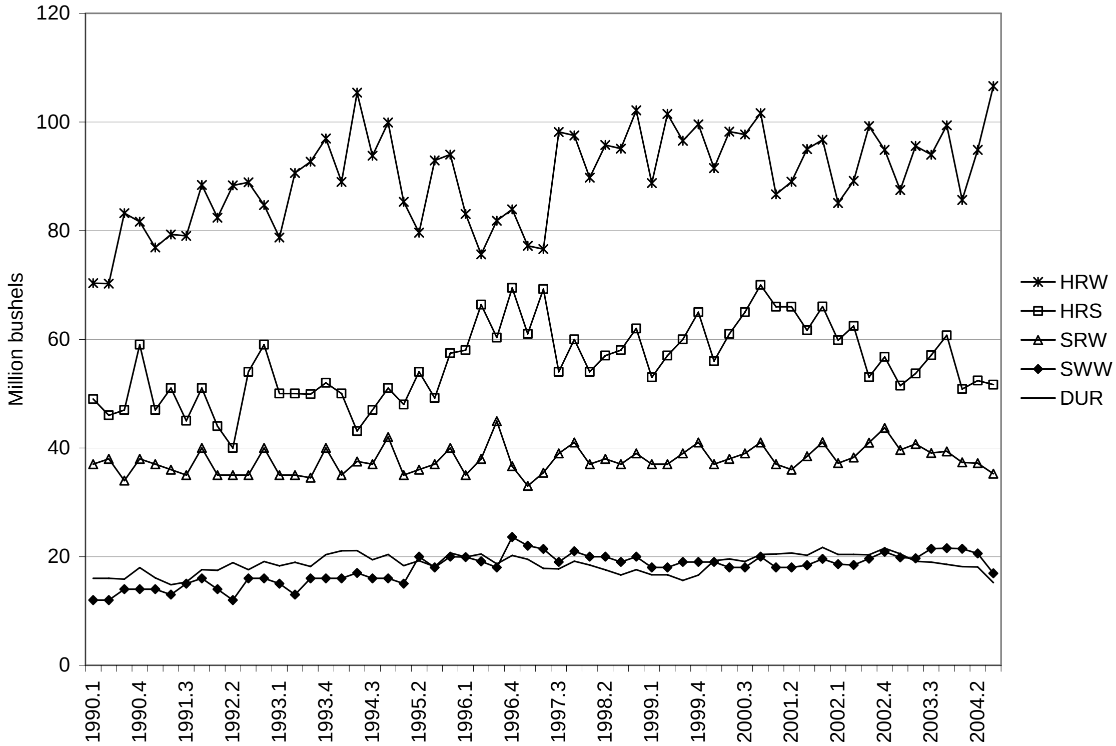

Figure 4. Quarterly Wheat Food Use by Class in U.S. 1990.1-2004.3

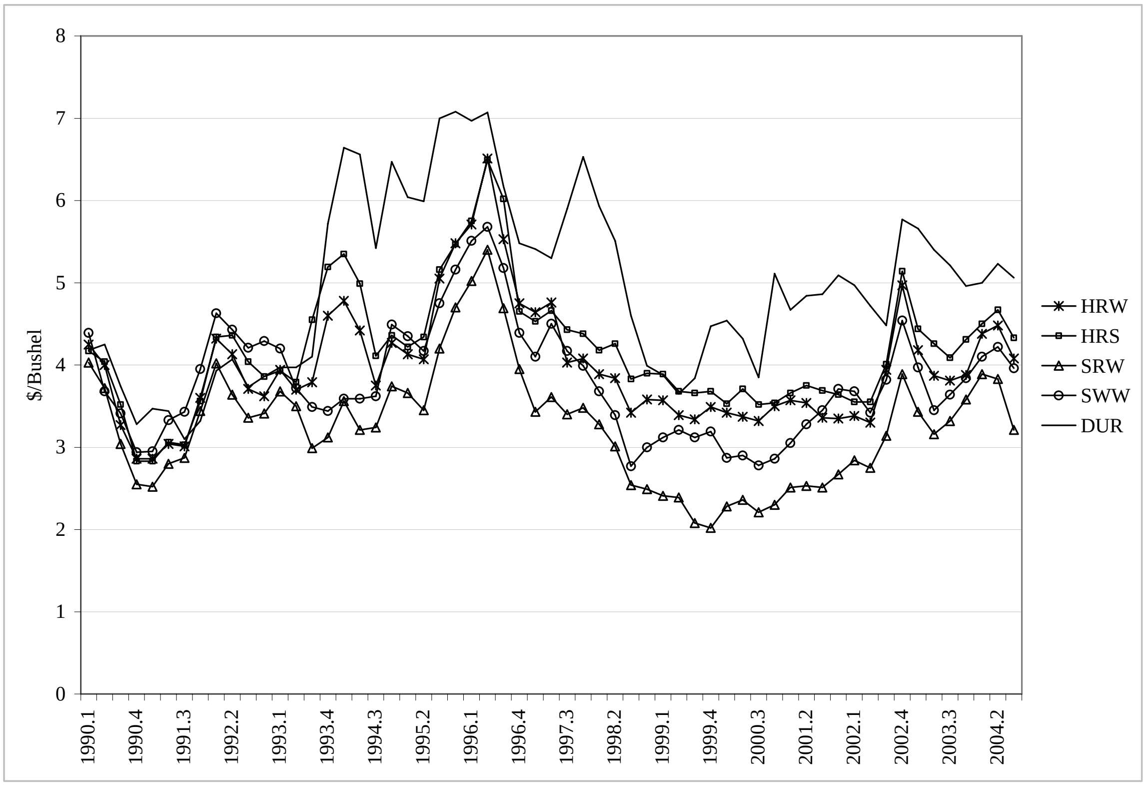

Figure 5. Quarterly Prices of Wheat Food Use by Class in U.S. 1990.1-2004.3

Appendix

A: Factor Demand System

A.1 Factor Demand System Estimated Parameters and T-ratios

		Coeff.	T-ratio	
Constant	c1	-94.011	-5.808	*
	c2	-52.529	-4.986	*
	c3	-31.401	-6.056	*
	c4	-13.331	-4.436	*
	c5	-16.383	-10.024	*
Antonelli matrix	g11	100.080	-3.195	*
	g12	-63.303	2.502	*
	g13	-8.088	-0.671	
	g14	-1.175	0.672	
	g15	0.627	1.145	
	g22	61.143	-1.925	*
	g23	-18.175	0.992	
	g24	4.224	0.190	
	g25	5.725	-0.399	
	g33	6.455	0.00000054	
	g34	-0.414	-0.00000026	
	g35	-1.544	-0.00000023	
	g44	0.965	0.00000010	
	g45	0.521	0.00000002	
	g55	0.560	0.00000001	
Time	G16	-0.097	-0.696	
	G26	-3.035	-3.103	*
	G36	-6.107	-0.519	
	G46	3.086	-3.043	*
	G56	-0.351	-0.395	
Quarter dummy 1	G17	1.398	-2.068	*
	G27	-3.143	1.169	
	G37	3.582	-1.295	
	G47	-0.028	-0.921	
	G57	-0.725	2.370	*
Quarter dummy 2	G18	-3.240	-3.732	*
	G28	0.715	-2.381	*
	G38	-0.116	-5.128	*
	G48	-0.373	-2.837	*
	G58	-1.275	-2.412	*
Quarter dummy3	G19	-0.116	2.052	*
	G29	-0.010	2.949	*
	G39	0.596	1.200	

	G49	-0.694	-0.276
	G59	-0.152	-0.570
EU gluten imports	M11	-2.493	-0.576
	M21	7.575	0.556
	M31	-32.446	0.787
	M41	1.935	-0.430
	M51	4.518	-0.730
Australia gluten imports	M12	48.804	0.601
	M22	1.328	0.441
	M32	-4.420	-0.910
	M42	-23.559	-0.976
	M52	-0.515	-1.566
Other countries gluten imports	M13	-3.299	-0.836
	M23	12.837	1.571
	M33	-0.557	-1.579
	M43	-3.319	1.171
	M53	-7.521	-1.106
R-square	HRW	0.66	
	HRS	0.71	
	SRW	0.48	
	SWW	0.77	
	DUR	0.77	
ρ	RHO	0.659	10.819

* means statistically significant at 10% significant level.

A.2 The First-order Autocorrelation Test—AR(1):

H_0: no first-order autocorrelation exists in the system.

The likelihood ratio (LR) statistic is -2[(-610.212)-(-556.86)]=106.704>3.84 critical value with 1 degree of freedom at the 0.05 level.

Conclusion: reject H_0, which means that the system needs first-order autocorrelation correction.

A.3. Convexity and Symmetry Tests with AR(1) Correction

Hypotheses	Adjusted LR Test statistics for the system*	Critical value at 5% level	Conclusion
H_0: no convexity, symmetry H_a: no convexity, no symmetry	8.66	15.63	Fail to reject H_0
H_0: symmetry, convexity H_a: symmetry, no convexity	4.13	25	Fail to reject H_0
H_0: convexity, symmetry H_a: no convexity, no symmetry	12.73	37.65	Fail to reject H_0

* The Adjusted Likelihood Ratio Statistic is given by: $\lambda = LR[mn - 0.5(Ku - Kr) - 0.5m(m+1)]/(mn) \sim \chi^2(J)$,

where $LR = 2[\ln(Lu) - \ln(Lr)]$ is unadjusted Likelihood Ratio Statistic, *Lu* and *Lr* are likelihood values for unrestricted and restricted models respectively; *m* is the number of equations in system; *n* is the observation numbers in each equation; *Ku* and *Kr* are the number of parameters in unrestricted and restricted model respectively; *J* is the number of restrictions.

A.4 Estimated Demand Elasticities for Wheat Food Use by Class

	HRW	HRS	SRW	SWW	DUR
HRW	-0.4150	0.2768	0.0329	0.0075	-0.0051
HRS	0.4250	-0.4481	0.1236	-0.0536	-0.0562
SRW	0.0962	0.2356	-0.0765	0.0209	0.0264
SWW	0.0395	-0.1848	0.0379	-0.0305	-0.0267
DUR	-0.0194	-0.1410	0.0345	-0.0195	-0.0188

B. Inverse Demand System

B.1 The First-order Autocorrelation Test—AR(1):

H_0: no first-order autocorrelation exists in the system.

The likelihood ratio (LR) statistic is -2[1938.578-1856.784]=163.588>3.84 critical value with 1 degree of freedom at the 0.05 level.

Conclusion: reject H_0, meaning the system needs first-order autocorrelation correction.

B.2 Concavity and Symmetry Tests with AR(1) Correction

Hypotheses	Adjusted LR Test statistics for the system	Critical value at 5% level	Conclusion
H_0: no concavity, symmetry H_a: no concavity, no symmetry	-1472.39	12.59	Fail to reject H_0
H_0: symmetry, concavity H_a: symmetry, no concavity	3.42	18.3	Fail to reject H_0
H_0: concavity, symmetry H_a: no concavity, no symmetry	-1468.97	26.29	Fail to reject H_0

B.3 Endogeniety Test of Imported Gluten

The null hypothesis of the test is that the imported gluten is exogenous. The Hausman-Wu test statistics for the *HRW*, *HRS*, *SRW*, and *SWW* equations were 0.88, 0.63, 0.27, and 0.64, respectively. For a critical value of 3.84 at the 0.05 level of significance, exogeneity of imported glutens could not be rejected for each equation. The instruments used for this test included one period lagged gluten imports, one period lagged wheat quantities, time trend, and seasonal dummies.

B.4 Endogeneity Test of Wheat Quantities

Tests for endogeneity of own quantities were conducted on each inverse demand equation using the Hausman-Wu test statistic, which is an asymptotically distributed chi-square with 1 degree of freedom (Hausman 1978). The null hypothesis is that quantities are exogenous. The Hausman-Wu test statistics for the *HRW*, *HRS*, *SRW*, and *SWW* equations were 2.14, 1.59, 2.37, and 0.73, respectively. For a critical value of 3.84 at the 0.05 level of significance, exogeneity of own quantities could not be rejected for each equation. The instruments used for this test included one period lagged gluten imports, one period lagged wheat quantities, time trend, and seasonal dummies.

B.5 Normality Test of Residuals

The Kolmogorov-Smirnov-Lilliefors test statistic was used to test for normality of residuals equation-by-equation with the null hypothesis that the residuals are normally distributed (Mittelhammer 1996). The null hypothesis is that residuals follow normal distribution. The test statistics for the HRW, HRS, SRW and DUR equations were -1.045,-0.775,-1.495 and -0.801, respectively. For a critical value of 0.1184 at the 0.05 level of significance, the normality of residuals could not be rejected in all cases.

B.6 Test of Origin Effects of Gluten Imports

H_0: no individual origin effects of gluten imports exist.

The likelihood ratio (LR) statistic is -2[1634.0267- 1645.1309] = 22.2084> 7.81 critical value with three degree of freedom at the 0.05 level.

Conclusion: reject H_0, meaning the effects of gluten imports from EU, Australia, and other countries on domestic wheat prices are significantly different at the 0.05 level.

CHAPTER THREE

EVALUATION OF THE EFFECTIVENESS OF ADVERTISING AND PROMOTION FOR D'ANJOU PEARS

Summary

This study analyzes the effectiveness of advertising and promotional activities conducted by the Pear Bureau Northwest (PBN) on D'Anjou pears during the 1998/1999 to 2004/2005 crop marketing seasons. The key results of this study show a predominately positive and significant role of advertising expenditures in promoting D'Anjou demand and in gaining positive marginal net returns to pear growers. However, the advertising effectiveness varies across regions and promotional types. As a particular interest of this study, the new advertising management system, which has been in effect since the 2002/03 marketing season, has been found to produce greater returns to pear growers than the old system did in most regions. Meanwhile, in each of four regions, Ad buys worked better than Demos. Finally, this study also found that domestic demand for D'Anjou pears in the U.S. continental states is significantly related to a number of other factors.

Introduction

Advertising plays an important role in market creation and development. The Fresh Pear Committee is a federal marketing order that has authority to collect revenues from pear producers in the Northwest. All marketing and promotional responsibilities of the Fresh Pear Committee are contracted to the Pear Bureau Northwest (PBN), which for many years has engaged in various forms of advertising and promotional activities on pears that are grown primarily in Washington, California and Oregon (Cook, 2002). Evaluating the effectiveness of these promotional activities and searching for more effective advertising approaches are always at the center of attention for the Fresh Pear Committee, the Pear Bureau Northwest, as well as pear producers. The results from this study are expected to provide important empirical evidence for the pear industry to evaluate the effectiveness of advertising expenditures and draw implications to make plans for future marketing efforts to assure the effective use of pear producers' funds.

We were interested in empirically analyzing the effectiveness of promotional spending on D'Anjou pears by estimating marginal net returns to pear growers over a period from the 1998/99 through 2004/05 seasons. In particular, we investigated a new advertising management system which was placed into effect by the PBN in the 2002/03 season by comparing market returns to promotional spending between the old and the new advertising systems. Specifically we identified and measured the effects of factors influencing market demand for D'Anjou pears, which accounts for the largest percentage of all winter pears in the U.S.

Although many studies investigating the effects of advertising and promotional programs on agricultural commodities such as apples, almonds, and meat products can be found in the literature (e.g. Richards et al., 1997; Halliburton and Henneberry, 1995; Piggott et al., 1996), only one study focuses on Northwest pears, a dominant industry product in fresh-market production (Cook, 2002). Erickson et al. (1997) evaluated the effectiveness of advertising expenditures on Ad buys, demos, magazines, billboards and bus signs by the Pear Bureau. Their study used data from 1989 to 1995. The U.S. pear markets were divided into 11 regions. Differently from Erickson et al. (1997), our study narrowed the investigating scope to two promotional types, Ad buys and demos, which together account for a dominant share in total market promotional spending by the Pear Bureau. In addition, we used data from 1998 to 2004, and the U.S. pear markets were grouped into four regions, which could better reflect the discrepancy of pear promotional efforts across regions according to the Pear Bureau experiences. In particular, since our study period spanned across both the old and new advertising management systems, we were able to directly evaluate and compare the effectiveness of promotional activities under two systems, which has not been investigated in the past.

The remainder of this paper is organized in the following manner. Section 2 provides necessary background. Section 3 presents a brief literature review. Section 4 derives regional pear demand functions and estimation methods, followed by a briefly data description in section 5. The estimated results and empirical analyses are presented in section 6. The final section summarizes the main results and provides a discussion of their implications.

Background

Marketing advertising and promotion usually play an important role in sales of pears

(Erickson et al., 1997). Ad buys and Demos are two major advertising tools. Recently, the management of marketing advertising and promotional activities conducted and overseen by the Pear Bureau Northwest (PBN) for U.S. pears has transitioned into a more market-oriented system.

Before June of 2002, most of Ad buys and Demos advertising and promotional activities were managed by the PBN themselves. They basically provided a fixed amount of expenditure to selected advertising agencies such as retail chains with a predesigned strategy. The agencies then conducted the advertising activities according to the given strategies within a specified period. Under this management system, the advertising agencies neither have motivation to pursue the effectiveness of advertising efforts nor do they have incentive to inform the PBN and be overseen. As a result, the PBN lacks information about the agent's actual activities, leading to potential inefficiency of marketing.

Since June of 2002, this strategy of a predesigned advertising management system has been changed to be objective-oriented. The new system has at least two significant differences from the previous one. First, the contract (usually it is "take-it-or-leave-it" style) between the PBN and advertising agencies, mainly consisting of retail chains, clearly specifies penalties and incentive terms on the basis of advertising performance. Under this contract, the PBN will not fully pay in advance to the agency as they did before. Instead, the agency will be fully reimbursed if they achieve the targeted sales, along with an award commensurate with extra performance in sales; otherwise, agencies are subject to partial loss. Second, the PBN no longer offers any advertising package to the agencies. Instead, the agencies have more flexibility to choose advertising strategies and make marketing actions.

Several consequence of the advertising system changes on expenditure allocation between Ad buys and Demos have emerged. Figure 1 presents these two major advertising approaches' expenditures on D'Anjou Pears from the 1998/99 to 2004/05 crop years. From the figure, it is easy to see that advertising expenditures on D'Anjou pears during the first three marketing years were almost equally split between Ad buys and Demos. In 2002/03, the first marketing year since the new advertising system was put into effect, the expenditure in Demos was in dominant. In the following two marketing years, however, the combination of advertising expenditures were inverse. The share of Demos in total advertising and promotional expenditure greatly decreased, while that of Ad buys increased over the same period. These adjustments are likely to reflect the process by which advertising agencies pursue maximum profit. Figure 1 also shows that the combined expenditures of Ad buys and Demos during the last three marketing seasons were relatively lower than previous seasons.

Literature Review

With the rapid expansion and spread of modern media and information delivery networks such as TV and the internet, advertising has become an incredibly important marketing approach for almost all business. Thus, there have been many attempts to estimate the effectiveness of advertising and promotion (e.g., Piggott et al., 1996; Halliburton and Henneberry, 1995; Liu and Forker, 1990; Richards and Patterson, 1998).

Liu and Forker (1990) identified the optimal advertising expenditure for the New York state fluid milk promotion program. Given the prorated national fluid expenditures, their results indicate that the advertising spending level of the New York state promotional unit in New York City and Albany should be reduced by about 10%, while the spending level for Syracuse should be increased. This result suggests that a reallocation of the existing total expenditures across markets can increase overall performance of the total expenditure. In addition, their result also shows that the effect of advertising on retail fluid milk sales has significant seasonal variation.

Previous studies of demand response to advertising have found that advertising effects tend to persist, so that current consumption responds to advertising in previous periods (Goddard and Amuah, 1989; Piggott et al., 1996). In addition, Piggott et al. (1996) and Duffy (1995) also found significant advertising cross-commodity effects. Using the Almost Ideal Demand System developed by Deaton and Muellbauer (1980) and data from Australia covering chicken, beef and lamb, Piggott et al. (1996) showed that advertising conducted by the Australian Meat and Livestock Corporation (AMLC) had no effect on demand for lamb, while increasing the demand for beef. Their study also found that a negative effect of AMLC advertising on chicken demand might be consistent with the objectives of the beef and lamb industries. Their findings call into question the desirability of a cooperative approach to advertising between producers of products that are close substitutes. Goddard and Amuah (1989) also found inter-commodity effects of advertising on the demand for Canadian fats and oils.

Many studies have focused on identifying and evaluating the effectiveness of promotions for exports. Rosson et al. (1986) analyzed how U.S. exports of apples, poultry, and unmanufactured tobacco respond to foreign market development expenditures. Their results determined that apple and tobacco exports were responsive, while poultry exports were not.

Halliburton and Rastegari Henneberry (1995) determined the effectiveness of the U.S. government's nonprice promotion programs for almonds in the Pacific Rim. The empirical evidence from their study suggests that promotional expenditures in South Korea and Singapore were ineffective during the 1986-92 period, while results concerning Japan, Taiwan, and Hong Kong depended on the estimated function form. More recently, Richards, Van Ispelen and Kagan (1997) analyzed the effectiveness of U.S. export promotional programs on the demand for U.S. apples in Singapore and the U.K. The estimated results from a two-stage Linear Expenditure System (LES)/Almost Ideal Demand System (AIDS) model show that promotion increased consumption of apples in both countries, but increased U.S. market share only in the U.K. More importantly, this study suggests that U.S. export promotional programs have significant free-riding effect.

In addition, Erikson et al. (1997) evaluated pear promotion effectiveness by estimating demand equations for winter pears based on a dataset spanning the 1989 to 1995 crop years. Their primary results showed that the promotion and advertising methods, in a large majority of cases, generated positive rates of return to pear growers for which dollar returns significantly exceeded their expenditures on advertising activities conducted by the Pear Bureau. In terms of promotion type, their results indicate that the national magazine advertising campaign generated the best return on investment (ROI) at the margin. While other promotion and advertising methods did not yield positive profits in all regions, the average returns in the entire country were very favorable.

In terms of demand function, the previous studies regarding the effectiveness of advertising and promotions have heavily used various parametric forms, including the translog, Rotterdam, and AIDS, the two-stage LES/AIDS (e.g., Baye, Jansen and Lee, 1992; Cox, 1992; Duffy, 1995; Goddard and Amuah, 1989; Richards, Van Ispelen and Kagan, 1997). However, a few studies used a non-parametric approach (Erikson et al., 1997; Mariel and Orbe, 2005). The current study used a non-parametric regression analysis to determine the effectiveness of advertising expenditures by the Pear Bureau for D'Anjou pears in the U.S. In non-parametric regression analysis, neither the distribution of errors nor the functional form of the regression function are pre-specified, yielding very flexible specifications for the pear demand models.

Methodology

Regional Demand Model Specification

This section starts with a brief discussion of a demand model for an individual agent. Let **q** denote an *n*-vector of commodities consumed with an *n*-vector of corresponding prices **p** and income *m*. We define **z** to be a vector of advertising or promotional expenditures (e.g., Ad buys or Demos), and **y** to be a vector of other shift variables. Then, the economic agent's maximization problem is

(1) $$\max_{q_i} \left\{ u(\mathbf{q};\mathbf{z},\mathbf{y}) \mid m = \sum_{i=1}^{n} p_i q_i \right\}$$

where $u(\mathbf{q})$ reflects the individual's utility function with appropriate properties[1]. Then, the individual agent's demand for a vector of commodities can be represented by

(2) $$\mathbf{q} = f\left(\mathbf{p}, m; \mathbf{z}, \mathbf{y}\right)$$

[1] See Deaton and Muellbauer (1990) for background details related to demand systems.

This implies that demand for pears should be a function of the price of pears, its substitutes or complements, advertising and promotional expenditures, and other shift variables.

The individual demand functions represented in equation (2) can be linearly aggregated as $Q^* = \sum_{i=1}^{S} q_i$ by region to construct regional demand. Here *S* indicates the regional population. Thus, regional per capita demand can be derived by dividing regional population, as

(3) $$Q = \frac{Q^*}{S} = \sum_{i=1}^{S} q_i / S = f\left(\mathbf{p}, \frac{M}{S}; \mathbf{z}, \mathbf{y}\right)$$

where *M/S* is per capita income in the region.

Empirically, the regional per capita demand model for D'Anjou pears was specified as

(4) $$Q_{anj,t} = F\left(P_{anj,t}, P_{app,t}, CPI_{Ft}, M_t, AB_{anj,t}, DM_{anj,t}, Q_{other,t}, Q_{anj,t-1}, Q_{anj,t-12}, IMP_t\right) + \varepsilon_t$$

where *F*( ) is the regression function and ε_t are the unobserved errors[2], subscript *t* indicates the associated month, and subscript *anj* represents D'Anjou pears, $Q_{anj,t}$ is the regional per capita pear shipments (boxes/person), $P_{anj,t}$ is the region's pear wholesale price ($/box), $P_{app,t}$ is the region's apple wholesale price ($/box), CPI_{Ft} is the region's consumer price index for food, M_t is the region's income per capita ($), $AB_{anj,t}$ is the region's expenditure on Ad buys for D'Anjou pears ($), and $DM_{anj,t}$ is the region's expenditure on Demos for D'Anjou pears ($). $P_{anj,t}$, $P_{app,t}$, CPI_{Ft}, M_t, $AB_{anj,t}$, and $DM_{anj,t}$ are normalized by the region's total consumer price index (or CPI-U). $Q_{other,t}$ is the region's per capita consumption of other winter pears

[2] Preliminary analysis that included other fruit prices in the demand model did not necessarily yield more statistically appealing or parsimonious model results. As a result, we used apple price as an alternative fruit.

(boxes/person) in month *t*, $Q_{anj,t-1}$ is the region's per capita consumption of D'Anjou pears lagged one month, or *t*-1, and $Q_{anj,t-12}$ is the region's per capita consumption of D'Anjou pears lagged twelve months, or *t*-12. IMP_t is the pear imports to the United States, scaled to per capita level by regional population.

Several comments about the demand equations specified in (4) are in order. First, the demand functions are specified to exhibit the economic property of homogeneity of degree zero in prices and income. This is imposed mathematically by normalizing all prices and income by the region's total consumer price index. It implies that if the level of all prices and the level of income rises (or falls) by precisely the same proportions, demand will remain unchanged.

Second, the quantity of other winter pears was included in the model instead of the price of other winter pears. A complete price series for other winter pears was not available. Including the quantity of other pears (as opposed to the price of other pears) results in what is known as a conditional demand model in which demand effects are analyzed given that a certain level of a specified good is consumed (Pollak 1969). Similarly, the total quantity of per capita pear imports, instead of the import price, was specified in the model.

Third, several lagged variables were included in the model, yielding a dynamic specification of the demand model. The variable $Q_{anj,t-12}$ accounts for seasonal pear consumption evident in the data and found in previous studies. The variable $Q_{anj,t-1}$ accounts for short run habit persistence in consumption patterns from month to month. It is anticipated that these parameters are positive (indicating that increases in past quantity demanded tends to increase future quantity demanded) and less than one in magnitude (for stability).[3] In this manner, persistent patterns of pear demand can be captured from month-to-month and year-to-year.

Nonparametric Estimation

A D'Anjou pear demand model in (4) was estimated separately for four regions using a nonparametric Nadaraya-Watson (NW) regression procedure in GAUSS[4] given the complex nature of pear demand and multifaceted nature of advertising and promotional activities. In non-parametric regression analysis, neither the distribution of errors nor the functional form of the regression function in equations (4) are pre-specified, yielding very flexible specifications of the pear demand models, which can protect from model misspecification and incorrect inferences (Judge et al. 1988).

The basic framework of the nonparametric approach is to assume that the demand models in (4) have a general representation as $y = F(x_1,....x_q) + \varepsilon$, then the partial derivatives of F with respect to the explanatory variables, $\partial F(.)/\partial x_j = \beta_j$, are of interest, which can be estimated by using a nonparametric estimator of the expectation of Y conditional on X, $\hat{F}$, and then estimate $\partial F(.)/\partial x_j$ with $\partial \hat{F}(.)/\partial x_j$.

One estimate of F is based on the definition of a regression function and on kernel estimation of marginal and joint densities. For a q dimensional x and one-dimensional y the joint

[3] For a discussion about parameter stability in regression models, see Judge et al. 1988.
[4] See Hardle (1990) for a review of applied nonparametric regression estimators. See Mittelhammer (2000) for sample GAUSS code.

density can be estimated as:

$$(5)\quad \hat{f}(y, x_1, ..., x_q; h) = \frac{1}{nh^{q+1}} \sum_{i=1}^{n} K\left(\frac{Y_i - y}{h}, \frac{X_{i1} - x_1}{h}, ..., \frac{X_{iq} - x_q}{h}\right)$$

where n is the number of observations, h is the "smoothing parameter", $y, x_1, ..., x_q$ are points of evaluation, $Y_{i,} X_{i1}, ..., X_{iq}$ are data, and K is the multivariate kernel, which is specified as the product of the univariate kernels. In this study, the univariate kernel is a Gaussian kernel, which mathematically equals

$$(6)\quad K(u) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2}u^2\right)$$

An estimate of the conditional expectation of Y follows straightforwardly from the usual definition of conditional expectation as

$$(7)\quad \hat{E}(Y \mid X = x) = \frac{\int_{-\infty}^{\infty} y\hat{f}(y, x)dy}{\hat{f}(x)}$$

which can be shown to be equal to

$$(8)\quad \hat{E}(Y \mid X = x) = \hat{F}(x; h) = \frac{\sum_{i=1}^{n} K\left(\frac{X_{i1} - x_1}{h}, ..., \frac{X_{iq} - x_q}{h}\right) y_i}{\sum_{i=1}^{n} K\left(\frac{X_{i1} - x_1}{h}, ..., \frac{X_{iq} - x_q}{h}\right)} = \frac{\hat{g}(x)}{\hat{f}(x)}$$

which is called the Nadaraya-Watson (N-W) kernel estimator (Ullah and Pagan, 1999).

The derivatives of $F(x; h)$ can be estimated using the derivative of the estimated conditional mean, $\partial\hat{F}(x; h) / \partial x_j$, as

(9) $\hat{\beta}_j(x;h) = \hat{f}(x)^{-1}[\hat{g}_j^{'}(x) - \hat{f}_j^{'}(x)\hat{F}(x)]$

where

$$\hat{g}_j^{'}(x) = -\frac{1}{nh^{q+1}}\sum_{i=1}^{n} Y_i K_j^{'}\left(\frac{X_i - x}{h}\right),$$

(10) $$\hat{f}_j^{'}(x) = -\frac{1}{nh^{q+1}}\sum_{i=1}^{n} K_j^{'}\left(\frac{X_i - x}{h}\right),$$

$$\hat{f}(x) \ = \frac{1}{nh^{q+1}}\sum_{i=1}^{n} K\left(\frac{X_i - x}{h}\right),$$

and K_j' denotes the first derivative of the kernel with respect to x_j. Ullah and Pagan (section 5.5) show that under general regularity conditions, $\hat{\beta}_j$ is subject to an asymptotic normal distribution

(11) $$(nh^{2+k})^{1/2}(\hat{\beta} - \beta) \overset{a}{\sim} N\left(0, \frac{\sigma^2}{f(x)}\int_{R^q}\left(K^{'}(z)\right)^2 dz\right),$$

where $z = \left(\left(X_{i1} - x_1\right)/h, ..., \left(X_{iq} - x_q\right)/h\right), \left(K^{'}(z)\right)^2 = \left(\partial K(z)/\partial z\right)\left(\partial K(z)/\partial z^{'}\right)$, the variance of the noise component of the model, σ^2, can be estimated by $\hat{\sigma}^2 = n^{-1}\sum_{j=i}^{n}(Y_j - \hat{F}(x_{j.}))^2$, and the joint density, $f(x) = f(x_{1,...,}x_q)$, can be estimated by an application of (5).

Each of the estimates of densities, conditional expectations, and partial derivatives are calculated using a smoothing parameter, *h*, which in this study was chosen via the principle of the lease squares cross validation (LSCV) to minimize the squared discrepancy between *y* and $\hat{F}_{-j}$ as

(12) $$h_{LSCV} = \arg\min_h \left[\sum_{i=1}^{n} \left(Y_i - \hat{F}_{-j}(x) \right)^2 \right]$$

where $\hat{F}_{-j}$ is the leave-one-out estimator of *F.* That is, *F* from (4) are estimated excluding one observation as

(13) $$\hat{F}_{-j}(x) = \frac{\sum_{\substack{i=1 \\ i \neq j}}^{n} K(z) Y_i}{\sum_{\substack{i=1 \\ i \neq j}}^{n} K(z)}$$

Test statistics for individual response coefficients were constructed using a standard bootstrap Monte Carlo technique. Response coefficients and elasticities reported were calculated from the bootstrapped simulation.[5] The reported goodness of fit test is the R-square between the actual and predicted quantity demanded of pears. To test the null hypothesis that the error terms of each regression model were independent and identically distributed, the

[5] More specifically, using all available observations, the median response coefficients were retained for each bootstrap sample and the average of theses values were then used to represent the response coefficients. Note also that the median is asymptotically normally distributed under general conditions (Bain and Engelhardt 1987). Erickson et al. (1997) used the mean to represent the response coefficients, but dropped problematic observations. We chose the median because it provided a more robust measure across all the alternative models and data observations that were estimated over the course of this study. Overall, it offered a more conservative estimate of the response coefficients and, hence, marginal net returns. It should be pointed out that in the final model specification, the mean and median response coefficients were nearly identical.

Wald-Wolfowitz runs test statistic was calculated.[6]

Measurement of Promotional Effectiveness

Marginal net return (MNR) to pear growers is used to measure promotional effectiveness to growers. MNRs are calculated as the net price return to growers per box times the change in quantity demanded for a one dollar change in promotional expenditures. For this study we calculated and reported two types of MNR: immediate and cumulative effects. The immediate (or first round) MNR is due to the change in demand that the advertising or promotion induced in the month that it occurred. The cumulative effect of advertising and promotion efforts is defined as the accumulation of all of the increases in quantity demanded over 12 months that is induced by a given promotional effort[7]. In other words, the cumulative net returns are representative of the total impact over one year starting from the month that a given promotion occurred.

From its definition, the marginal net return to pear growers can be expressed as

$$(14) \qquad MNR = P^{NR}\, \partial Q / \partial Promo$$

where $Promo$ indicates promotional spending on Ad buys or Demos, and P^{NR} represents the net return price to the grower calculated as the FOB price/box less packing costs of $7.75/box and less the Pear Bureau assessment charge of $0.49/box adjusted by a percentage net return of 34%. All of these production related costs were obtained from Clark Seavert at Oregon State University. According to Erickson et al. (1997), the item $\partial Q/\partial \mathrm{Promo}$ in equation (14) can be derived from a price linkage function and the regional demand model (4). For convenience, the

[6] See Mittelhammer (1996) for details of the Wald-Wolfowitz runs test.
[7] Because marginal net return since the twelfth month was close to zero, we only reported the cumulative effects over the first 12 months.

mathematical formulae used to calculate the immediate and cumulative MNR are provided in Appendix[8]. The specification for the price linkage function can also be found in Erickson et al. (1997).

Figure 2 provides a visual illustration to further help interpret MNRs from a single advertising and promotional activity. In the Figure, TNR represents total net returns and MNR represents marginal net returns. Both TNR and MNR curves are hypothetical, but economically plausible. Along the horizontal axis is advertising and promotional expenditures labeled as E. Moving from left to right beginning at E=0, the MNR is positive and the TNR increases (but at a decreasing rate) until E*. At E* the MNR=0, which coincides with the maximum total net return value of TNR* on the vertical axis. Then, as advertising and promotion expenditures exceed E* the TNR begins to decrease. Hence, for $0<E<E^*$ the MNR is positive and the TNR is increasing, and for $E^*<E<E^1$ the MNR is negative and the TNR is decreasing.

Data Description

Data collection and region definition

Data used in this study were collected from multiple sources. D'Anjou pear shipment quantities and promotion expenditure data were obtained from the Pear Bureau records. The units for the quantity of shipped pears were selected to be a 44 lb box. LA lugs were assumed to be 1/2 standard box and were adjusted accordingly. Wholesale fruit prices were collected from Agricultural Marketing Service (AMS) reports and the U.S. Department of Agriculture, covering 15 major U.S. cities. Annual state population data were collected from the U.S. Bureau of the

[8] Detailed discussion about these formulae also can be found in Erickson et al. (1997).

Census. Quarterly personal income data in each state were obtained from the Regional Economic Information System, the Bureau of Economic Analysis, and the U.S. Department of Commerce. A Fruit Price Index (PPI) and Food Consumption Price Index (CPI) were assembled from the U.S. Bureau of Labor Statistics (BLS). Pear imports were collected from the USDA, covering all pear imports from outside of the U.S. All data are converted into monthly level.

Geographically, the 48 contiguous states of the United States were grouped into four regions. Each region was composed of nine or more states[9]. The specific regions, and the representative wholesale competing fruit market information in selected cities for each of the regions, are as follows:

West Region (11 states; 3 wholesale markets): California, Oregon, Washington, Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah, and Wyoming. Major wholesale competing fruit markets in the west region include Los Angeles, San Francisco, and Seattle.

Central Region (12 states; 3 wholesale markets): Iowa, Kansas, Minnesota, Missouri, Nebraska, North Dakota, South Dakota, Illinois, Indiana, Michigan, Ohio, and Wisconsin. Major wholesale competing fruit markets in the central region include Chicago, Detroit, and St. Louis.

South Region (16 states; 5 wholesale markets): Arkansas, Louisiana, Oklahoma, Texas,

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[9] Geographically, pear advertising and promotion by the Pear Bureau has covered all 50 states of the U.S., and in most years even extended to Canadian provinces (e.g., British Columbia, Ontario, Alberta). Advertising and promotional activities in Hawaii, Alaska, and abroad (Canada) conducted by the Pear Bureau are excluded from this study.

Alabama, Kentucky, Mississippi, Tennessee, Delaware, Florida, Georgia, Maryland, North Carolina, South Carolina, Virginia, and West Virginia. Major wholesale competing fruit markets in the south region include Baltimore, Atlanta, Dallas, Miami, and District of Columbia.

East Region (9 states; 4 wholesale markets): Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, Vermont, Pennsylvania, New Jersey, and New York. Major wholesale competing fruit markets in the east region include Boston, New York, Philadelphia, and Pittsburgh.

Data statistical description

All of these collected data were converted into month level by region through a series of algebraic calculations[10]. The final constructed data set included: a) population weighted average monthly prices of D'Anjou pears (including Red D'Anjou) and apples; b) monthly *per capita* quantity of D'Anjou shipped into the region; c) monthly CPI, PPI, income, and population for the region; and d) monthly pear imports. The statistical means and standard deviations of monthly data by region are presented in Table 1.

Table 2 shows yearly Ad Buy and Demo expenditures during the study period by region. As previously seen in Figure 1, obvious structural changes, including fund allocation between Ad Buy and Demo and total advertising expenditure, can be found in the last three marketing years. But these changes across regions are inconsistent. In the east and south regions, total advertising expenditures significantly reduced since the marketing year 2002/03, while changes in the central and west regions were mainly embodied by reallocating funds between Ad buys and

[10] Monthly population and income data for each region were interpolated using trend regression.

Demos.

D'Anjou pear shipments, D'Anjou wholesale prices and pear imports to the U.S. are presented in Figures 3 through 5, respectively. D'Anjou shipments appear to have significant seasonality over the study period, which is consistent with availability of the crop across all regions. More specifically, shipments start in August or September and increase to a peak near the end of a calendar year or in the first quarter of the subsequent year. Shipments then decrease until June or July. Over all seven marketing seasons, the west region had the highest number of shipments, followed by the south and east regions, and then the central region (see Figure 3).

Regional wholesale price series for D'Anjou pears also exhibit characteristics consistent with seasonal availability of D'Anjou pears. However, the wholesale prices vary across the regions. For example, the price of D'Anjou pears in the west region was typically lower than that in other regions. The differences across the regions are likely due to a combination of differing marketing strategies relating to the passing through/absorption of fluctuations in FOB prices, as well as transportation costs, differing market power from firm concentration levels, and efficiencies in the various regions (see Figure 4).

U.S. pear imports also followed a significant seasonal pattern. The first chunk of imports appears in February, which is about one month behind the peak month of domestic shipment in the same year, implying a possible contra-seasonal demand-driven import. Pear imports reach the peaking point every March and maintain significant volumes in April and May, and then make a huge drop down to less than 200,000 boxes (even nothing) per month in the following months until the next February. It is interesting to note that both pear imports and domestic shipments touch the bottoms of their curves in July and August (see Figure 5).

Empirical Results

Table 3 presents the results of nonparametric regressions by region. Importantly, the models exhibit a majority of significant response coefficients. The R-square values for the east, south, central, and west regions are 0.95, 0.96, 0.96, and 0.99, respectively, indicating a very high explanation of pear demand for each of the regions. Outcomes of the Wald-Wolfowitz runs test statistic for each region indicate that the null hypothesis of independent and identical error terms can not be rejected. This provides strong evidence against problems such as autocorrelation and heteroskedasticity in the error terms of the regression models that can add another layer of complication to the empirical analysis.

As expected, the estimates of own-price elasticity at means for each of the four models were significantly negative, which is consistent with the economic law of demand. The price elasticity of largest magnitude was in the south region (-0.596), followed by the central (-0.493), east (-0.271), and west (-0.225) regions, respectively (see Table 4). For instance, this indicates that a 10% increase in the price of D'Anjou pears in the central region will yield a 5.96% decline in the quantity demanded in that region. However, since these elasticties are consistently lower than one in magnitude, the demand for D'Anjou nationwide is called "price inelastic."

Both ad buy and demo promotional expenditures were found to be positive and statistically significant related to shipment demand for D'Anjou pears for each of the four regions. This provides strong evidence that increases in promotional expenditure significantly increased demand for D'Anjou pears. These results are basically consistent with the findings by

Erickson et al. (1997). However, the regional shipment demands for D'Anjou pears are inelastic with respect to both types of promotion (see Table 4). It is also noticed that the demand elasticity with respect to Ad Buy promotions is consistently greater than that to Demos in each region.

A set of variables was also found to be significantly related to shipment demand for D'Anjou pears. Apple price response coefficients were negative and statistically significant for all regions, reflecting that D'Anjou pears and apples are gross complements to one another in the consumer's bundle of purchases. Demand for D'Anjou pears in a current month is also demonstrated to be consistently related to demand for other winter pears and D'Anjou consumption in past months. The positive and significant estimate for the quantity of other winter pears in each region suggests that increased demand for other winter pears was associated with increased demand for D'Anjou pears. In addition, the estimated results indicate that demand for D'Anjou pears in the current period was significantly and positively related to the previous month's consumption, indicating habit formation in the demand for pears. Quantities lagged twelve months were also found to be positively and significantly associated with current demand for pears, which accounts for seasonality in consumer demand for D'Anjou pears. The parameters of the lagged variables were bounded between 0 and 1 for each region, satisfying stability conditions for the estimated models over time.

The demand for domestic D'Anjou pears was also found to be significantly and positively associated with the per capita pear imports except in the east region. These results suggest that, overall, imported pears were complementary to domestic pears. This is consistent with Cook (2002) who reports that "the vast majority of imports (to the U.S.) are contra-seasonal, limiting the effect on the domestic industry.” However, this finding must be interpreted with some caution, as the modeling approach used per capita total imports for the U.S. in each regional model (not imports specific to each region). Indeed, it is possible that specific regions recognize competition between imported and domestic pears when the marketing seasons of these products overlap. Our findings suggest that on average, the amount of total pear imports in a current period tends to be associated with a positive increase in domestic pear demand within the same period. In other words, international pear consumption seemingly complements and reinforces domestic pear consumption. We point out that these results are not necessarily inconsistent with Gutman, Mittelhammer, and Schotzko (2001), who report a negative relationship between pear price and quantity of imports. For example, in the case when increased imports induce decreased domestic pear price, consumers are likely to purchase more pears.

Marginal Net Returns:

In the discussion below, the immediate and cumulative marginal net returns for a representative grower can be interpreted in the following manner. For example, consider the immediate and cumulative MNRs due to Ad buys for D’Anjou pears in the east region estimated as \$3.29 and \$4.28, respectively. For the immediate MNR this implies that an additional \$1 spent on Ad buys for D’Anjou pears in a month results in an additional \$3.29 in grower net return in that month. For the cumulative MNR this implies that an additional \$1 spent on Ad buys for D’Anjou pears yields an additional \$4.28 in net returns over the current and remaining eleven months. The difference between the immediate and cumulative values is a pass-on effect over time from the advertising and promotion activities.

Nationally, the advertising efforts for D'Anjou pears by the Pear Bureau during the study period gained \$0.78 immediate and \$0.98 cumulative marginal net returns, meaning that an additional \$1 of expenditure for marketing promotion on D'Anjou pears resulted in an additional \$0.78 in grower net return in the current month, and a \$0.98 cumulative marginal net return over the entire 12 months. The positive MNRs suggest that total net returns from these efforts are still increasing in the entire nation (see Figure 6).

Marginal net returns, however, varied across regions, by promotional type, and over years. The east and south regions exhibited the largest net returns to D'Anjou growers, being \$1.54 and \$1.33 in immediate effects and \$2.01 and \$1.62 in cumulative, respectively. The central and west regions, however, achieved less than a one dollar return for every dollar of expenditure by the Pear Bureau. The cumulative MNRs have similar patterns as the immediate MNRs across regions (See Figure 6). It is interesting to notice that the MNRs gradually reduce as a result of the region being geographically closer (east, south, central and west, sequentially) to the Pacific Northwest, the major D'Anjou production area in the U.S.

Marginal net returns to D'Anjou pear growers from Ad buy promotions are greater than those from Demos in each region. Nationally, the MNRs of Ad buy expenditures for D'Anjou pears were \$1.50 for the immediate first round and \$1.89 for the cumulative return. These are much larger than the Demos' \$0.20 and \$0.26, respectively (see Figure 7). From each region, one dollar's worth of spending on Ad buys achieved more than a one dollar cumulative return. The largest net returns for Ad buys were in the east region (\$3.29 for the first month and \$4.28 for the following one year in cumulative), followed by the south region (\$2.41 immediate and \$2.95

cumulative returns) and central region ($0.85 immediate and $1.13 cumulative returns). In contrast, the net returns due to Ad buys for D'Anjou pears in the west region, and Demos in all regions, were smaller and less effective in increasing total net returns. Figure 7 also shows that the geographic overall downward trend from the east to west shown in Figure 6 was dominantly contributed by Ad buys rather than Demos.

The overall marginal net return to D'Anjou growers from advertising spending under the new management system is greater than that under the previous system, suggesting a higher effectiveness of the new system over the old one. Figures 8 through 11 present estimated MNRs over years for each of four regions. These figures provide a visible comparison of advertising effectiveness between two systems. Apparently, in east, central, and west regions, the promotional activities under the new systems gained less-than-previous MNRs in the first crop year (2002/03), and then the MNRs rapidly increased the following two seasons, exceeding levels in any years prior to implementation of the new system. The promotional activities under the new system performed basically the same as under the previous system, but with a slightly higher overall return in the comparison. These comparisons suggest that the new adverting management system is capable of achieving higher returns for pear growers than did the old one. The loss-then-win pattern is consistent with the learning-by-doing approach that the contracted advertising agencies have been following to adjust their promotional strategies for increasing returns to advertising[11].

[11] In the beginning year, contracted agencies (retailers) might have lacked understanding about the pear market and consumers' purchasing behavior, which as a result may have mislead their choice for advertising strategies and caused a loss for them. In the following years, they might follow a so-called learning-by-doing approach (Tirole,

Conclusion

This study analyzed the effectiveness of advertising and promotion conducted by the Pear Bureau Northwest on D'Anjou pears during the 1998/1999 to 2004/2005 crop marketing seasons. The particular focus was to provide economic evidence for the PBN to evaluate a newly adopted market-oriented advertising management system. We did this by answering whether this system could produce higher marginal net returns to pear growers than did the old one. Two types of major marketing promotional activities, Ad buy and Demo, were investigated in four regional markets in the U.S. A nonparametric technique was used for parameter estimation. Key findings are summarized as follows:

First, the key results of this study empirically demonstrated the predominately positive and significant impacts of advertising and promotional expenditures on increasing D'Anjou pear demand, which in turn generated notably positive rates of returns to the Pear Bureau and pear growers. Ad buys performed significantly better in marginal net returns to pear growers than did Demos. An interesting observation is that the regional performances of both Ad buys and Demos diminish when the region is closer to the major D'Anjou production area, the Pacific Northwest, mainly due to the disparity of Ad buys' output across regions. These apparent differences of MNRs across regions and between promotional types suggest that reallocating total expenses among regions and between promotional types could result in D'Anjou pear growers reaping higher returns.

Second, this study clearly shows that the new adverting management system resulted in a

1988) to adjust their promotional strategies.

painful loss in the first crop year in which it was put into effect in the east, central and west regions, and then achieved higher-than-ever marginal net returns in the following two seasons. These changes reflect an expected process that contracted advertising pear retailers followed to maximize their profits from advertising pears under the new system. In the south region, the new system resulted in marginal net returns to pear growers that were the same as for the old system.

Finally, domestic D'Anjou pear demand in the U.S. continental states was also found to be significantly related to a number of other factors. In nearly all cases, pear demand was significantly impacted by the price of pears and the price of apples (with apples being a complementary good). D'Anjou demand was also significantly impacted by patterns of seasonal availability of pears, as well as patterns of habit formation, meaning that increases in quantity of pears demanded in a particular month tended to increase quantity demanded in the following months. The total quantity of imported pears was significantly and positively associated with demand for domestic pears in every region except for the east. However, we did not find a consistent income effect on pear demand across regions. Meanwhile, nationally, pear imports to the U.S. were not found to be a significant competition with domestic pears. Contra-seasonal import pattern might be the reason.

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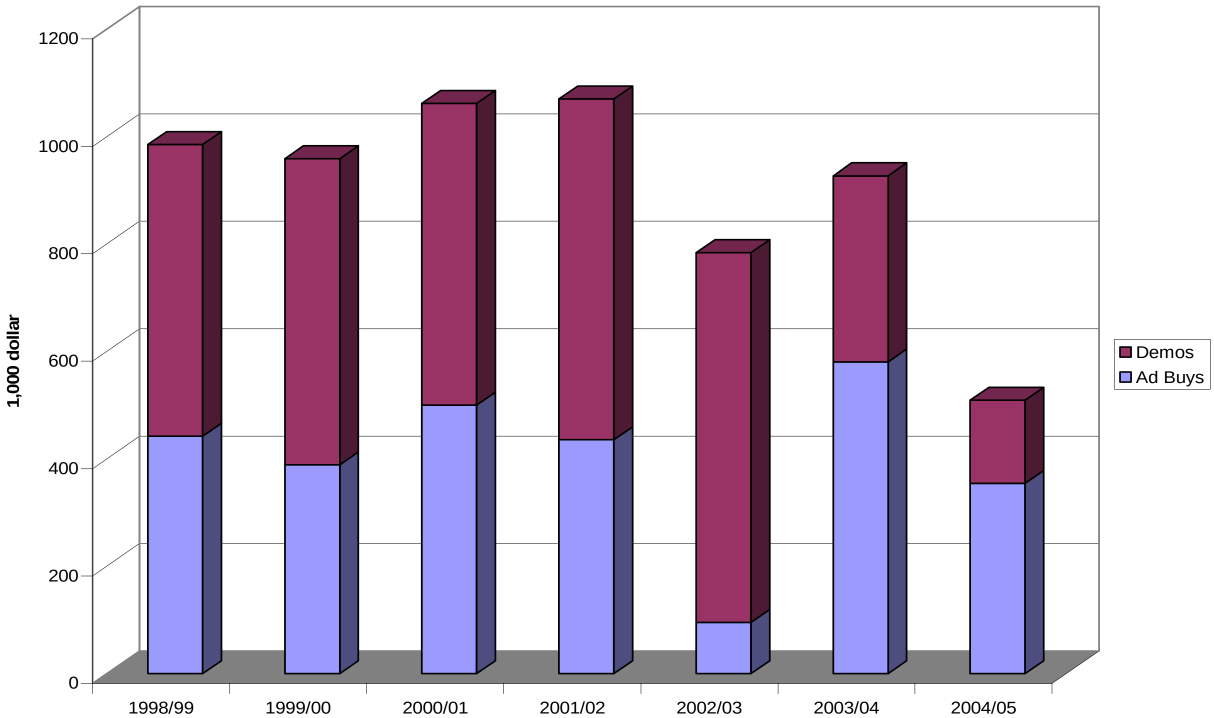


Figure 1 Ad Buy and Demo Expenditures for D'Anjou Pears

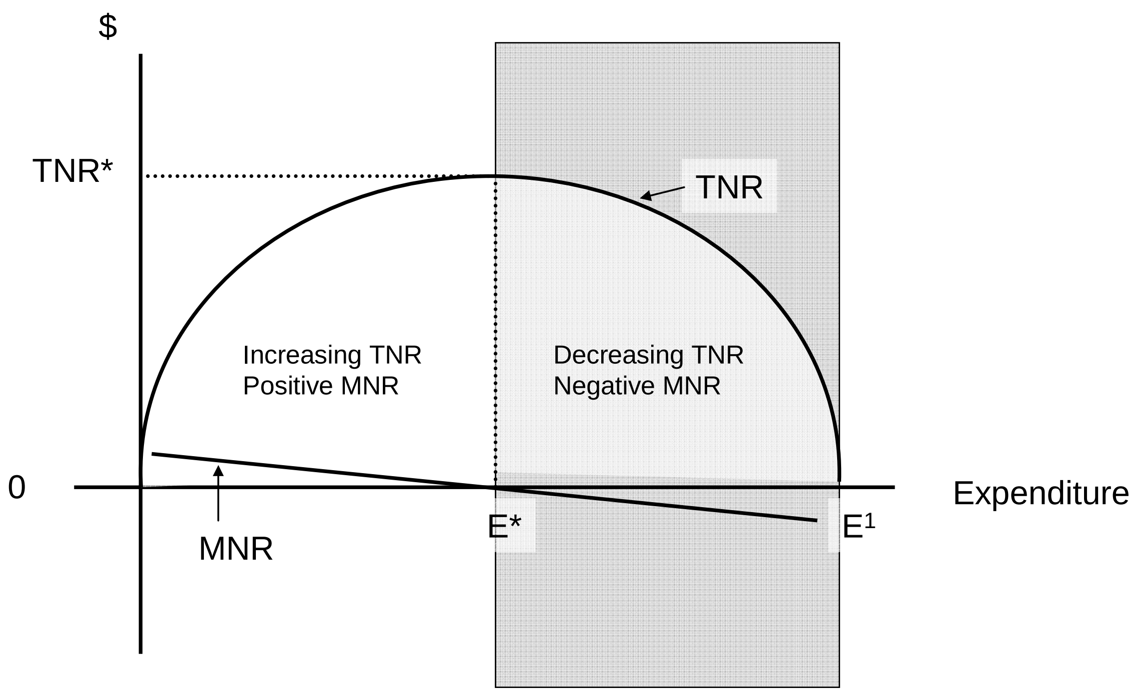


Figure 2 Total Net Return (TNR) and Marginal Net Return (MNR) Curves

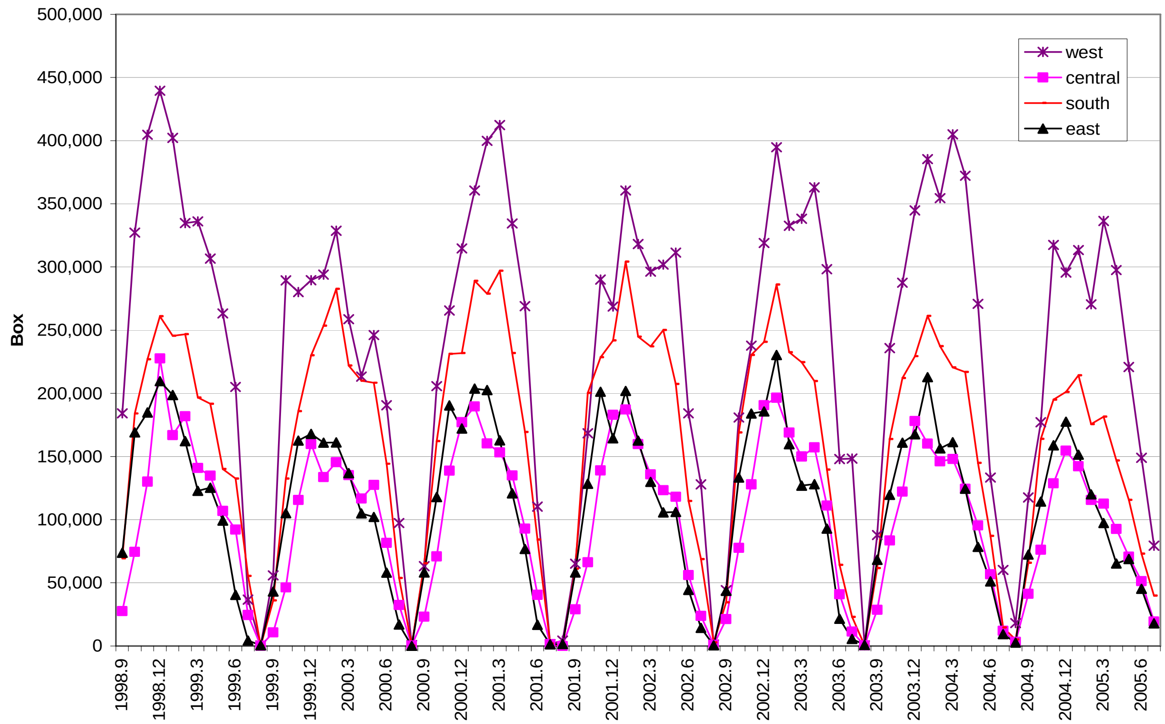


Figure 3 Monthly Shipments of D'Anjou Pears by Region

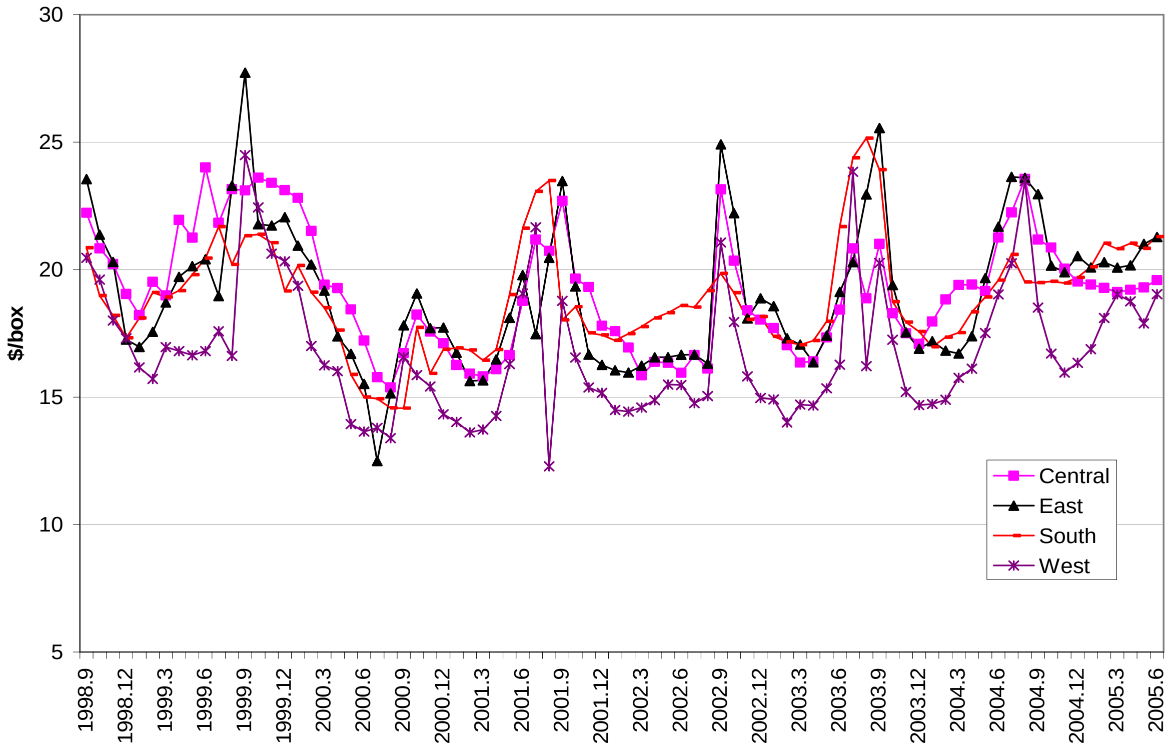


Figure 4 Monthly D'Anoju Pear Wholesale Prices by Region

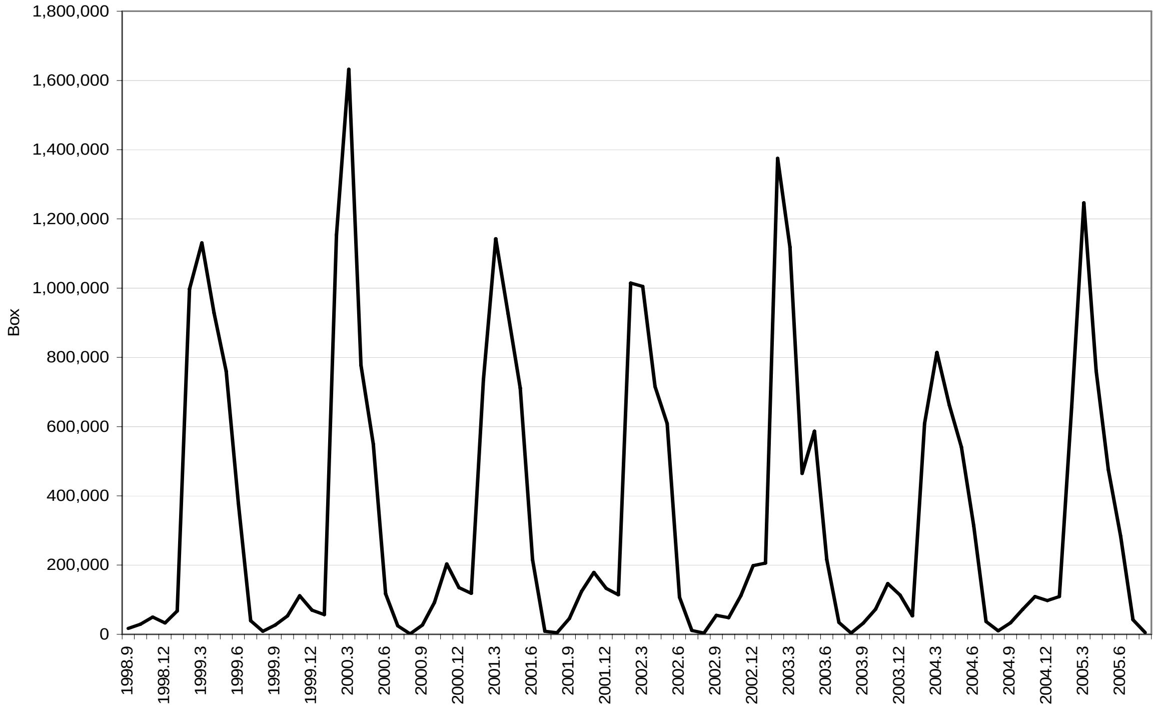
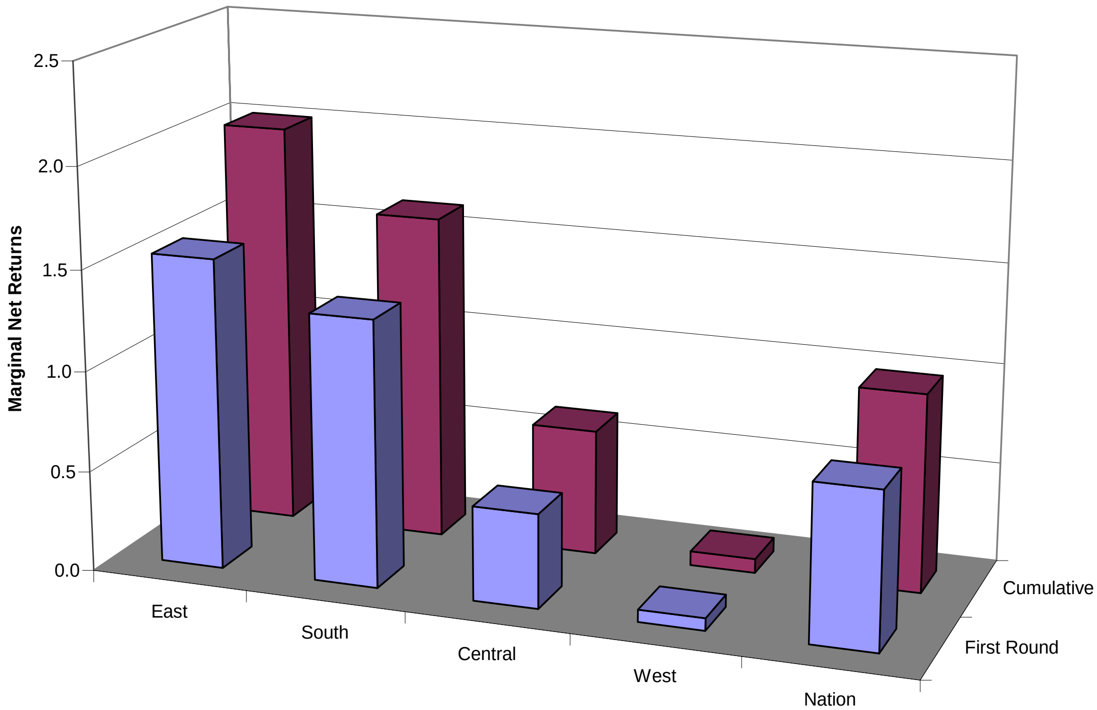
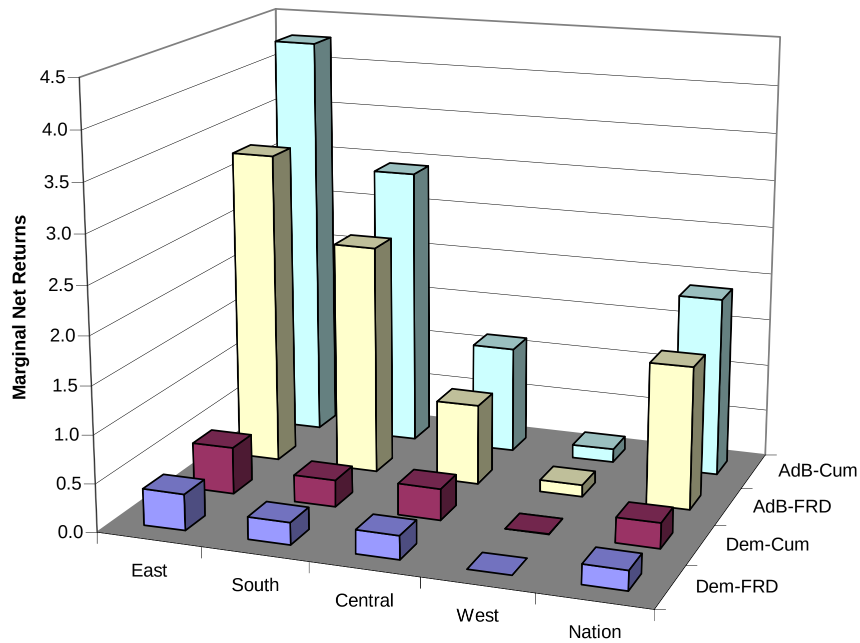


Figure 5 Monthly Pear Imports to the United States



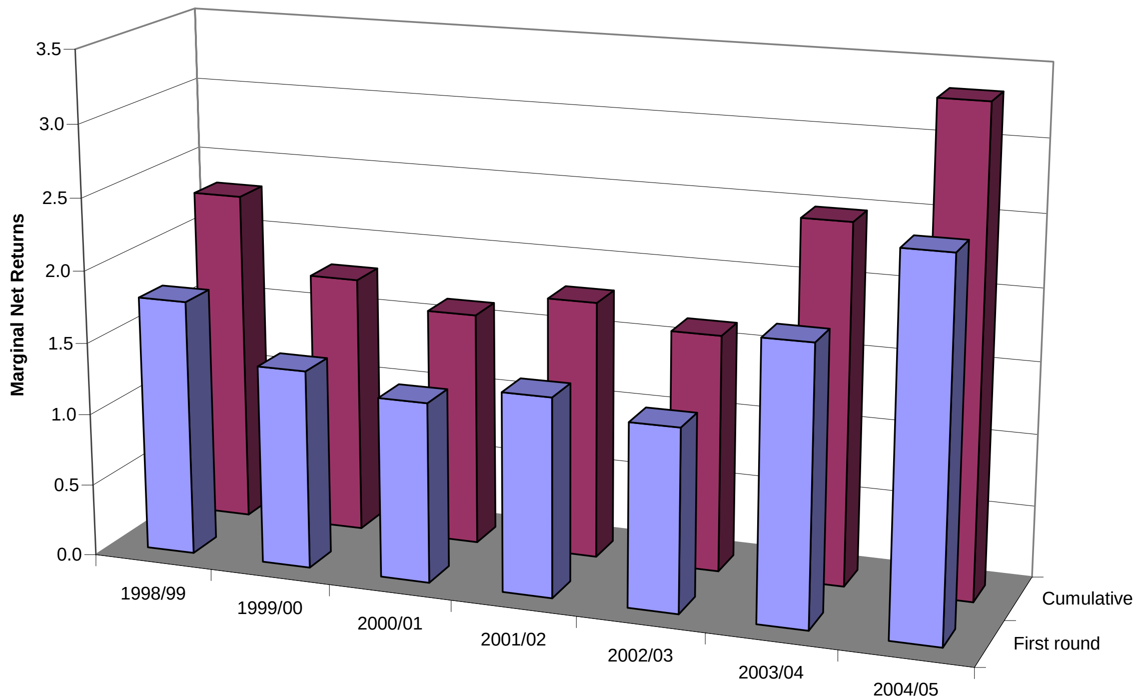
	East	South	Central	West	Nation
First Round	1.54	1.32	0.47	0.06	0.78
Cumulative	2.01	1.62	0.63	0.07	0.98

Figure 6 Marginal Net Returns to Growers of D'Anjou Pears



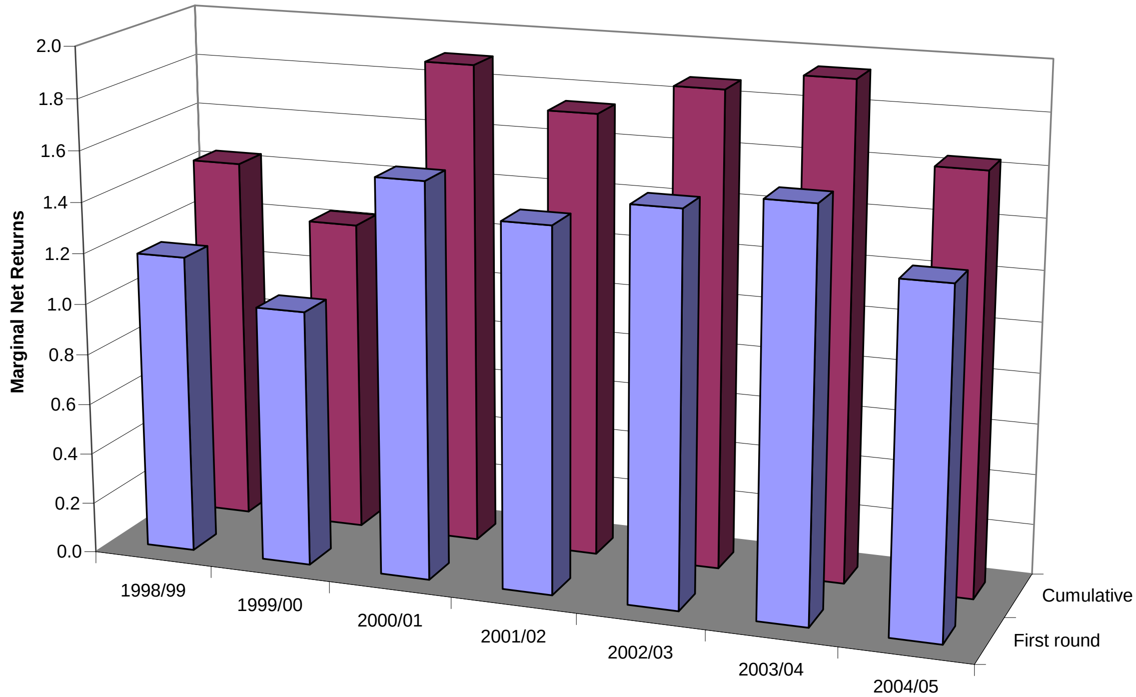
	East	South	Central	West	Nation
Dem-FRD	0.376	0.230	0.244	0.001	0.204
Dem-Cum	0.490	0.281	0.327	0.001	0.264
AdB-FRD	3.288	2.410	0.845	0.125	1.495
AdB-Cum	4.280	2.947	1.131	0.143	1.891

Figure 7 MNRs by Region and Promotional Type for D'Anjou Pears



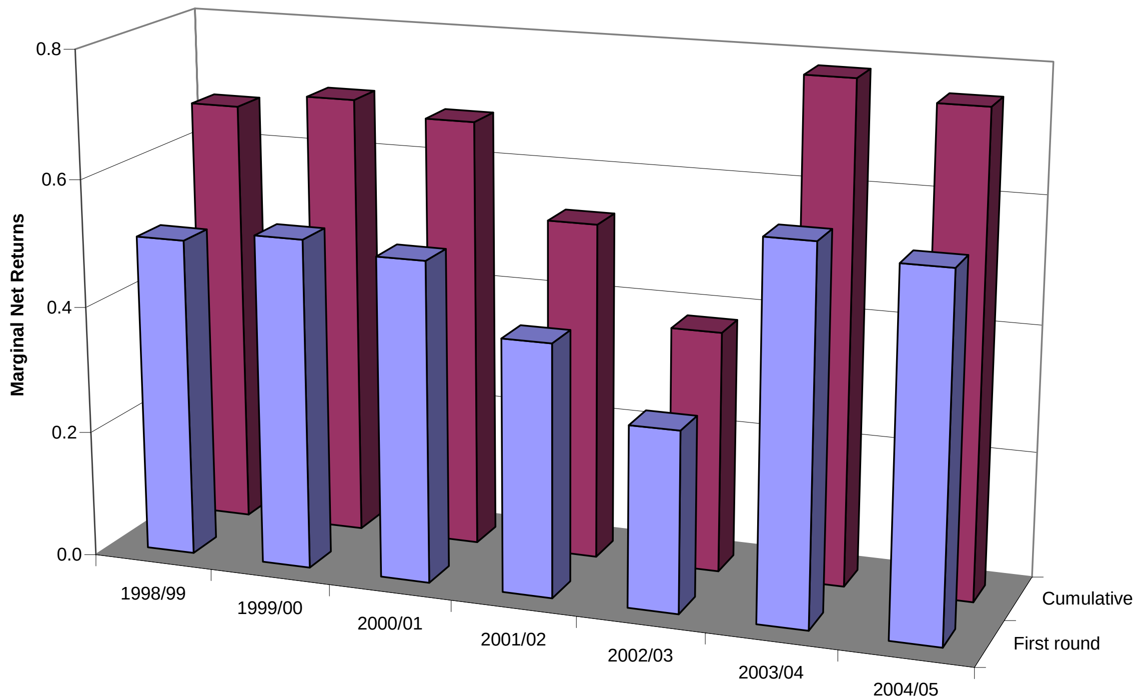
	1998/99	1999/00	2000/01	2001/02	2002/03	2003/04	2004/05
First round	1.78	1.38	1.25	1.38	1.26	1.91	2.56
Cumulative	2.31	1.80	1.63	1.79	1.65	2.49	3.34

Figure 8 MNRs of Promotion for D'Anjou Pears over Years in the East



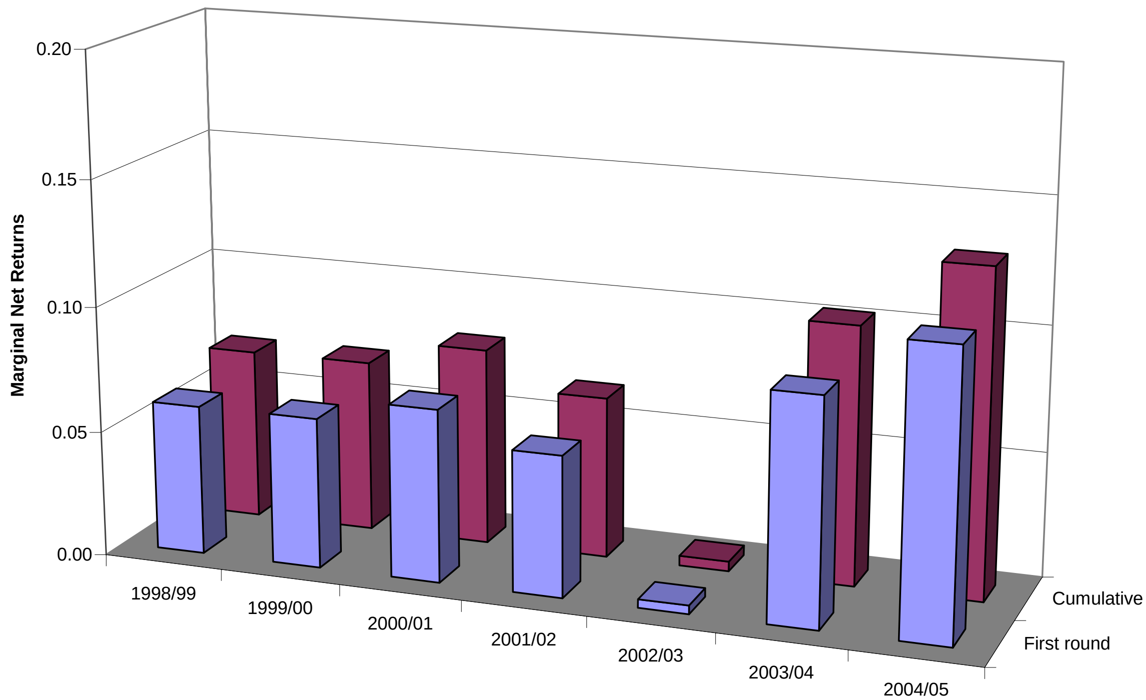
	1998/99	1999/00	2000/01	2001/02	2002/03	2003/04	2004/05
First round	1.18	1.01	1.55	1.43	1.53	1.59	1.34
Cumulative	1.44	1.23	1.90	1.75	1.87	1.94	1.64

Figure 9 MNRs of Promotion for D'Anjou Pears over Years in the South



	1998/99	1999/00	2000/01	2001/02	2002/03	2003/04	2004/05
First round	0.50	0.52	0.51	0.40	0.28	0.59	0.56
Cumulative	0.67	0.70	0.68	0.53	0.38	0.78	0.75

Figure 10 MNRs of Promotion for D'Anjou Pears over Years in the Central



	1998/99	1999/00	2000/01	2001/02	2002/03	2003/04	2004/05
First round	0.06	0.06	0.07	0.06	0.00	0.09	0.11
Cumulative	0.07	0.07	0.08	0.06	0.00	0.10	0.13

Figure 11 MNRs of Promotion for D'Anjou Pears over Years in the West

Table 1 Means and Standard Deviations of Monthly Data in Four Regions, 1998.9-2005.6

	East	South	Central	West
Quantity of D'Anjou pears (box)	109,138	162,877	100,193	237,514
	(65,719)*	(87,922)	(60,481)	(121,672)
Quantity of other winter pears (box)	59,043	44,805	27,661	77,095
	(52,056)	(36,999)	(22,936)	(66,026)
Price of D'Anjou pears ($/box)	20.73	20.52	20.77	18.37
	(3.24)	(2.68)	(2.51)	(2.98)
Price of apples ($/box)	20.55	20.77	21.23	17.60
	(2.58)	(2.47)	(2.31)	(2.41)
Ad buy promotions on D'Anjou pears ($)	5,790	9,936	7,755	10,630
	(6,730)	(10,683)	(9,836)	(23,568)
Demo promotions on D'Anjou pears ($)	8,549	9,751	13,171	11,203
	(12,599)	(13,037)	(18,706)	(16,807)
Regional population (person)	54,045,833	102,072,399	64,963,240	65,008,918
	(431,829)	(2,701,586)	(589,689)	(1,927,843)
Regional income (nominal dollar)	1,917,064	2,890,530	1,955,370	2,031,649
	(138,576)	(266,666)	(135,293)	(185,605)
Imports of all pears (box)	309,243	309,243	309,243	309,243
	(399,453)	(399,453)	(399,453)	(399,453)

*Numbers in parentheses represent standard deviation.

Table 2 Ad Buy and Demo Expenditures by Region Unit: $1,000

	East		South		Central		West	
	Ad Buy	Demo	Ad Buy	Demo	Ad Buy	Demo	Ad Buy	Demo
1998/99	64.3	69.3	151.1	195.8	124.3	164.3	102.4	113.5
1999/00	69.9	133.0	111.4	200.3	114.0	133.4	93.9	103.0
2000/01	78.0	182.5	165.3	106.7	125.9	163.8	131.0	108.5
2001/02	67.4	128.8	164.8	135.0	70.3	205.7	132.9	165.2
2002/03	37.7	86.0	31.0	21.0	19.1	267.6	7.4	314.3
2003/04	86.8	77.9	119.2	71.9	130.7	99.6	243.8	97.1
2004/05	70.6	23.4	71.8	68.9	51.6	45.5	160.4	16.9

Table 3 Nonparametric Estimates for D'Anjou Pear Demand Models

	East		South		Central		West	
Anjou Price	-0.00009	**	-0.00013	***	-0.00010	***	-0.00015	***
	(0.00005)[a]		(0.00004)		(0.00005)		(0.00003)	
Apple Price	-0.00014	*	-0.00007	**	-0.00010	***	-0.00008	***
	(0.00007)		(0.00003)		(0.00005)		(0.00003)	
Food CPI	0.00004	**	0.00001		0.00003		0.00002	
	(0.00004)		(0.00002)		(0.00003)		(0.00002)	
Income	0.00001		0.00000		0.00003		0.00002	
	(0.00004)		(0.00002)		(0.00003)		(0.00002)	
Ad Buy	0.00020	***	0.00013	***	0.00010	***	0.00004	***
	(0.00008)		(0.00005)		(0.00004)		(0.00001)	
Demo	0.00014	**	0.00008	**	0.00010	**	0.00008	***
	(0.00006)		(0.00003)		(0.00004)		(0.00003)	
Qother	0.00031	***	0.00018	***	0.00022	***	0.00019	***
	(0.00011)		(0.00006)		(0.00008)		(0.00004)	
Qt-1	0.00031	***	0.00019	***	0.00027	***	0.00031	***
	(0.00010)		(0.00006)		(0.00008)		(0.00006)	
Qt-12	0.00037	***	0.00023	***	0.00030	***	0.00028	***
	(0.00011)		(0.00007)		(0.00009)		(0.00004)	
Imports	0.00004		0.00007	***	0.00011	***	0.00008	***
	(0.00003)		(0.00003)		(0.00004)		(0.00001)	
R-square	0.95		0.96		0.96		0.99	

Note: *** Represents that estimated coefficients are statistically significant at 95% confidence level; **represents that estimated coefficients are statistically significant at 90% confidence level.

[a] Numbers in parentheses represent standard errors.

Table 4 Estimated Own-price and Promotional Elasticities for D'Anjou Pears

	East	South	Central	West
Own-price Elasticities	-0.271	-0.596	-0.493	-0.225
Demo Promotion	0.007	0.003	0.008	<0.001
Ad Buy Promotion	0.043	0.037	0.017	0.001

Appendix

<u>Immediate MNR:</u>

The price linkage equation in Erickson et al. (1997) was specified as

A.1 $$P_{anj} = a_1 P^* + a_2 Q * P^* + a_3 T * P^* + a_4 C$$

where P_{anj} is the wholesale price for D'anjou, Q is the volume of product, C is the cost of other inputs (such as labor, energy, and office expenses), P^* is the FOB price, and T represents trends of technology and other potential factors influencing marketing services.

From the price linkage function, we have

A.2 $$dP_{anj} = a_2 P^* dQ$$

From the shipment demand equation for D'Anjou pears in equation (4), we have

A.3 $$dQ = \partial f / \partial P_{anj}\,(dP_{anj}) + \partial f / \partial Promo\,(dPromo)$$

Substitute A.2 into A.3 to have

A.4 $$dQ = \partial f / \partial P_{anj}\,(a_2 P^* dQ) + \partial f / \partial Promo\,(dPromo)$$

Then, the marginal change in quantity from a change in promotions *Promo* can be derived as

A.5 $$dQ/d\text{Promo} = (\partial f / \partial \text{Promo}) / (1 - \partial P_{anj} / \partial Q * (\partial f / \partial P_{anj}))$$

From equation (4), we also have $\partial f / \partial \text{Promo} = \partial Q / \partial \text{Promo}$ and $\partial f / \partial P_{anj} = \partial Q / \partial P_{anj}$. By substituting them back into A.5, the marginal change in quantity from a change in a promotion can be rewritten as

$$dQ/d\text{Promo} = \frac{\frac{\partial Q}{\partial Promo}}{(1 - \frac{\partial P_{anj}}{\partial Q} * \frac{\partial Q}{\partial P_{anj}})}$$

A.6
$$= \frac{\frac{\partial Q}{\partial Promo} * \frac{\overline{Promo}}{\overline{Q}}}{(1 - \frac{\partial P_{anj}}{\partial Q} * \frac{Q}{P_{anj}} * \frac{\partial Q}{\partial P_{anj}} * \frac{P_{anj}}{Q})} * \frac{\overline{Q}}{\overline{Promo}}$$

$$= \frac{Elasticity_{promo}}{1 - Flexibility_{anj} * Elasticity_{promo}} * \frac{\overline{Q}}{\overline{Promo}}$$

Then for given observations $\overline{Q}, \overline{Promo}$ the immediate MNR can be derived as (*j*=0):

A.7
$$MNR_{t=0} = P^{NR} * \frac{Elasticity_{promo}}{1 - Flexibility_{anj} * Elasticity_{promo}} * \frac{\overline{Q}}{\overline{Promo}}$$

<u>Cumulative MNR over the first 12 months (including the month that the advertising occurs):</u>

Let $b_1 = \frac{\partial Q}{\partial P_{anj}}, b_2 = \frac{\partial f}{\partial Promo}, b_3 = \frac{dQ_t}{dQ_{t-1}}$ $, a_2 P^* = \frac{dP_{anj}}{dQ}$

From the demand equations we can derive the following:

A.8
$$dQ_{t+1} = (b_1)dPanj_{t+1} + (b3)dQ_t = (b_1)(a_2 P^* dQ_{t+1}) + (b_3)dQ_t$$

The cumulative marginal change in quantity from a change in promotions can be expressed as

A.9
$$\frac{dQ_{t+1}}{d\text{Promo}_t} = \frac{dQ_{t+1}}{dQ_t} * \frac{dQ_t}{d\text{Promo}_t} = \frac{b_3}{1 - b_1(a_2 p^*)} * \frac{dQ_t}{d\text{Promo}_t}$$

So we can derive the following expression in terms of elasticities and flexibilities for $j=1$ as

$$\frac{dQ_{t+1}}{d\mathrm{Promo}_t} = \frac{\frac{dQ_t}{dQ_{t-1}}}{1-\frac{dQ}{dP}*\frac{dP}{dQ}}*\frac{dQ_t}{d\mathrm{Promo}_t} = \frac{\frac{dQ_{t+1}}{dQ_t}}{1-\frac{dQ}{dP}*\frac{dP}{dQ}}*\frac{dQ_t}{d\mathrm{Promo}_t}$$

A.10

$$= \frac{\frac{dQ_{t+1}}{dQ_t}*\frac{Q_t}{Q_{t+1}}*\frac{Q_{t+1}}{Q_t}}{1-(\frac{dQ}{dP}*\frac{P}{Q})(\frac{dP}{dQ}*\frac{Q}{P})}*(\frac{dQ_t}{d\mathrm{Promo}_t}*\frac{\mathrm{Pr}\,omo_t}{Q_t})*\frac{Q_t}{\mathrm{Promo}_t}$$

$$= \frac{Elasticity_{lag1}*\frac{Q_{t+1}}{Q_t}}{1-Elasticity_{anj}*Flexibility_{anj}}*Elasticity_{promo}*\frac{Q_t}{\mathrm{Promo}_t}$$

$$= \frac{Elasticity_{lag1}}{1-Elasticity_{anj}*Flexibility_{anj}}*Elasticity_{promo}*\frac{Q_t}{\mathrm{Promo}_t}$$

Similarly, we can derive the expression for *j*=2

A.11

$$\frac{dQ_{t+2}}{d\mathrm{Promo}_t} = \{\frac{b_3}{1-b_1(a_2P^*)}\}^2*\frac{dQ_t}{d\mathrm{Promo}_t} = \frac{b_3}{1-b_1(a_2P^*)}*(\frac{b_3}{1-b_1(a_2P^*)}*\frac{dQ_t}{d\mathrm{Promo}_t})$$

$$= \frac{b_3}{1-b_1(a_2P^*)}*\frac{dQ_{t+1}}{d\mathrm{Promo}_t}$$

In general, we have the following expression: (*j*=1, 2,….11)

A.12
$$\frac{dQ_{t+j}}{d\mathrm{Promo}_t} = \frac{Elasticity_{lag1}}{1-Elasticity_{anj}*Flexibility_{anj}}*\frac{dQ_{t+j-1}}{d\mathrm{Promo}_t}$$

Hence, the cumulative MNR over the first 12 months is

A.13
$$MNR_{cum} = p^{NR}*\sum_{j=0}^{11}\frac{dQ_{t+j}}{d\mathrm{Promo}_t}\frac{dQ_{t+j}}{d\mathrm{Promo}_t}$$

CHAPTER FOUR

LATENT INCIDENCE OF INEFFICIENCY IN U.S. COMMERCIAL BANKS, 1990-2000

Summary

This study analyzes the latent proportional incidence of inefficiency for U.S. commercial banks by applying a recently proposed Bayesian approach. To overcome a misspecification problem of the estimated data envelopment analysis (DEA) efficiency scores, uniform ignorance Bayesian *prior* is used to infer an appropriate posterior distribution for the latent incidence of inefficiency. Results imply that the inferred latent incidence of inefficiency from the Bayesian method could be more accurate than the DEA method when the sample size used in the study is limited. Banking efficiency has been shown to increase over time; however, the estimated DEA scores could be significantly greater than what they should be in reality. In addition, this study has also proven that the DEA estimation results are sensitive to sample size. Finally, the increasing banking efficiency over the studying period and the decreasing proportion of efficient banks in the industry may reflect the consequence of banking consolidation in the 1990s.

Introduction

The unique role of commercial banking in a monetized market economy places the evaluation of banking industry efficiency at the forefront of public policy attention. Banking efficiency can be defined as the extent to which a decision-making unit (DMU) or a bank can increase its outputs without increasing its inputs, or reduce its inputs without reducing its outputs. Rapid banking technological and regulatory changes such as the development of new bank services (from ATM machines to internet banking), deregulation of deposit interest rates, revisions to capital requirements, and elimination of many state and federal restrictions on branch banking have had dramatic effects on banking efficiency. Banking efficiency estimates can help bank managers, market analysts, and researchers to identify opportunities for reducing costs or increasing revenues, to predict bank failures and merger activity, and to examine the effects of technological innovations and regulatory changes.

Data envelopment analysis (DEA) has become one of the most popular tools to investigate banking efficiency. However, in practice, DEA often suffers from two drawbacks. First, the incidence of inefficient banks in DEA could be undercounted because of the nature of its sample-based procedure that could lead to a truly inefficient firm or a decision-making unit (DMU) being treated as efficient (Friesner et al., 2006), heretofore referred to as mismeasurement. Second, DEA generally assumes that there is no random error, and this easily causes misspecifying the distribution of DEA scores when economic effects are studied (Schmidt 1985).

Several studies have made significant efforts to overcome these drawbacks of DEA.

Simar and Wilson (2007) employed semiparametric regression techniques to estimate the second stage model, suggesting supplementing an MLE-based regression with a specific form of bootstrapping to adjust for any potential mismeasurement. However, this approach requires the researcher to identify an appropriate distribution for the likelihood function; furthermore, bootstrap methods cannot solve the problem of missing truly efficient DMUs in DEA samples. Berger (1993) and Kneip et al. (1998) have specified asymptotic distribution for DEA scores and the asymptotic rate of convergence at which randomly sampled DEA scores converge to these distributions. However, these contributions in nature are only diminishing the drawbacks instead of solving them because (1) even a census of the population may not suffice to solve the DEA's overestimation of the efficiency problem (Friesner et al., 2006), and (2) the true distribution of DEA scores is unknown.

In this study, we applied a recently proposed method by Friesner et al. (2006) to infer the incidence of inefficiency for U.S. commercial banks from 1990 to 2000. In their approach, the incidence of inefficiency of banking within a DEA sample is shown to be a latent variable, which consists of the "observed" inefficient banks in DEA estimates and a noisy sample-based categorization of inefficiency. To avoid misspecification of the estimated DEA scores, a Bayesian approach was involved to infer an appropriate posterior distribution for the latent incidence of inefficiency. This approach places little a *priori* structure on the nature of the banking production process being studied so that inferences are applicable in very general problem contexts such as cases where the efficient frontier is not (twice) continuously differentiable or even in cases where the frontier is not representable via a parametric functional form (Friesner et al., 2006).

The remainder of this paper is organized in the following manner. First, we review related literature. Second, we present methodology, followed by data description. Third, we provide a discussion of results. Finally, we finish with some concluding remarks.

Literature Review

Banking efficiency has been heavily studied in the past decades, especially in the U.S. (Berger and Humphrey, 1997). In the early stage, the bulk of studies concentrated on the examination of scale and scope economics. Kim (1986) and Gilligan et al. (1984) found scope economies in commercial banking. Berger et al. (1993) developed a new multi-product economy measure, which combines scale and scope effects in examining the potential competitive pressure from banks. The consensus of these studies is that economies of scale were found for large-size banks, while they were limited for entire commercial banks (Kaparakis et al., 1994).

During the 1990s, much of the research attention centered on investigating a series of issues associated with consolidation over the period 1985 through 1997. According to Reports of Condition and Income (Call Report) for commercial banks, during the period the banking industry was consolidating rapidly, with the number of banks declining by more than 1/3 in 13 years. Merger activity mostly contributed to the consolidation. While research commonly recognizes that the inefficiencies generally decrease over time and with bank size due to the consolidation, some studies have shown more details with a closer look. For example, Berger and Mester (1999) found that cost productivity decreased while profit productivity increased from 1991-1997, particularly for banks involved in mergers. By decomposing the Malmquist productivity index into changes in pure technical and scale efficiency, Wheelock and Wilson

(1999 and 2001) found that, during the period from 1984 to 1993, large banks gained efficiency by applying advanced technologies into operations, while small banks experienced significant decreases in both efficiency and productivity because of the general failure to adopt these technologies, and eventually were ruled out.

In methodology, despite that diverse measurements have been used for measuring efficiencies of banks in past studies, a primary consensus is that researchers have to first identify and "construct" a frontier, since the true efficient frontier is unknown. The industrial efficiency or individual bank's efficiency is then measured by comparing their production to the constructed frontier. Recently, the nonparametric approach has replaced the parametric way to become the most often used method for "constructing" the frontier, as the former allows the data to speak for themselves and thus overcome the often plagued misspecification of function form in parametric ways (Berger and Humphrey, 1997; Lee, 2002; Wheelock and Wilson, 2006). Among various nonparametric approaches, data envelopment analysis (DEA) has become the most popular in banking efficiency studies.

Many studies have applied the DEA method in banking efficiency studies in all over the world. For example, Berg et al. (1993) applied DEA in banking efficiency studies in Norway, Sweden and Finland; Favero and Papi (1995) in Italy; Fukuyama (1993) in Japan; Taylor et al. (1997) in Mexico; Drake and Howcroft (1994) in the United Kingdom; and Chen et al. (2005) in China. There are also many studies evaluating banking efficiency in the U.S. using DEA, such as Elyasiani and Mehdian (1990), English et al., (1993), Ferrier et al. (1993), Wheelock and Wilson (1999), and Miller and Noulas (1996).

While most of the DEA applications assume that the financial processes consist of one stage, some studies argue that banks often produce intermediate outputs and then use them to produce the final outputs (e.g., Berger and Humphrey, 1997; Ferrier and Lovell, 1990; Kaparakis, Miller, and Noulas, 1994; Wheelock and Wilson, 2001). To address such problems, researchers have developed a two-stage DEA model. In the first stage, researchers usually estimate efficiency for sampled banks by using the DEA approach; in the second stage they apply a censored regression to investigate the impact of several regulations on banks' efficiency. For example, Chang and Chiu (2006), Simar and Wilson (2007), Rho and An (2007), and Pasiouras (2008), in separate studies, applied the two-stage DEA to the data from the banking industry.

Methodology

In this study, we applied a newly proposed method by Friesner et al. (2006) to infer the incidence of inefficiency for U.S. commercial banks in 1990, 1995 and 2000. Since their method offers significant contributions to solving the mismeasurement problem of DEA, we start this section with a simple description of this problem.

Mismeasurement Problem of Data Envelopment Analysis

Data envelopment analysis (DEA) is a sample-based method. By analyzing sampled banks (i.e. DMUs), DEA first identifies those banks in the sample that produce the most outputs for a given set of inputs (e.g. banks A, B, I, and J in Figure 1), where an output-oriented production process with two outputs is assumed. DEA then attempts to represent a production frontier by examining all possible convex combinations of these banks. Each bank lying on the constructed frontier is signed a score of 1, representing "completely efficient." For each bank operating below the frontier (i.e., an inefficient bank), such as bank C, DEA projects a ray from the origin through this inefficient bank to the “constructed” frontier (i.e., the line IABJ). The proportion of the ray length that lies between the inefficient bank and the origin is the efficiency score of that bank. For example, the efficiency score of bank C is OC/OH in Figure 1; and it is OE/OB for bank E.

However, when a bank with true maximal output for a given set of inputs was not contained in the sample based on DEA, e.g., bank B, the bank with the greatest outputs in the sample will be wrongly categorized as efficient, e.g., bank G. Given that other banks do not change in the sample, this case could lead to the line IAGJ rather than IABJ to become the “construct” frontier in DEA; and OE/OG instead of OE/OB becomes the DEA efficiency score for bank E. As a result, the estimate of the proportion of inefficient firms in the population will be biased, resulting in the mismeasurement problem.

To what extent the mismeasurement problem would occur is clearly linked to the sample size. Friesner et al. (2006) show that even if one applies DEA to the entire population of decision-making units (DMUs), the mismeasurement problem still can happen. However, from the above discussion, one can easily see that the mismeasurement problem would be reduced when a bigger sample size is involved for DEA calculation.

Economic model

A direct output-oriented distance function for the banking industry is defined from which we derive the efficiency score for each bank. The standard properties of a distance function are that it is homogenous of degree one, convex and non-decreasing in output, and non-increasing in input quantities (Coelli et al., 1998). Define the distance function as

(1) $$d(\mathbf{x},\mathbf{q}) = \min_{\delta}\{\delta : (\mathbf{q}/\delta) \in P(\mathbf{x})\}$$

where $\mathbf{q} = (q_1,...,q_m)'$ and $\mathbf{x} = (x_1,...,x_l)'$ are m outputs and l inputs for each bank, respectively. If output vector $\mathbf{q}$ belongs to the production possibility set of $\mathbf{x}$ (i.e., $\mathbf{q} \in P(\mathbf{x})$), then $\delta \le 1$, meaning that the bank is inefficient with values closer to zero, indicating increasing levels of inefficiency. Distance is equal to unity (i.e., $\delta = 1$) if $\mathbf{q}$ belongs to the "frontier" of the production possibility set, meaning that the bank is efficient. Output-oriented distance function represents a rescaling of all the output levels consistent with a given input level. Intuitively, an output distance function considers a maximal proportional expansion of the output vector, given an input vector.

DEA involves the use of linear programming methods to construct a non-parametric piece-wise surface (or frontier) over the data. Efficiency measures are then calculated relative to this surface. Assume that we have n banks. The $l \times n$ input matrix, **X**, and the $m \times n$ output matrix, **Q**, represent the data for all banks. Consider that the following output-oriented variable returns to a scale model (Coelli et al., 1998):

(2) $$\max_{\phi,\lambda} \phi \quad \text{s.t.} \quad \begin{array}{l} -\phi q_m + \mathbf{Q}\lambda \ge 0 \\ x_l - \mathbf{X}\lambda \ge 0 \\ \mathbf{I}1'\lambda = 1 \\ \lambda \ge 0 \end{array}$$

Where ϕ is a scalar ($1 \le \phi < \infty$) and λ is a $n \times 1$ vector of constants. **I** denotes $n \times n$ identity matrix, and **1** is a $n \times 1$ vector of ones. q_m and x_l are defined as in the above distance function. The value of ϕ is the proportional increase in outputs that could be achieved by the n -th bank, with input quantities held constant. Note that $\delta = 1/\phi$ defines a technical efficiency score for each bank that varies between zero and one. If $1/\phi$ is equal to a value of 1, this indicates a bank on the frontier, hence a technically efficient bank.

Empirical model: Inferring the Incidence of Latent Inefficiency

From above discussion of the mismeasurement problem in DEA, it is easy to see that banks on the true efficiency frontier can never be falsely categorized as inefficient, but banks below the true frontier can be falsely categorized as efficient if truly efficient banks are not in the sample. With this observation, we now present the latent method proposed by Friesner et al. (2006), as follows.

Let *x* be the number of inefficient banks in a random sample of size n drawn from the population with finite N banks and K incidences of inefficiency without replacement. Then, the probability of selecting *x* inefficient banks is characterized by the hypergeometric density as

$$(3) \qquad f(x \mid N, \pi = \frac{K}{N}, n) = \begin{cases} \dfrac{\binom{N-K}{n-x}\binom{K}{x}}{\binom{N}{n}} & \max[0, n-(N-K)] \le x \le \min[n, k] \\ 0 & otherwise \end{cases}$$

where $\pi = K/N$ denotes the proportional incidence of inefficiency in the population. The support for π is precisely equal to $\pi \in \{\gamma/N,\ for\ \gamma = 0,1,...,N\}$. Following Friesner et al. (2006), the prior information on the incidence of inefficiency, π, is assumed to be represented by a discrete Beta probability distribution function as

(4) $$f(\pi \mid \alpha, \beta, N) = \begin{cases} \tau^{-1} \int_{\pi - \frac{1}{2N}}^{\pi + \frac{1}{2N}} f(\pi \mid \alpha, \beta) d\pi & for\ \pi \in \Omega = \{\frac{\gamma}{N},\ for\ \gamma = 1, 2, ..., N-1\} \\ 0 & for\ \gamma = 0 \text{ or } \gamma = N \end{cases}$$

Where, $\alpha, \beta > 0, \Gamma(\alpha) = \int_0^\infty z^{\alpha-1} e^{-z} dz$, is the gamma function, and $\tau = \int_{\frac{1}{2N}}^{1-\frac{1}{2N}} f(\pi \mid \alpha, \beta) d\pi$. It is known that Beta distribution is highly flexible and capable of representing an extremely wide range of distributional patterns over the appropriate supports for the value of π . Note that the probability of the events that all banks are efficient or that all banks are inefficient is assumed a *priori* zero.

Then, the joint distribution of X and π can be represented as

(5) $$\begin{aligned} f(x, \pi \mid \alpha, \beta, N, n) &= f(x \mid N, \pi, n) f(\pi \mid \alpha, \beta, N) \\ &= \tau^{-1} \int_{\pi - \frac{1}{2N}}^{\pi + \frac{1}{2N}} f(\pi \mid \alpha, \beta) d\pi \frac{\binom{N-K}{n-x}\binom{K}{x}}{\binom{N}{n}} \end{aligned}$$

Now suppose that DEA is used to estimate the true efficient frontier for this sample with *n* banks. As we discussed above, if none of the (N-K) efficient banks appear in the sample, then any banks categorized as inefficient are, in fact, inefficient, but any banks categorized as efficient are incorrectly categorized.

We assume that the outputs of N banks can be produced in *M* different fixed ratios (or technology). In other words, if we draw lines between each bank output point and the origin, we will form *M* rays. All N banks lie on any of these rays through the origin. Apparently, the (N-K) of truly efficient banks lie on any endpoint of the *M* rays, and the remaining truly inefficient K banks in the population are dispersed at various points along the *M* rays, excluding the origin and endpoints. Once the sample outcome of the DEA analysis is observed, it is revealed which of the *M* rays have observations that place them on the sample production frontier. As discussed above, due to the sample-based nature of DEA, some truly inefficient banks could be placed on endpoints of these rays in the sample, and thus could be incorrectly categorized as efficient banks by DEA, while other truly inefficient banks lying between the origin and the endpoint are correctly categorized as inefficient.

Let the number of truly inefficient banks in the sample be represented by $x^* = x + e$ where *x** is an unobservable *latent* variable, *x* continues to represent the number of banks categorized as inefficient based on the sample DEA methodology, and *e* represents the unobserved error in categorization. Assume there are *m* rays in sample, then $e \in Unique\{\sum_{i \in J} n_E^i, \text{ for } \mathrm{J} \subset I_E\}$, and thus the support of x^* is given by

$\boldsymbol{\psi} = Unique\{x + \sum_{i \in J} n_E^i, \text{ for } \mathrm{J} \subset I_E\} \ for \ \mathrm{I_E} \subset \{1, 2, ..., m\}$, where $Unique\{\bullet\}$ is the uniqueness operator returning only the unique items within any list $\{\bullet\}$, n_E^i represents the number of banks categorized as efficient by DEA analysis for the i^{th} ray in the sample, $n_E = \sum_{i=1}^{m} n_E^i$.

If at least one truly efficient bank is placed on each endpoint of the *m* rays in the sample, then *e*=0 and *x**=*x*; if the sample contains only inefficient banks, then $e = n_E > 0$ and $x^* > x$; and if at least one of the endpoints in the sample contains one or more truly efficient banks, but not all endpoints contain one or more truly efficient banks, the set of possible events for *e* depends on how many of the truly inefficient banks are incorrectly categorized as efficient by DEA and whether two or more of these wrongly classified banks occur precisely on the endpoint of any ray. In our dataset, we have proven that no two banks occur precisely on the endpoint of any ray in the population, as in sample[1]. In this case, the support of *e* is $\{0,1,2,...,E\}$, and thus support of x^* is $\Psi = \{x, x+1, x+2, ..., x+E\}$, where *E* is the number of banks which are categorized as efficient in DEA analysis.

Similarly with *x*, the probability of selecting *x** inefficient banks can be characterized by the hypergeometric density as

$$f(x^* \mid N, \pi = \frac{K}{N}, n) = \begin{cases} \dfrac{\binom{N-K}{n-x^*}\binom{K}{x^*}}{\binom{N}{n}} & \max[0, n-(N-K)] \le x^* \le \min[n,k] \\ 0 & otherwise \end{cases} \tag{6}$$

and the joint probability distribution of the unobservable x^* and π so that

$$\begin{aligned} f(x^*, \pi \mid \alpha, \beta, N, n) &= f(x^* \mid N, \pi, n) f(\pi \mid \alpha, \beta, N) \\ &= \tau^{-1} \int_{\pi - \frac{1}{2N}}^{\pi + \frac{1}{2N}} f(\pi \mid \alpha, \beta) d\pi \frac{\binom{N-K}{n-x^*}\binom{K}{x^*}}{\binom{N}{n}} \end{aligned} \tag{7}$$

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[1] In output-oriented DEA, if two DMUs occur precisely on the endpoint of any ray, then their outputs have equal distance to the origin and must be produced in a single fixed ratio, i.e., their outputs normalized by one of the outputs must satisfy $\frac{y_{i1}}{y_{j1}} = \frac{y_{i2}}{y_{j2}} = ... = \frac{y_{iw}}{y_{jw}} = 1 \;\; for \;\; i = 1, ..., N, \; j = 1, ..., N, i \ne j$ and *w* is the number of outputs that each firm produces. We checked our data, and we did not find that any two banks in our population satisfied this condition, meaning that any two banks in our population do not occur precisely on the endpoint of any ray.

Assuming the prior on π is the uniform ignorance prior, i.e. $\alpha = \beta = 1$, then the joint probability distribution of x^* and π becomes

(8) $$f(x^*, \pi \mid 1, 1, N, n) = \frac{1}{N-1} \frac{\binom{N-K}{n-x^*}\binom{K}{x^*}}{\binom{N}{n}}$$

Further, the joint probability distribution of $\{x^*, \pi\}$ in (7), conditional on $(x, n_E^1, ..., n_E^m, n_E)$, can be defined as

(9) $$f(x^*, \pi \mid 1, 1, N, n, x, n_E^1, ..., n_E^m, n_E) = \frac{f(x^*, \pi \mid 1, 1, N, n)}{\sum_{x^* \in \Psi} \sum_{\pi \in \Omega} f(x^*, \pi \mid 1, 1, N, n)} = \frac{\binom{N(1-\pi)}{n-x^*}\binom{N\pi}{x^*}}{\sum_{x^* \in \Psi} \sum_{\pi \in \Omega} \binom{N(1-\pi)}{n-x^*}\binom{N\pi}{x^*}}$$

$for\ \{x^*, \pi\} \in \Psi \times \Omega$, where $\Psi = \{x, x+1, x+2, ..., x+E\}$ and $\Omega = \{\frac{\gamma}{N},\ for\ \gamma = 1, 2, ..., N-1\}$.

Then, the posterior distribution of π, conditioning on only observables by marginalizing out the unobservable latent variables x^* from (9), is given by

(10) $$f(\pi \mid N, n, x, n_E^1, ..., n_E^m, n_E) = \sum_{x^* \in \Psi} f(x^*, \pi \mid N, n, x, n_E^1, ..., n_E^m, n_E) = \frac{\sum_{x^* \in \Psi} \binom{N(1-\pi)}{n-x^*}\binom{N\pi}{x^*}}{\sum_{x^* \in \Psi} \sum_{\pi \in \Omega} \binom{N(1-\pi)}{n-x^*}\binom{N\pi}{x^*}}$$

From (10), Bayesian estimated expectation of π can be calculated by

$$(11) \qquad E(\pi) = \Sigma \pi f(\pi \mid N, n, x, n_E^1, \ldots, n_E^m, n_E) = \sum_{\pi \in \Omega} \pi \frac{\sum_{x^* \in \Psi} \binom{N(1-\pi)}{n - x^*} \binom{N\pi}{x^*}}{\sum_{x^* \in \Psi} \sum_{\pi \in \Omega} \binom{N(1-\pi)}{n - x^*} \binom{N\pi}{x^*}}$$

which is served as the inferred incidence of inefficient banks in this study.

Data Description

In this study, we chose to follow the intermediation approach to select data for measuring the incidence of inefficiency in U.S. commercial banks. The intermediation approach views banks as financial intermediates that collect purchased funds and transforms them to loans and other assets. The data are from the 1990, 1995 and 2000 Call Report information for commercial banks. Following Kaparakis et al. (1994) and Wheelock and Wilson (2001), five outputs and five inputs are included in our analysis. The five outputs include loans to individuals ($y1$), real estate loans ($y2$), commercial and industrial loans ($y3$), federal funds, securities purchased under agreements to resell, plus total securities held in trading accounts ($y4$), and agricultural loans ($y5$). Inputs include interest-bearing deposits excluding certificates of deposits greater than \$100,000 ($x1$), purchased funds (certificates of deposits greater than \$100,000, federal funds purchased, and securities sold plus demand notes) and other borrowed money ($x2$), number of employees ($x3$), book value of premises and fixed assets ($x4$), and noninterest bearing deposits ($x5$). The data used in the empirical model are based on average quarterly values across a given year.

To arrive at the final data sets for estimation, several data management steps were taken. First, we excluded banks that reported negative inputs or outputs. Secondly, to account for extreme outliers, we excluded banks that were 6 or more standard deviations away from the mean of the input and output values. Third, we excluded banks with total assets less than $50 million and only considered relatively larger banks in our analysis; our reasoning is that some small banks appeared in the 1990 dataset but might have disappeared in 1995 or 2000 because of the consolidation or mergers which occurred in the 1990s. Then we excluded banks that do not appear in any of the three years; this means that we got a panel dataset with an interval of four years. After these steps, the dataset used in this study contains 2912 commercial banks. All of them appear in 1990, 1995 and 2000. This final dataset used in this study represents a population of the U.S. commercial banks that had $50 million or more total assets during these three years.

Estimated Results

Random samples, without replacement, of n=50, 100, and 190 banks were extracted from the population[2]. We first applied the DEA method to estimate an efficiency score for each sampled bank. Based on these scores, the proportion of inefficient banks in the sample was calculated, which is recognized as the incidence of inefficiency in DEA (i.e., the proportion of incidence of inefficient banks in DEA). Then we applied the Bayesian method to derive posterior distribution for the true incidence of inefficient banks based on information from DEA. The expectation of the posterior distribution of π was then calculated using (7), which is recognized as the latent incidence of inefficiency in the population (i.e., the proportion of inferred inefficient banks).

A Monte Carlo bootstrap technique with 200 iterations was applied for each sample size

[2] Given the population size of 2912 banks, the maximum sample size that GAUSS could deal with for calculating number of combinations is 192.

in each of three years. Table 1 presents the means of the estimated efficiency scores in DEA, the incidence of inefficiency in DEA, and the latent incidence of inefficiency from Bayesian methods. The mean of bias between the latent and DEA incidence of inefficiency and 95% confidence intervals is also reported in the Table.

The estimated DEA efficiency scores show that the efficiency of U.S. commercial banks with total assets over $50 million was gradually increasing in the 1990s. For example, with a sample size n=190, the estimated DEA efficiency score was 0.915, 0,922 and 0.929 in 1990, 1995, and 2000, respectively. This increasing trend of banking efficiency does not rely on the sample size in the DEA calculation. This result is consistent with most previous studies which have shown that banking efficiency has been increasing over time (e.g. Humphrey and Pulley, 1997; Wheelock and Wilson, 1999; Alam, 2001). Alam (2001) report an estimated DEA efficiency score of 0.897, 0.920 and 0.929 in 1980, 1985 and 1989, respectively. Wheelock and Wilson (1999) report the estimated mean changes in scale of technology of 0.987, 0.990 and 0.999 in 1984, 1989 and 1992, respectively. Adoption of new technologies, productivity change, deregulation, financial innovations and intensified competitive pressure all contributed to the efficiency increases.

Although the DEA method would not change the increasing trend of banking efficiency over time, the efficiency scores from this approach might be overestimated because of its sample-based nature. This could be demonstrated to a large extent by the following comparisons of the estimated proportions of inefficient banks in the population between the DEA method and the latent inferring method used in this study.

As expected, the estimated incidence of inefficiency in DEA was less than the latent incidence of inefficiency. Confidence intervals of 95% generated from a bootstrap technique with 200 iterations show that the bias[3] of the incidence of inefficiency between the DEA and the latent method is statistically significant. This finding is consistent across different sample sizes and over years. The underestimated proportion of inefficient banks in the sample by DEA indicates that some of truly inefficient banks are falsely categorized as efficient, thus causing the efficiency of each bank in the sample to be inflated.

In addition, Table 1 clearly shows that the DEA results associated with banking efficiency are sensitive to the sample size used for the DEA estimation. When the sample size was 190 banks, the estimated DEA efficiency score was 0.915, 0.922 and 0,928 in 1990, 1995 and 2000, respectively. These efficiency scores increased to 0.975, 0.979 and 0.981 in these three years, respectively, as the selected sample size decreased to n=50. Also, as the sample size decreased, the estimated DEA incidence of inefficiency noticeably decreased (or the incidence of efficiency increased). For example, in 1990, it decreased from 0.531 to 0.385 and then to 0.246 as the sample size decreased from 190 to 100 to 50. Consistent results are also found in 1995 and 2000. This is not surprising, when one considers that a higher percent of truly inefficient banks in a small sample could be incorrectly classified as efficient with DEA constructing the frontier than in a larger sample.

Although the inferred latent incidence of inefficiency displays a similar pattern with the DEAs in response to sample size change, the former is significantly more insensitive than the

[3] The bias is generated by subtracting the DEA incidence of inefficiency from the latent incidence of inefficiency.

latter. The increasing bias of incidence of inefficiency between DEA and the latent methods provides support for this result. This finding suggests that the inferred incidence of inefficiency from the latent method can be more accurate than the DEA method when the sample size used in the study is small.

The last but not least observation from Table 1 is that when the entire banking industry efficiency increases over time, the proportion of efficient banks in the sample decreases, and so does the proportion of efficient banks in the population, given that the sample was randomly drawn from the population. This finding reflects the process of consolidation of banks during the study period. When consolidation continues, fewer larger banks gain more market power, and thus they become more efficient in production (Kaparakis et al., 1994; Berger and Mester., 1999; Alam, 2001; Marsh et al., 2003). Therefore, even if the efficiency of the entire banking industry could improve because hundreds and thousands of middle size and small size banks would follow large banks to improve their operational efficiency, the number of banks lying on the "completely efficient" production frontier is declining over time because of consolidation.

Conclusion

An issue of considerable interest to banking analysts and economists alike is whether the intensified competitive pressure, generated by banking deregulation and notable financial innovations, has enhanced banking efficiency. During the 1990s, much of the research attention has centered on investigating efficiency changes associated with consolidation over the period from 1985 through 1997. Based on the sample-based DEA efficiency estimates, this study applied a recently proposed method by Friesner et al. (2006) to infer the incidence of inefficiency of U.S. commercial banks in 1990, 1995 and 2000. The Bayesian method was used to derive posterior distribution of the latent incidence of inefficiency in the population. The advantage of this proposed Bayesian method is the ability to recognize the true inefficient banks from being incorrectly categorized as efficient banks. This recognition will avoid the inflated estimated efficiency scores calculated by the DEA method and provide an alternative way for banking analysts and economists alike to investigate the incidence of inefficient changes in the banking industry.

The key results of this study indicate that the efficiency of U.S. banks was increasing in the 1990s. However, the estimated DEA efficiency scores could be significantly greater than what they should be in reality. This is mostly because the incidence of inefficiency in DEA tends to be significantly undercounted due to the sample-based nature of the DEA approach. In the DEA procedure, the true efficiency frontier can never be falsely categorized as inefficient, but banks below the frontier can be falsely categorized as efficient if truly efficient banks are not included in the sample.

In addition, this study has also proven that the results from DEA estimation are quite sensitive to sample size. As the sample size decreases, the DEA efficiency score tends to increase and so does the bias of the DEA efficiency from the true efficiency. The biased DEA efficiency may strongly relate to the increasing severity of the mismeasurement problem of DEA when sample size is decreased. Meanwhile, although the inferred latent incidence of inefficiency displays a similar pattern to DEA with response to sample size change, the former is significantly more insensitive than the latter, suggesting that the inferred incidence of inefficiency from the latent method could be more accurate than the DEA method when the sample size used in the study is limited.

Finally, the increasing banking efficiency over the studying period and the decreasing proportion of efficient banks in the industry may reflect the consequence of banking consolidation, mostly through merger activity, in the 1990s. When consolidation continues, fewer large banks gain more market power, and become more efficient in production. The rest of banks in the industry face two choices: following the large banks to improve their efficiency or being ruled out from the industry. Both ways would improve the efficiency of the entire industry.

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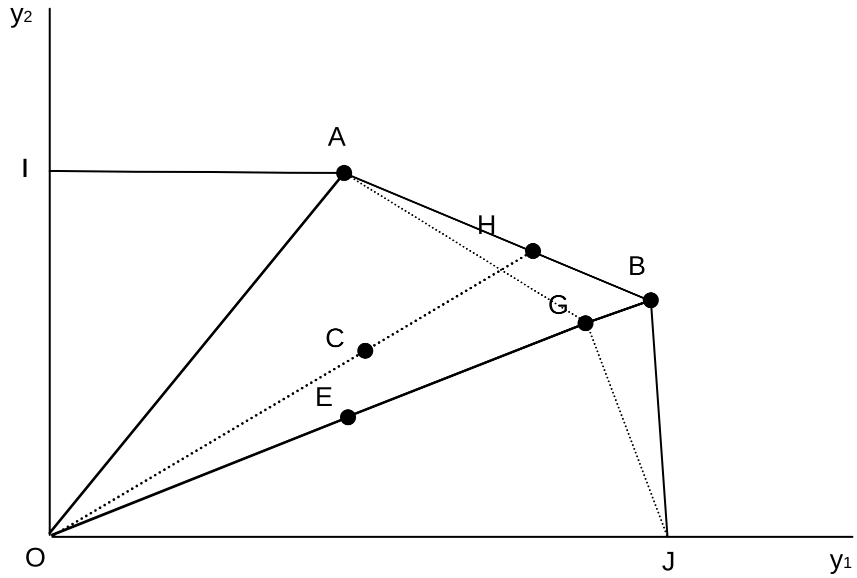

Figure 1. An Illustration of Data Envelopment Analysis

Table 1. Estimated results from DEA method and Bayesian estimation

Sample Size		1990	1995	2000
190	DEA Efficiency Score	0.915	0.922	0.928
	DEA incidence of inefficiency	0.531	0.558	0.563
	Latent incidence of inefficiency	0.763	0.776	0.779
	Bias between DEA and Latent	0.232	0.218	0.216
	95% confidence intervals for the bias			
	Lower	0.189	0.171	0.168
	Upper	0.277	0.264	0.258
100	DEA Efficiency Score	0.951	0.955	0.959
	DEA incidence of inefficiency	0.385	0.394	0.404
	Latent incidence of inefficiency	0.689	0.693	0.698
	Bias between DEA and Latent	0.304	0.299	0.294
	95% confidence intervals for the bias			
	Lower	0.240	0.230	0.245
	Upper	0.362	0.352	0.352
50	DEA Efficiency Score	0.975	0.979	0.981
	DEA incidence of inefficiency	0.246	0.241	0.252
	Latent incidence of inefficiency	0.618	0.616	0.621
	Bias between DEA and Latent	0.373	0.375	0.369
	95% confidence intervals for the bias			
	Lower	0.303	0.292	0.313
	Upper	0.438	0.448	0.417