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Estimating Degree of Market Power and Price-Response Strategies in a Product-Differentiated Oligopoly: The Case of Canned Tuna Industry in a Local Market

Apichart Daloonpate
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To the Graduate Council:

I am submitting herewith a dissertation written by Apichart Daloonpate entitled "Estimating Degree of Market Power and Price-Response Strategies in a Product-Differentiated Oligopoly: The Case of Canned Tuna Industry in a Local Market." I have examined the final electronic copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Economics.

Dr. Matthew N. Murray, Major Professor

We have read this dissertation and recommend its acceptance:

Dr. Robert A. Bohm, Dr. Hui Chang, Dr. David B. Eastwood

Accepted for the Council:
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Vice Provost and Dean of the Graduate School

(Original signatures are on file with official student records.)

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ESTIMATING THE DEGREE OF MARKET POWER AND PRICE-RESPONSE STRATEGIES IN A PRODUCT-DIFFERENTIATED OLIGOPOLY: THE CASE OF THE CANNED TUNA INDUSTRY IN A LOCAL MARKET

A Dissertation
Presented for the
Doctor of Philosophy
Degree
The University of Tennessee, Knoxville

Apichart Daloonpate
August 2002

DEDICATION

This dissertation is dedicated to my wonderful parents,

Colonel Suporn and Mrs. Sudjai Daloonpate,

to my brothers,

Pol. Lt. Col. Adul and Mr. Phichit Daloonpate,

to my sister

Capt. Sineenuch Daloonpate,

and to the rest of the family

for always believing in me, inspiring me, and encouraging me to achieve my goals.

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I would like to thank my big brothers, Adul and Pichit Daloonpate, my younger sister, Sineenush Daloonpate, and the rest of my family for their unlimited support and love. Finally, I would like to express my gratefulness for the unending love, support and encouragement of my wonderful parents, Suporn and Sudjai Daloonpate. I love you, Dad and Mom.

ABSTRACT

This dissertation estimates the degree of market power and strategic-price responses among brands in the canned tuna industry in a local market. Weekly scanner data on the purchases of canned-tuna in Knoxville, Tennessee collected by Information Resources, Incorporated (IRI) were used for the estimation of the degree of market power and strategic-price responses. Four canned tuna brands were investigated including the three leading brands, *Starkist*, *Chicken of the Sea*, and *Bumble Bee*, and the competitive small-market share brands aggregated into *Allother*.

There are two empirical parts. The first part focuses on estimation of the degrees of market power and strategic-price responses among canned tuna brands in the market based on a static approach. The second part investigates strategic-price responses based on a dynamic approach.

In the first part, the market is assumed to be operated under Bertrand competition such that price is a strategic variable, and brands make their choices simultaneously. Measures of the degree of market power include the Rothschild index (*RI)*, the O index (*OI*) and the Chamberlin quotient (*CQ*). In order to calculate these measures, each firm's own-and cross-price elasticities and price-response elasticities are needed. These elasticities are estimated by using simultaneous equations, including the linear approximate almost ideal demand system (LA/AIDS) with the corrected Stone price index and price-reaction equations. The static analysis finds evidence of market power in the canned tuna market. *Starkist* and *Chicken of the Sea* have high market power derived from both unilateral and coordinated market power, whereas *Bumble Bee* maintains its market power without coordination. The strategic-price responses among brands are investigated through the estimated price-reaction equations. The results show that *Bumble Bee* conducts warfare against *Starkist* and *Chicken of the Sea.* *Starkist* and *Chicken of the Sea* positively respond to each other's price; however, they do not respond to *Bumble Bee*'s price.

In the second part, the Bertrand-competition assumption is replaced by an assumption that a firm in the market sets its price depending on its own past prices and those of rivals. A vector autoregressive (VAR) model is employed and its applications, including the Granger-causality test, the impulse response function (IRF) analysis, and the forecast error variance decomposition (FEVD) analysis, are used to investigate the dynamic price relationships. This study finds that although *Starkist* and *Chicken of the Sea* do not respond *Bumble Bee*'s price strategy during the same time period, they do over time. The findings of the second part offer valuable insights in that the study of strategic-price responses based on both static and dynamic approaches provide significantly better understanding in firms' pricing behaviors.

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GENERAL INTRODUCTION

Motivations

One of the most important issues in industrial organization concerns market structure. The elements that indicate the market structure in industrial organization generally include concentration, product differentiation, and entry barriers. Industrial organization economists have tried to analyze the degree of competitiveness of industrial markets in several directions based on these elements. Appelbaum (1982) and Schroeter (1988) used the concept of market concentration to study the degree of market power in industrial markets by estimating the Lerner index, the difference between price and marginal cost as a proportion of price. To estimate such an index, the studies had to assume that products are homogeneous. Therefore, the estimated Lerner index for each industry represented the degree of market power of that industry as a whole, but the degree of market power among firms in the industry was not estimated. Although economists consider some industrial products to be homogeneous, product differentiation does occur in industrial markets. Unlike competitive markets, firms in oligopolies or monopolistically competitive markets are able to set their prices differently from one another and higher than their marginal costs because their products are differentiated.

Several researchers have investigated the degree of market power among firms in product-differentiated oligopolies using different methods. Liang (1989) estimated the degree of market power in the ready-to-eat breakfast cereal industry by estimating price-conjectural variations and price-response elasticities. The degree of market power in Liang's research is based on the ability of pairs of firms to engage in collusion. Nevo (2001) examined the nearly collusive-pricing behavior and intense non-price competition in the ready-to-eat cereal industry by the estimation of price-cost margins. Cotterill

(1994) and Vickner and Davies (1999) estimated the degree of market power in the carbonated-soft drink industry and the spaghetti sauce industry, respectively. The degree of market power in both studies is derived from two sources, unilateral market power and coordinated market power, and is estimated by three measures; the Rothschild Index (*RI*), the O Index (*OI*) and the Chamberlain Quotient (*CQ*). This dissertation is motivated by the work of Cotterill, and Vickner and Davies.

Research Objectives

There are two main objectives of this dissertation. The first objective is to estimate the degree of market power in a product-differentiated oligopoly, the canned tuna industry in a local market. The second objective is to investigate price-response relationships among firms in the industry based on the static and dynamic approaches.

This study chooses the domestic canned tuna industry as a representative processed agricultural product in a product-differentiated oligopoly to estimate the degree of market power and strategic price response for various reasons. It is a structural oligopoly in which products are manufactured mainly by the big three companies, *Starkist, Bumble Bee,* and *Chicken of the Sea*, with their combined market share in 2000 approximately 82 percent of the $2.1 billion canned tuna industry in the U.S. (Fulmer, 2001). Tuna has been the largest selling seafood in the U.S. in the past several years (Maclean Hunter Media Inc., 1997). Canned tuna is a durable good because its shelf life exceeds the period of time between price changes (Tirole, 1988). Since canned tuna can be stored over time, consumers can store the product when its price is decreased. Therefore, it turns out to be an inter-temporal substitute for itself. Several canned-tuna brands are sold in the same stores, and consumers are able to compare prices across the brands. As a result, each brand faces not only its inter-temporal substitute, but also the inter-brand competition. Moreover, canned tuna products are differentiated by brand, flavor, package, size, and advertising. Since there is product differentiation, firms potentially are able to set prices above marginal costs. In addition, firms' pricing behaviors are interdependent because they operate in an oligopoly market. For these reasons, it is of interest to study the degree of market power along with the price-response strategies among firms.

The scanner data used in this research are primary data that represent a readily current and timely source of precise product-specific information including price, quantity, expenditure, and marketing activities for a large number of products available on a daily basis. Nayga (1992) argued that "scanner data may become the most detailed and definitive source of retail food industry statistics available to researchers and marketing executives". This study uses the weekly scanner data of canned-tuna prices, quantity purchased, and promotional information in a local market, Knoxville, Tennessee. The scanner data in this study were collected weekly for 157 weeks over the period of January 4, 1998 to December 31, 2000 from 134 supermarkets in Knoxville, Tennessee by Information Resources, Incorporated (IRI), a market-research company that processes scanner data into a usable format for researchers.[1]

[1] This research was funded by a grant from the Scholarly Research Grant Program of the College of Business Administration at The University of Tennessee.

Estimating Degree of Market Power

With respect to the first objective, this study estimates the degree of market power based on the three measures: the *RI*, *OI* and *CQ*. In order to calculate these measures, each firm's own-and cross-price elasticities and price-response elasticities are needed. These elasticities are estimated by simultaneous demand-supply equations based on the Bertrand competition assumption such that price is the strategic choice variable and firms make their choices simultaneously. Following Cotterill (1994), this study employs the linear approximate almost ideal demand system (LA/AIDS) proposed by Deaton and Muellbauer (1980) to estimate the demand for canned tuna in the market and the price-reaction functions to investigate strategic-price response among firms. The LA/AIDS is a modification by Deaton and Muellbauer from their almost ideal demand system (AIDS) to replace the non-linear price index with the Stone price index. Cotterill (1994) and Vickner and Davies (1999) used the LA/AIDS in estimating the degree of market power.

Use of the Stone index in the LA/AIDS causes estimated parameters to be biased and inconsistent (Pashardes, 1993 and Moschini, 1995). This dissertation uses the corrected Stone index suggested by Moschini (1995) in the LA/AIDS estimation. The results of the measures of market power found in this dissertation are consistent with those of Cotterill (1994) and Vickner and Davies (1999) in that the leading firms which are able to maintain high prices and market shares have high degrees of market power. In addition, this dissertation re-estimates the simultaneous equations with the use of the traditional Stone index in the LA/AIDS and the parameter estimates are compared to those of the corrected version. The results from both versions are found to be very close giving the interpretation of market power in the same fashion. This study found that

Starkist, the highest-market share brand, has the highest degree of market power. The market power of *Starkist* and *Chicken of the Sea* is derived from both unilateral and coordinated market power, whereas that of *Bumble Bee* is derived from its own unilateral market power, not from coordinated market power.

Investigating Price-Response Strategies

The investigation is divided into two parts because the second objective in this dissertation is to investigate the strategic price-response relationships among firms in the canned tuna industry based on both static and dynamic approaches. In part one, the price response relationships are investigated through the price-reaction functions from the estimated simultaneous equations. This investigation is based on the static approach because Bertrand-competition assumes that the price strategies are made simultaneously by each firm. *Starkist* and *Chicken of the Sea* are found to respond positively to each other. *Bumble Bee* seems to conduct price war against its rivals since it responds negatively to *Starkist*'s and *Chicken of the Sea*'s price strategies. On the other hand, both *Starkist* and *Chicken of the Sea* do not respond to *Bumble Bee*'s price strategy during the same time period. However, *Bumble Bee* is one of the leading brands in the market; therefore, the results in the first part raise the interesting question of whether *Bumble Bee*'s price strategy in past periods may affect *Starkist*'s and *Chicken of the Sea*'s price strategies in the current period.

The second part of this dissertation investigates further the price-response relationships among firms based on a dynamic approach. The Bertrand-competition assumption is replaced by an assumption that a firm in the market sets its price depending on its own past prices and those of rivals. A vector autoregressive (VAR) model is employed. The strategic-price responses are investigated using the VAR's applications including the Granger-causality test, the impulse response function (IRF) analysis, and the forecast error variance decomposition (FEVD) analysis. The Granger-causality test examines whether the dynamic price-response relationships exist. The IRF analysis graphically reveals the direction of the effect of a one-time shock to one of the innovations on future values of the endogenous variables, whereas the FEVD analysis measures proportions of a brand's price variations that can be explained by shocks to its own price and it rivals' prices for each forecast horizon. Although the results from part one indicate that *Starkist* and *Chicken of the Sea* do not respond *Bumble Bee*'s price strategy during the same time period, the Granger-causality results show that both *Starkist* and *Chicken of the Sea* respond negatively to *Bumble Bee*'s past price. The results from the IRF and FEVD analyses also support the Granger-causality test results for the three-leading canned-tuna brands' relationships.

In summary, this dissertation estimates the degree of market power and investigates strategic-price responses among firms in the canned tuna industry in the Knoxville, Tennessee market. The strategic-price responses are investigated using both static and dynamic approaches. Part one estimates the degree of market power and price-response relationships based on a static approach. Part two investigates the dynamic price-response relationships. Overall, the results from both parts of this dissertation provide helpful insights on the degree of market power and strategic-price responses among firms in the canned tuna market.

Contributions of this Dissertation

The first contribution of this dissertation is to improve the model specification in estimating the degree of market power as developed by Cotterill (1994) and followed by Vickner and Davies (1999). In their studies, Cotterill (1994), and Vickner and Davies (1999) measured the degree of market power in the carbonated soft drink industry (Cotterill) and the spaghetti sauce industry (Vickner and Davies) by estimating the LA/AIDS model and price reaction functions simultaneously. In this study, the corrected Stone index suggested by Moschini (1995) is used in the LA/AIDS model.

Second, this study is the first to examine the degree of competitiveness of brands of a manufactured food product at the local level. Work to date on food manufacture degree of market power and pricing strategies has been conducted at the aggregate national level (Appelbaum, 1982; Schroeter, 1988; Baker and Breshnahan, 1985; Liang, 1989; Cotterill, 1994; and Vickner and Davies, 1999). These studies have not captured local market effects on pricing conduct and local demand. Only the studies of Cotterill (1994), and Vickner and Davies (1999) have used scanner data in investigating the degree of market power. Nayga (1992) suggested that due to the enormous information and the high cost of acquisition involved with scanner data, an individual researcher may not be able to efficiently collect or organize the volume of information. Individual researchers might have to form a team and combine their efforts when conducting research in a national or regional level to become cost effective. Otherwise, “individual researchers should just focus on a local retail firm with multiple stores” (Nayga, 1992). Nayga (1992) suggested that scanner data from supermarkets in a particular location present a controlled situation. Therefore, the community specific results may not contribute to broad regional or national inferences. This dissertation estimates the degree of market power and strategic price response in canned tuna industry in a specific local market, Knoxville, Tennessee. Although demographic information is not available, the study should provide information regarding the degree of competitiveness and price strategies among firms in a local market.

Third, this dissertation not only refines Cotterill's, and Vickner and Davies' work, but also extends their research to dynamic analysis. Due to the previous work (Cotterill, 1994; and Vickner and Davies, 1999), the Bertrand price reaction model yields information of strategic price response through the price-response elasticities. These results show pricing behaviors among firms in a static way. In other words, a firm sets its price responding to its rivals' prices in the present time. In fact, firms' strategies may respond to one another depending not only on today's information, but also on past information. This study employs a vector autoregressive (VAR) model to investigate dynamic price relationships among firms in the canned tuna market.

Regarding previous industrial-organization research in this area, Vickner and Davies (2000) estimated strategic-price response between two leading brands in the canned pineapple industry using the VAR and vector error correction model. The Granger causality test and the IRF analysis were applied to investigate the price relationships. With respect to the IRF analysis, confidence intervals are used to evaluate the statistical reliability of the estimated results. However, confidence intervals were not included in Vickner and Davies' IRF analysis. This may affect the interpretation of their empirical results. This dissertation improves the price-response study by including confidence intervals in the IRF results to determine whether the estimated price-response relationships are asymptotically and statistically significant. In addition, the FEVD analysis, one of the useful VAR applications which measures proportions of a brand's price variations that can be explained by shocks to its own price and it rivals' prices for each forecast horizon, was not employed in the Vickner and Davies study. The FEVD results can give additional information to the IRF and Granger-causality results in estimating price-response effects. Therefore, this dissertation includes the FEVD analysis to rigorously investigate pricing relationships.

Limitations and Extensions

Limitations of this dissertation mainly involve the data. First, demographic and brands' cost data are not included. Second, this study was not able to take into account the effects of the use of brands' coupons because IRI does not report the extent of their use. Third, the time period of observations is short. Therefore, strategic-price responses among firms in the long run may not be captured. Finally, the price-response analysis in the second part investigates only whether the price relationships exist. The VAR's applications do not provide statistical magnitudes concerning the price relationships.

This dissertation can be extended in several ways. In a local market, store brands such as Kroger and BI-LO may have some effects on the national brands' demand and price strategies. One extension is to include store brands as key variables in the estimation of the degree of market power and price-response strategies among the canned tuna brands in a local market. Another extension is to find a way to include both static and dynamic information in the estimation of the degree of market power. Measures of the degree of market power need information of demand and price-response elasticities based on a static approach. Since this dissertation has shown that firms' price strategies are both static and dynamic, future studies might find a method to measure the degree of market power that is able to take into account both static and dynamic information in their investigations.

PART 1: ESTIMATING THE DEGREE OF MARKET POWER AND PRICE-RESPONSE STRATEGIES IN THE CANNED TUNA INDUSTRY: A STATIC APPROACH

Chapter One

Introduction

A firm is said to have market power if the firm is able to raise price profitably above its marginal cost without losing its market share. One reason this can occur is because the products are differentiated. Consumers perceive that brands in a market are imperfect substitutes. As a result, a firm may raise its price above that of its rivals without losing its market share. In this case, the competitive tactics of firms in the market may use advertising to emphasize product features. However, in a product-differentiated oligopoly, although products differ, they can be substituted. Firms are interdependent in the way that if a firm's price is too high compared to that of its rivals, consumers may switch to competitors. Therefore, price is also a strategic variable in the product-differentiated oligopoly market.

Objectives

The main objectives of this first part are to estimate the degree of market power and to investigate strategic-price responses among firms in the canned tuna market at the local level. The $2.1 billion canned tuna market is selected as a representative product-differentiated oligopoly (Casamar Group, Inc., 2001). This dissertation focuses the estimation on the local level with Knoxville, Tennessee as a representative local market. The data are scanner data which have been actively used in food marketing and economic research since the 1980s (Nayga, 1992). The scanner-data set in this study were collected weekly by Information Resources, Incorporated (IRI) for 157 weeks over the period of January 4, 1998 to December 31, 2000 from 134 supermarkets in Knoxville, Tennessee.

In an oligopolistic market, when a firm's product is differentiated from the others, a demand curve facing the firm is downward-sloping. Carlton and Perloff (2000) stated "that if a firm faces a downward-sloping demand curve, it has market power." The firm's downward-sloping demand curve becomes less elastic if the firm has high market power; however due to the presence of substitution it is more elastic than that of a monopolist, which is a market-wide demand curve. If the firm increases price and can influence all of its rivals to follow its strategy, the demand curve facing the firm becomes a close reflection of the market-wide demand curve, and the firm is said to have extremely high market power with full collusion.

Rothschild (1942) introduced a theoretical measure of the degree of market power called the Rothschild Index (*RI*). Later, Cotterill (1994) modified the *RI* to be more applicable with the use of elasticities. The main idea of the *RI* is that it compares a firm's own-price elasticity of demand when none of its rivals are collusive, which is called the non-followship demand elasticity, with the fully collusive demand elasticity. The closer to one the *RI* is, the greater the degree of market power. However, the *RI* measures only unilateral market power, ignoring the effects of partial collusion among firms. Basically, firms in a product-differentiated oligopoly are interdependent. Therefore, partial collusion exists. Cotterill introduced two more measures of market power called the O Index (*OI*) and the Chamberlin Quotient (*CQ*) in order to take into account market power from partial collusion of which Cotterill called coordinated market power.

In order to calculate the *RI*, *OI*, and *CQ*, own-price and cross-price elasticities of demand and price-response elasticities of each firm are needed. Following Cotterill (1994), this dissertation employs the demand-supply simultaneous equations to estimate such elasticities assuming that the canned tuna market is operated under Bertrand competition such that price is strategic variable and firms make their decisions simultatneousely. On the demand side, the Linear Approximate Almost Ideal Demand System (LA/AIDS) developed by Deaton and Muellbauer (1980) is used. Price-reaction equations represent the supply-side of the system. In their research, Cotterill (1994) and Vickner and Davies (1999) used the Stone index in the LA/AIDS in estimating the degree of market power. However, some studies found that the use of the Stone index in the LA/AIDS causes estimated parameters to be biased and inconsistent (Pashardes, 1993 and Moschini, 1995). This dissertation uses a corrected Stone index suggested by Moschini (1995) in the LA/AIDS estimation to estimate the degree of market power among brands in the canned tuna market. In addition, the estimated price-reaction functions are used to investigate strategic-price responses among brands in the market.

Four canned tuna brands are estimated: *Starkist*, *Chicken of the Sea*, *Bumble Bee*, and *Allother*. The study finds consistency between firms' market shares and their market power in a positive way. *Starkist*, the brand with the highest market share, has the highest degree of market power. Its market power is derived from both unilateral and coordinated market power. Interestingly, *Bumble Bee* is able to maintain its market power without collusion from its rivals. With respect to the price relationships, *Starkist* and *Chicken of the Sea* respond positively to each other strategy, but they do not respond to the *Bumble Bee* strategy. In addition, the study finds an evidence of price war on *Bumble Bee* against *Starkist* and *Chicken of the the Sea*.

The remainder of this first part is organized as follows. The theoretical framework and literature review are presented in Chapter Two. Chapter Three discusses the scanner data followed by a presentation of the econometric method used in this research. Chapter Four reports the estimated results and Chapter Five presents a conclusion.

Chapter Two

Theoretical framework and Literature Review

The degree of market power in this study was measured in three ways: the Rothschild and O indices, and the Chamberlin Quotient. In order to calculate these measures, we have to estimate partial own- and cross-price elasticities, and price-response elasticities for each brand. In this study, the partial own- and cross-price elasticities were estimated using the Linear Approximate Almost Ideal Demand System (LA/AIDS), whereas the price-response elasticities were estimated using price reactions functions. This chapter reviews the relevant theoretical and empirical literature associated with LA/AIDS and price-reaction functions. It provides a structure for extensions of the models and associated empirical work described in subsequent chapters.

The Market Power Analysis

One of the main objectives of this dissertation is to estimate the degree of market power in the canned tuna industry. Greer (1992) states that "market power is the ability to influence market price and/or subdue rivals". Greer indicates that it is market structure that determines ability. Variations in the features of market structure cause variations in demand and supply. Perfect competition and monopoly are the two polar cases of market structure. In a perfectly competitive market, the demand curve facing a firm is horizontal because each firm has no control over price. On the other hand, a monopolist's demand curve represents the market-wide demand curve because the monopolist has no competition.

Between these two polar cases, an oligopoly market is an intermediate situation of "rivalry" among a small number of firms. An oligopolistic firm potentially faces two kinds of downward-sloping demand curves; a followship demand curve and a non-followship demand curve, "neither of which is the market-wide demand curve. The firm might face either one or both or portions of both of these demand curves, depending on what assumptions it makes concerning its rivals' behavior." (Greer, 1992)

1. The followship demand curve (FD).

The FD curve facing a firm occurs if firms try to maintain their market shares. For example, a price increase by one firm is matched by its competitors such that their market shares are unchanged. Hence, the followship demand curve could be called a "constant share" demand curve. Greer mentions that the followship demand curve is "a close reflection of the market-wide demand curve" (Greer, 1992). If the firm has an ability to influence the market price and then its rivals follow, this indicates the firm has some market power. In economic applications with an oligopoly market, the followship demand curve facing a firm can be viewed as the firm's demand curve with perfectly tacit collusion.

2. The non-followship demand curve (NFD).

The NFD curve facing a firm occurs if the firm has no power to influence the market price. Therefore, an increase in its price is not matched by its rivals and that firms' market share changes. The NFD curve could be called a "changing market share curve." The elasticity of the NFD curve is much higher than the elasticity of the FD curve in absolute value because a firm will get a substantial increase in quantity sold in the market if it cuts its price, and a considerable decrease in customers if it raises its price since its rivals do not match the price change. The NFD curve varies in elasticity across firms within a given market. In economic applications with an oligopoly market, the non-followship demand curve reflects a non-collusive situation.

Figure 2.1 shows these demand relationships for a representative brand, namely brand 1. Assume that demand curves are linear and the market is in equilibrium at P_0 Q_0. In addition, assume that the brand 1 firm decides to raise price to P_1. An increase in price yields a decline in quantity sold to Q_1.

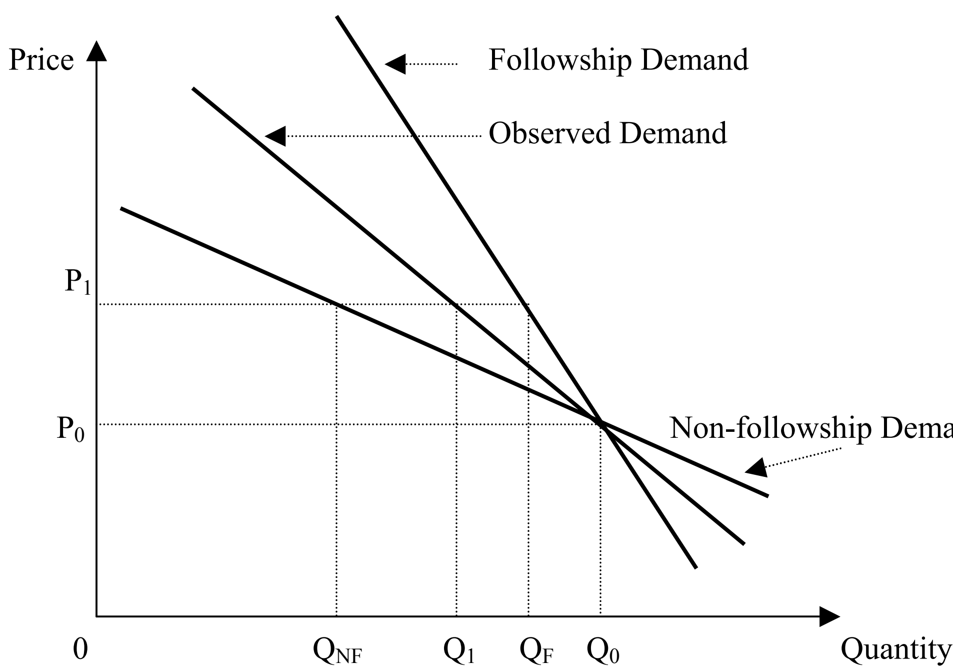


Figure 2.1 Followship, Non-Followship, and Observed Demand Curves

If there is perfectly tacit collusion among firms, the output will decline only to Q_F because the firm has market power to influence the market price and its rivals follow, and if there is no tacit collusion, the quantity demanded will decline to Q_{NF} implying that the firm does not have enough market power to affect the market price and no one follows.

Rothschild (1942) introduced a theoretical measure of the degree of market power called the Rothschild Index (*RI*). It is the slope of the non-followship demand curve divided by the slope of the followship demand curve.

$$RI = \text{slope of NFD curve/slope of FD curve}$$

$$\text{and} \quad 0 \leq RI \leq 1.$$

Under perfect competition the slope of NFD curve would be zero implying that a competitive firm has no control over price and no effect on its rivals. If the NFD curve is identical to the FD curve, the *RI* will be equal to 1 implying that the demand curve is the market-wide demand curve of a monopolist. From these two extreme cases using the measure of *RI*, we would be able to measure a degree of market power from an observed demand with the *RI* ranging from zero to one.

Cotterill (1994) has modified the Rothschild Index (*RI*) to be more applicable by converting the slope of the NFD curve and FD curve into elasticities. This approach leads to the use of econometric methods to measure the degree of market power in empirical research. With respect to Figure 2.1, let ΔP be the change in price ($P_1 - P_0$), ΔQ_{NFD} equals the change in quantity sold ($Q_0 - Q_{NF}$) on the NFD curve, and ΔQ_{FD} is the change in quantity sold ($Q_0 - Q_F$) on the FD curve.

$$RI = \frac{\frac{\Delta P}{\Delta Q_{NFD}}}{\frac{\Delta P}{\Delta Q_{FD}}}$$

Assume that the going price and quantity are P_0 and Q_0 and that the elasticities of NFD curve and FD curve are calculated at this point. Multiplying the numerator and denominator by $\frac{Q_0}{P_0}$.

$$RI = \frac{\frac{\Delta P}{\Delta Q_{NFD}} \times \frac{Q_0}{P_0}}{\frac{\Delta P}{\Delta Q_{FD}} \times \frac{Q_0}{P_0}}$$

$$= \frac{\frac{1}{\eta_{NFD}}}{\frac{1}{\eta_{FD}}}$$

$$= \frac{\eta_{FD}}{\eta_{NFD}},$$

where η_{NFD} represents the non-followship demand elasticity and η_{FD} represents the followship demand elasticity. This measure of *RI* using elasticities retains the same interpretation of market power as the *RI* did in terms of slopes. If the market is perfectly competitive, η_{NFD} will be infinitely negative, and the RI will be equal to zero. If η_{NFD} is equal to η_{FD}, the *RI* will be equal to one, meaning that the market has monopoly power.

Baker and Breshnahan (1985) were the first to estimate the degree of market power in a differentiated oligopoly by combining demand analysis with industrial organization concepts. Cotterill (1994) has extended the approach by developing a brand level analysis of demand and market power based upon a more general theory. He assumed that an industry is differentiated and that Bertrand competition occurs such that price is the strategic variable. Then the demand for brand 1 in the *n*-brand industry is a function of its price and its rival's prices, that is:

$$q_1 = q_1(p_1, p_2 \ldots p_n, D) \tag{2.1}$$

where:

q_1 = the quantity of brand 1,

p_i = the price of brand i, i = 1,…, n, and

D = a vector of demand shift variables.

If we take the total derivative of this equation, with respect to p_1, we will obtain

$$\frac{dq_1}{dp_1} = \frac{\partial q_1}{\partial p_1}\frac{dp_1}{dp_1} + \frac{\partial q_1}{\partial p_2}\frac{dp_2}{dp_1} + \ldots + \frac{\partial q_1}{\partial D}\frac{dD}{dp_1}. \tag{2.2}$$

Assuming that demand shift variables are constant, the last term in equation (2.2) is equal to zero. Multiply equation (2.2) by $\frac{p_1}{q_1}$ and use the chain rule to account for oligopolistic price interdependence (for example, the second term of the right hand side would be $\frac{\partial q_1}{\partial p_2} \times \frac{p_2}{p_2} \times \frac{p_1}{q_1} \times \frac{dp_2}{dp_1}$). Some algebraic manipulation results in the following formula for the observable price elasticity of demand:

$$\eta_1^0 = \eta_{11} + \sum_{i=2}^{n} \eta_{1i}\varepsilon_{i1}, \tag{2.3}$$

where:

η_1^0 = observable price elasticity for brand 1,

η_{11} = partial-own price elasticity of demand,

η_{1i} = firm 1's cross-price elasticity with respect to p_i $(i \neq 1)$, and

ε_{i1} = rivals' price response elasticity or the conjectural price response of firm *i* with respect to firm 1's price $(i \neq 1)$.

Equation (2.3) is interpreted as follows. Brand 1's observable price elasticity is composed of two elements, its partial own-price elasticity and its coordinated market power component. The partial own-price elasticity of demand for brand 1 (η_{11}) represents the percentage change in quantity of brand 1 demanded in response to a percentage change in its own price when its competitors' prices are held constant. Therefore, the partial own price elasticity of demand can be interpreted as the non-followship demand elasticity, which measures the unilateral market power of the brand (Cotterill, 1994). The coordinated market power component is the summation of products between brand 1's cross price elasticities and its rivals' price-response elasticities. If there is tacit collusion among firms in a way that other brands follow a change in brand 1's price, ε_{i1} will be positive. Assuming that all brands are substitutes, though not perfect, the cross price elasticities, η_{1i}, are also positive. If the price-response elasticities and the cross-price elasticities are not zero, yielding coordinated market power, the observable price elasticity in equation (2.3) will be less elastic than the partial own price elasticity. The followship demand elasticity (η_1^F) can be obtained by adding up the partial own-price elasticity and all cross-price elasticities assuming that all the ε_{i1} are equal to one (full collusion), $\eta_1^F = \eta_{11} + \sum_{i=2}^{n} \eta_{1i}$. According to the fully collusive assumption, the followship demand elasticity is also called the *fully collusive elasticity*, which is used for the rest of this dissertation. The *RI* measures a degree of unilateral market power because it compares the fully collusive elasticity (η_1^F) and the non-followship elasticity(η_{11}).

Cotterill (1994) introduced a second measure of observed market power called the O Index (*OI*). The *OI* can be obtained by dividing the slope of the observed demand by the slope of the followship demand. Developed the same way as the *RI* Index, the *OI* is

$$OI = \frac{\eta_1^F}{\eta_1^0}, \qquad \text{and } 0 \le RI \le OI \le 1.$$

In perfect competition, the *OI* is zero because the partial own price elasticity or the non-followship elasticity (η_{11}) is infinitely negative (and so is the observable price elasticity), and there is no coordinated market power. If the market is perfectly collusive, the observed demand elasticity will be equal to the fully collusive elasticity resulting in the *OI* equal to one. Unlike the *RI*, the *OI* measures a degree of bilateral market power because the observed demand elasticity (η_1^0) in the *OI* accounts for both unilateral and coordinated market power. Moreover, since the observable price elasticity is less elastic than the partial own price elasticity, the *OI* of the observed demand is always greater than or equal to the *RI*. The closer to one the *OI* is, the greater the degree of market power.

In addition, Cotterill (1994) presented a new measure of market power called the Chamberlin Quotient (*CQ*).

$$CQ = 1 - \frac{RI}{OI} = 1 - \frac{\eta_1^0}{\eta_{11}}$$

and $0 \leq CQ \leq 1$.

The CQ measures the fraction of market power of the observed demand due to tacit collusion. The higher are levels of tacit collusion in a market, the lower is the observed demand elasticity (η_1^o) than the partial own-price elasticity (η_{11}), and, therefore, the higher the CQ.

The Demand System

In order to measure the degree of market power in any industry using the *RI*, *OI*, and *CQ*, the partial own- and cross-price elasticities, and price-response elasticities of each brand in the industry must be estimated. In this study, the partial own- and cross-price elasticities were estimated using the Linear Approximate Almost Ideal Demand System (LA/AIDS) developed by Deaton and Muellbauer (1980), and the price-response elasticities were estimated using the Bertrand price reactions functions.

Deaton and Muellbauer (1980) first developed the Almost Ideal Demand System (AIDS). They listed the advantages of their system as follows: it gives an arbitrary first-order approximation to any demand system; it satisfies the axioms of choice exactly; it aggregates perfectly over consumers; it has a functional form which is consistent with previous household budget data; it is simple to estimate in its linear approximate form; and it can be used to test the restrictions of homogeneity and symmetry. Deaton and Muellbauer (1980) noted that "although many of these desirable properties are possessed by one or other of the Rotterdam or translog models, neither possesses all of them simultaneously". Blanciforti and Green (1983) noted an additional desirable property that "the AIDS is indirectly nonadditive, allowing consumption of one good to affect the marginal utility of another good; whereas the linear expenditure system (LES) is directly additive, implying independent marginal utilities". Therefore, the AIDS does not require the strict substitution limitations implied by the additive demand models such as LES (Blanciforti and Green, 1983). While the AIDS has several desirable properties, it may be difficult to estimate. This is because the AIDS is non-linear. To simplify this problem, Deaton and Muellbauer suggested using a linear approximation. Several studies have shown that the AIDS and LA/AIDS models are equivalent or superior to other common demand specifications, e.g., translog (Lewbel, 1989); Rotterdam (Gao, Wailes, and Cramer, 1994); and LES (Green, Hassan, and Johnson, 1995). Because of their advantages, the AIDS and LA/AIDS models have been employed in both macro- and micro-demand analysis. A list of studies that have used either the AIDS or the LA/AIDS or both to investigate consumer behavior in various food markets is presented in Table 2.1.

Deaton and Muellbauer start their approach by setting a specific class of preferences, which represents exact aggregation over consumers (Muellbauer, 1975), known as the price-independent, generalized-logarithmic (PIGLOG) consumer preferences. The PIGLOG is represented through the consumer cost or expenditure function, which is defined as the minimum expenditure necessary to attain a specific utility level at given prices. The PIGLOG class is defined as:

$$\log c(u, p) = (1 - u)\log[a(p)] + u \log[b(p)], \qquad (2.4)$$

where u denotes utility ranging from 0 to 1, p is a price vector, and $a(p)$ and $b(p)$ are linearly homogeneous functions of prices to be specified. The expenditure function in

Table 2.1 Listing of Research on Food Product using the AIDS or LA/AIDS

Auther (Published year)	Research Time period	System	Objective
Deaton and Muellbauer (1980)	1954 – 1974	AIDS and LA/AIDS	Estimation of demand for eight commodities in UK, and comparison between AIDS and LA/AIDS
Blanciforti and Green (1982)	1948 – 1978	AIDS and LA/AIDS	Incorporation of habit effects in the system to estimate demand system
Blanciforti and Green (1983)	1948 – 1978	LES[1] and LA/AIDS	Estimation of demand for food groups and comparison between LES and LA/AIDS
Chalfant (1987)	1947 – 1978	LA/AIDS	Investigation of the demand for meat and fish products
Lewbel (1989)	1955 – 1984	Translog and LA/AIDS	Testing and comparison between the Translog and AIDS models
Green, Carman, and McManus (1991)	1957 – 1986	AIDS	Estimation of advertising effects in demand for dried fruits
Cotterill (1994)	1988 – 1990	LA/AIDS	Estimation of market power in carbonated soft drink industry
Gao, Wailes, and Cramer (1994)	1987 – 1988	Rotterdam, CBS[2], and LA/AIDS	Estimation of demand for rice and its substitutes using several models
Song, Liu, and Romilly (1997)	1960 – 1988	WLS[3], cointegration, error correction, AIDS, and TVP[4]	Analysis on demand for food in the U.S. and the Netherlands, and comparison of various econometric methods
Richards, Kagan, and Gao (1997)	1970 – 1991	LA/AIDS	Investigation of the demand for complex-carbohydrate products
Henneberry, Piewthongngam, and Qiang (1999)	1970 – 1992	LA/AIDS	Estimation of demand functions for fresh fruits and vegeTables
Vickner and Davies (1999)	1994-1996	LA/AIDS	Estimation of market power in spaghetti sauce industry
Cotterill, Putsis, and Dhar (2000)	1991 – 1992	LA/AIDS	Analysis the competitive interaction between private labels and national brands on six individual categories
Teisl, Roe, and Hicks (2000)	1988 – 1995	AIDS	Investigation of the dolphin-safe-label effect on the tuna demand

[1]LES-Linear Expenditure System, [2] CBS- the Central Bureau of Statistics model, [3] WLS-Weighted Least Squares, and [4] TVP-Time-Varying Parameter Technique

equation (2.4) includes two components. The expenditure *log a(p)* is interpreted as necessary expenditure, whereas the expenditure *log b(p)* is interpreted as luxury expenditure. It can be shown that the expenditure function is increasing in utility and nondecreasing in prices.

Deaton and Muellbauer (1980) suggest the specific functional forms of *log a(p)* and *log b(p)* as:

$$\log a(p) = a_0 + \sum a_i \log p_i + \frac{1}{2}\sum_i \sum_j \gamma_{ij}^* \log p_i \log p_j \tag{2.5}$$

and

$$\log b(p) = \log a(p) + u\beta_0 \prod_k p_k^{\beta_k}, \tag{2.6}$$

resulting in the cost function

$$\log c(u, p) = a_0 + \sum_i a_i \log p_i + \frac{1}{2}\sum_i \sum_j \gamma_{ij}^* \log p_i \log p_j + u\beta_0 \prod_k p_k^{\beta_k}, \tag{2.7}$$

where a_i, β_i, and γ_{ij}^* are parameters. The cost function *c(u, p)* is linearly homogeneous in p given that $\sum_i a_i = 1, \ \ \sum_i \gamma_{ij}^* = \sum_j \gamma_{ij}^* = \sum_j \beta_j = 0$.

By differentiating equation (2.4) with respect to prices and using Shepard's Lemma, they obtain the compensated or Hicksian demand functions.

That is $\dfrac{\partial c(u, p)}{\partial p_i} = q_i(u, p) = q_i$. (2.8)

By multiplying both sides by $p_i/c(u, p)$ equation (2.8) becomes:

$$\frac{\partial \log c(u, p)}{\partial \log p_i} = \frac{\partial c(u, p)}{\partial p_i} \times \frac{p_i}{c(u, p)} = \frac{p_i q_i(u, p)}{c(u, p)} = w_i(u, p), \tag{2.9}$$

where $w_i(u, p)$ is the market share of good *i*.

According to the cost function from equation (2.7), equation (2.9) becomes

$$w_i = \phi_i + \sum_j \gamma_{ij} \log p_j + \beta_i u \beta_0 \prod_k p_k^{\beta_k}, \tag{2.10}$$

where $\gamma_{ij} = \frac{1}{2}(\gamma_{ij}^* + \gamma_{ji}^*)$. (2.11)

Since total expenditure, Y, is equal to $c(u, p)$ in equilibrium for a utility-maximizing consumer, by solving for u (indirect utility) in terms of p and Y from equation (2.7), and substituting the result into equation (2.10), we obtain the AIDS in budget share form as:

$$w_i = \phi_i + \sum_j \gamma_{ij} \log p_j + \beta_i \log\left(\frac{Y}{P}\right), \tag{2.12}$$

where P is a price index defined by

$$\log P = a_0 + \sum_i a_i \log p_i + \frac{1}{2} \sum_i \sum_j \gamma_{ij}^* \log p_i \log p_j \tag{2.13}$$

The translog price index in equation (2.13) causes some empirical problems. First, its specification makes the AIDS a non-linear econometric model, and therefore, it is complicated to estimate the model (Deaton and Muellbauer, 1980). Second, the prices in equation (2.13) are likely to be highly correlated, and the high correlation among prices can cause collinearity problems. However, Buse (1996) used the AIDS model to estimate meat consumption in the U.S. and concluded that the collinearity among prices in the AIDS model was not a serious problem as was presumed in the literature. Nevertheless, several studies have replaced the translog price index, $\log P$, by the Stone index, $\log P^*$, where $\log P^* = \sum w_i \log p_i$, and P^* is assumed to be approximately proportional to P, such that $P^* = a_0 P + e$, and w_i is the ith firm's market share (Deaton and Muellbauer, 1980; Chalfant, 1987; Cotterill, 1994; and Vickner and Davies, 1999). Therefore, by using the Stone index the AIDS has been termed the "linear approximate almost ideal demand system" (LA/AIDS). Thus equation (2.12) becomes

$$w_i = \alpha_i + \sum_j \gamma_{ij} \log p_j + \beta_i \log\left(\frac{Y}{P^*}\right) + \omega_i, \tag{2.14}$$

where $\alpha_i = \phi_i + \beta_i a_0$. Using the Stone index makes the LA/AIDS in equation (2.14) a much simpler estimation problem. This can be done by calculating the Stone index directly and then treating the total expenditure, $\log\left(\frac{Y}{P^*}\right)$ in equation (2.14), as a predetermined variable before estimating equation (2.14) using OLS regressions (Deaton and Muellbauer, 1980). Deaton and Muellbauer (1980) suggest that by using the Stone index, the model becomes linear in the parameters, and the estimation can be done equation by equation by OLS, which is equivalent to maximum likelihood estimation for the system as a whole. Moreover, treating the Stone index as exogenous can reduce the collinearity problem (Chen, 1998). Deaton and Muellbauer estimated an eight-commodity demand system using aggregate annual UK data from 1954 to 1974 and concluded that there was no significant difference between the parameters obtained from the AIDS and the LA/AIDS. Alston, Foster, and Green (1994) conducted Monte Carlo experiments to investigate whether the Stone index is a good approximation. They concluded that "demand analysts can consequently have a certain degree of confidence when estimating the LA/AIDS". Therefore, the LA/AIDS model has been a popular tool for researchers in the analysis of both macro- and micro-demand system (Deaton and

Muellbauer, 1980; Blanciforti and Green, 1983; Chalfant, 1987; Cotterill, 1994; Asche, Bjorndal, and Salvanes, 1998; Henneberry, Piewthongngam, and Qiang, 1998; Vickner and Davies, 1999).

Chalfant (1987) and Green and Alston (1990) suggested elasticity formulas that can be used with the parameters obtained from the LA/AIDS and the Stone index. The formula of the partial own- and cross price elasticities of demand (η_{ij}) suggested by Chalfant (1987), and Green and Alston (1990) is:

$$\eta_{ij} = \frac{d \ln Q_i}{d \ln P_j} = -\delta_{ij}^k + \frac{\gamma_{ij}}{w_i} - \frac{\beta_i}{w_i} w_j \,, \qquad (2.15)$$

where δ_{ij}^k is the Kronecker delta ($\delta_{ij}^k = 1$ for $i = j$; $\delta_{ij}^k = 0$ for $i \neq j$), w_i and w_j are average market shares of brand *i* and *j*, and γ_{ij} and β_i are parameters estimated from the LA/AIDS. Several studies used this elasticity formula in their work (Cotterill, 1994; Richards, Kagan, and Gao, 1997; Asche, Bjorndal, and salvanes, 1998; Henneberry, Piewthongngam, and Qiang, 1999, Vickner and Davies, 1999). Alston, Foster, and Green (1994) conducted Monte Carlo experiments to investigate the appropriate formula to compute elasticities. They found that equation (2.15) is quite accurate relative to alternatives because it is a reasonably good approximation to the true AIDS.

The studies of Cotterill (1994), Vickner and Davies (1999), and Cotterill, Putsis, and Dhar (2000) are related to the first part of this dissertation. They estimated the demand system using the LA/AIDS simultaneously with the supply system using price-reaction functions. In addition, they estimated the LA/AIDS using the Stone index.

It has been found that the Stone index can cause econometric problems. Pashardes (1993) examined the effect of using the Stone index by comparing analytical expressions and empirical findings obtained from the AIDS model with and without the Stone index approximation. Pashardes found that the Stone index causes the parameter estimates to be biased. Buse (1994) investigated the LA/AIDS using the Stone index and concluded that the seemingly unrelated estimator of the LA/AIDS was inconsistent.

Another problem of using the Stone index is the units-of-measurement problem. According to the study of Cotterill, Putsis, and Dhar (2000), one assumption made in their price-reaction functions was that, in order to observe a manufacturer's wholesale price (w_i), the retailer's price (P_i) is used as a proxy and assumed to be proportional to its wholesale price. In other words, the wholesale price (w_i) is scaled up by a constant number (m) to represent a proportional mark up rule of the retailer's price decision, that is, $P_i = mw_i$. Moschini (1995) suggested caution in using the Stone price index in the LA/AIDS due to the units-of-measurement problem, such as when prices are scaled up. Due to Moschini's work, the LA/AIDS model with scaled prices could be shown to be different from the original AIDS model, and thus the estimated parameters would generally be biased. Moschini concluded that for the purpose of estimating the LA/AIDS model, "the standard Stone index should be avoided" (Moschini, 1995). Moschini suggested that a price index should meet a desirable property in which an appropriate price index should be invariant to the units of measurement of prices. This desirable property is called the commensurability property (Diewert, 1987; and Moschini, 1995). However, Moschini suggested that the units-of-measurement problem may be solved by using a price index that satisfies this property. Moschini recommended several price indices that may be used to maintain the specification of the AIDS linear and that satisfy the commensurability property. The indices recommended by Moschini were the Tornqvist index, the corrected Stone index, and the Laspeyres price index.

The Tornqvist index is written as:

$$\log(P_t^T) = \tfrac{1}{2}\sum_{i=1}^{n}(w_{it} + w_i^0)\log\left(\frac{p_{it}}{p_i^0}\right). \tag{2.16}$$

The corrected Stone index is written as:

$$\log P_t = \sum_{i=1}^{n} w_{it}\log\left(\frac{p_{it}}{p_i^0}\right). \tag{2.17}$$

The Laspeyres price index is written as:

$$\log(P_t^L) = \sum_{i=1}^{n} w_i^0 \log(p_{it}), \tag{2.18}$$

where the zero superscript denotes base period values, such as mean values.

In a Monte Carlo experiment, Moschini found that the LA/AIDS could approximate the AIDS well when the recommended price indices were used.

The Price-Reaction Functions

The LA/AIDS gives only own- and cross-price elasticities. In order to measure a firm's market power using the indices mentioned above, the conjectural price responses or the price-response elasticities are needed. The price-response elasticities can be obtained from the estimation of price-reaction functions. A firm's price reaction function is derived from the first order condition of the maximizing profit function of the firm, assuming that the market is characterized as Bertrand competition with differentiated products and that price is the strategic choice variable. Liang (1989) estimated demand functions and price-reaction functions simultaneously to measure the degree of market power in the ready-to-eat breakfast cereal industry. The demand and supply functions in Liang's work are linear. Cotterill (1994) studied the degree of market power in the carbonated-soft drink industry. He extended Liang's linear price-reaction functions to the double-log specification, that is

$$\log p_i = \mu_{i0} + \sum_{i \neq j, j=1}^{n} \phi_{ij} \log p_j + \lambda C_i + \nu_i, \tag{2.19}$$

where

p_i and p_j = the prices of brand *i* and *j*,

C_i = the vector of shift variables of brand *i*, and

ϕ_{ij} = the price-elasticity parameters to be estimated, for *i, j* = 1, 2, …, *n*.

Previous Empirical Findings

The empirical findings of Cotterill (1994), and Vickner and Davies (1999) are closely related to the first part of this study. Cotterill (1994) applied Baker and Breshnahan's (1985) demand approach and Liang's price-reaction functions to his work. He analyzed the degree of market power in the carbonated soft drink industry using quarterly time-series scanner data from 1988 to 1990. To investigate the demand-side of the market, he employed the LA/AIDS model in order to obtain the partial own and cross price elasticities of demand for each brand. On the supply-side of the market, Cotterill used the first-order conditions derived from an oligopolist's profit-maximizing function, assuming that the market is characterized by Bertrand competition, to estimate the price-response elasticities or the conjectural price response. He used error-components and three-stage least squares estimation methods to estimate both the LA/AIDS and price-reaction functions simultaneously. Cotterill used the *RI*, *OI*, and *CQ* to measure a brand's degree of market power using the estimated partial own-price, cross-price and price-response elasticities. Cotterill found that indices of Coke, Pepsi, Seven-Up and private labels behaved as expected. As the *RI* and *OI* are close to one, the estimated brand is interpreted to have a high degree of market power. The *CQ* measures the fraction of market power of the observed demand due to tacit collusion. Coke, for example, was estimated to have the *RI* equal to .71 indicating a high level of unilateral market power. Its *OI* was estimated to be equal to .84 showing a substantial amount of unilateral and coordinated market power, whereas its *CQ* was estimated to be equal to 14.7 percent meaning that 14.7 percent of Coke's market power is due to tacit collusion.

Following Cotterill's approach, Vickner and Davies (1999) estimated market power and pricing conduct in the domestic spaghetti sauce industry, a product-differentiated oligopoly. Vickner and Davies employed the simultaneous equations of the LA/AIDS model and the price-reaction functions to estimate the partial own- price and cross-price elasticities, and the price-response elasticities. The estimates led to inferences that the own-price elasticities were statistically significant and negative, and that demand for each brand was elastic. Their explanation for the elastic demands was that because the spaghetti sauce product was a durable good, consumers could stockpile the products when they were on sale. On the supply side, the results supported Bertrand competition in that the estimated price-response elasticities were generally upward sloping. Following Cotterill's study, Vickner and Davies measured the degree of market power by using the *RI*, *OI*, and *CQ*. They found some evidence of market power in the spaghetti sauce industry even though the extent was not as high as in the carbonated soft drink industry estimated by Cotterill. They also found that brands within a specific product category had high degree of tacit collusion. They pointed out in their study that one firm in the industry was capable of maintaining its market power without tacit collusion due to an advantage on its niche in the market.

The degree of market power is one of the crucial issues in industrial organization. Cotterill's and Vickner and Davies' work is one of several ways in which industrial organization economists have studied the degree of market power. Other studies of the degree of market power, which used different approaches from this dissertation, include those of Appelbaum (1982), Schroeter (1988), Liang (1989) and Nevo (2001).

One alternative is to estimate the mark-up, the difference between price and marginal cost as a proportion of price, and is called the Lerner index. To analyze the Lerner index, conjectural elasticity and price elasticity of demand have to be estimated because the Lerner index is positively related to the conjectural elasticity and inversely related to the elasticity of market demand. Appelbaum (1982) investigated four U.S. manufacturing industries: textiles, rubber, electrical machinery, and tobacco. Schroeter (1988) studied the beef packing industry. A disadvantage of the Lerner index is the assumption of homogeneous products. Therefore, the degree of market power among brands in an industry was not estimated. The estimated Lerner index for each industry represented the degree of market power of that industry as a whole.

Liang (1989) estimated the degree of market power in a product-differentiated oligopoly, the ready-to-eat breakfast cereal industry on the national level. Specifically, he examined price competition between pairs of ready-to-eat breakfast cereal products. The two brand demand functions and the two price-reaction functions were estimated simultaneously for each of the observed supermarkets using a nonlinear three stage least squares procedure. Price reaction elasticities were obtained from the estimated price-reaction functions, and the price conjectural variations were obtained from the estimated own- and cross-price elasticities of demand. Liang's findings suggested that prices in the ready-to-eat breakfast industry were highly non-competitive and the degree of pricing interdependence varied across the brand pairs. The hypothesis of collusive pricing could not be rejected if a brand had close substitutes. Conversely, a manufacturer was able to set price independently if its brand was found to be sufficiently differentiated from close substitutes. The major advantage of his approach was that it showed the difference between market power ascribed to demand elasticities and market power ascribed to collusive pricing conduct. A disadvantage of his study was that it estimated price competition between pairs of products. In fact, strategic price interaction among all brands in the industry should be taken into account in the analysis.

Nevo (2001) examined the nearly collusive-pricing behavior and intense non-price competition in the ready-to-eat cereal industry by the estimation of price-cost margins. Nevo used discrete choice models to estimate demand elasticities, which were used to compute price-cost margins. Nevo concluded that observed high degrees of price-cost margins were due to product differentiation. In addition, prices in the industry were consistent with non-collusive pricing behavior.

Chapter Three

Data and Econometric Methodology

An objective of this dissertation is to estimate the degree of market power in the canned tuna industry in a local market. The data used in this dissertation are scanner data for the canned tuna industry collected from supermarkets in Knoxville, Tennessee. The model specification in this dissertation is different from previous studies (Cotterill, 1994; and Vickner and Davies, 1999). It uses the corrected Stone index in the estimation of LA/AIDS. Estimates using the traditional Stone index are also generated and compared to those associated with the corrected Stone index. This chapter starts with a discussion of the data and then outlines the empirical approach.

Data

The Use of Scanner Data

This study uses weekly scanner data from the canned tuna industry to estimate firms' market power. Scanning systems were introduced during the mid-1970s, and they have become the industry standard. Scanner data are primary data that represent a readily current and timely source of product-specific information including price, quantity, expenditure, and marketing activities such as coupons, retail advertising and shelf-space location for a large number of products available on a daily basis (Nayga, 1992). Eastwood (1993) mentioned that the retailer's motivation for the introduction of scanners was primarily for time saving and more precision in the checkout process. Eastwood

(1993) argued that scanner data have desirable properties. First, the level of detail in scanner data allows researchers to examine relationships among close substitutes and complements. Second, the time period is more consistent than traditional data sets. Third, the data can be obtained much more quickly than traditional data sets. Finally, they can be used to test various merchandising hypotheses under market conditions. Thus, the scanner data are a non-traditional data source, which can be used in empirical research to investigate a product in terms of both demand and market structure.

There are some weaknesses associated with the use of scanner data. Capps and Nayga (1991) indicated that limitations of scanner data include the sheer volume of information, the lack of consumer socio-demographics, and the provision of information only for food eaten at home. Eastwood (1993) addressed two problems in constructing scanner data sets for marketing and demand research. The first problem involved classifying scanner data for variable-weight items into consumer demand categories. The second problem focused on the creation of an advertising data set that can be combined with scanner data to evaluate market strategies. Scanner data have been actively used in food marketing and economic research since the 1980s (Nayga, 1992). A list of research in food demand using scanner data is presented in Table 3.1.

There are some market research companies that process scanner data into a usable format for researchers, such as Information Resources, Incorporated (IRI), A.C. Nielsen, and Efficient Market Services. The scanner data set used in this study is from IRI. The company collects weekly scanner data from more than 32,000 supermarket, drug and mass merchandiser outlets across the United States. Included in their data are sales, share, prices, and marketing variables for thousands of consumer brands sold.

Table 3.1 Listing of Research on Food Demand using Scanner Data

Author (Published year)	Research Time Period	Objective
Jensen and Schroeter (1992)	1985 – 1987	Investigation of the TV advertising's effects on beef demand
Capps (1989)	1986 – 1987	Estimation of retail demand relationships for meat products
Capps and Nayga (1990)	1986 – 1988	Evaluation of effect of length of time on measured demand elasticities
Capps and Lambregts (1991)	1987 – 1988	Estimation of demand functions for finfish and shellfish products
Eastwood, Brooker, and Gray (1994)	1988 – 1991	Evaluation of effects of supermarket advertising on product sales
Cotterill (1994)	1988 – 1990	Estimation of market power in carbonated soft drink industry
Haller (1994)	1988 – 1992	Estimation of price strategies in the catsup and cottage cheese industries
Wessells and Wallstrom (1999)	1988 – 1992	Testing the stability of canned salmon demand
Jones (1997)	1990 – 1991	Estimation of demand functions for breakfast cereal and carbohydrate products, and comparison on different income and location
Seo and Capps (1997)	1991 – 1992	Estimation of regional variability of price and expenditure elasticities on spaghetti sauce products
Cotterill, Putsis, and Dhar (2000)	1991 – 1992	Analysis the competitive interaction between private labels and national brands on six individual categories
Park and Senauer (1996)	1994	Estimation of household brand-size choice models for spaghetti products
Vickner and Davies (1999)	1994 – 1996	Estimation of market power and pricing conduct in spaghetti sauce industry
Vickner and Davies (2000)	1994 – 1996	Estimation of strategic price-response on canned fruit industry
Teisl, Roe, and Hicks (2000)	1988 – 1995	Investigation of the dolphin-safe-label effect on the tuna demand

Several studies have used scanner data relying on the IRI data (Haller, 1994; Cotterill, 1994; Seo and Capps, 1997; Wessells and Wallstrom, 1999; and Vickner and Davies, 1999). Cotterill (1994) suggested that scanner data were the most appropriate source of data to analyze both demand and strategic interactions.

Previous studies (Cotterill, 1994; and Vickner and Davies, 1999) estimated the degree of market power in oligopoly markets at the national level. These studies have not captured market structure, pricing conduct, and demand at the local level. Nayga (1992) suggested that scanner data from supermarkets in a particular location present a controlled situation. The study of local market behavior would represent actual strategic interaction among firms precisely based on the actual local demand. This dissertation has chosen Knoxville, Tennessee as a representative local market.

The scanner data in this study were collected weekly by IRI for 157 weeks over the period of January 4, 1998 to December 31, 2000 from 134 supermarkets in Knoxville, Tennessee. Supermarkets from which IRI collected the data in this city have annual sales of $2 million and above. There is no information from IRI about individual supermarkets. Therefore, each variable in the data set represents time series data aggregated from the 134 supermarkets, including Kroger, Food City and BI-LO. Neither media advertising nor information about shoppers were available. This study assumes that there was no change in the marketing of canned tuna by the store chains or the processors or in the socioeconomic characteristics of shoppers over the three year period. For each of the 157 weeks, the sales and price information for canned tuna are standardized to account for differences in size. Package sizes and prices are converted into standardized 16-oz. equivalent units. The data set from IRI indicates that there are

120 barcodes for canned tuna. Aggregating sales by brand indicator, there are three leading brands that have total market shares that average over 80 percent of the market. These three leading brands are *Starkist*, *Chicken of the Sea*, and *Bumble Bee*. Besides the three leaders, there are other canned tuna brands, each of which possesses a small fraction of market share. Therefore, all other canned tuna brands are aggregated into a brand labeled *Allother*. All variables are listed in Table 3.2, and their descriptions follow.

Endogenous Variables

There are two endogenous variables; the market share of brand *i*, w_{it}, and the average price per unit of brand *i*, p_i. Brand *i*'s market share represents the percent of the brand's total dollar sales of all brands in the market. According to the LA/AIDS, this

Table 3.2 Variables Used in the Estimation

Variable	Definition
w_i	Dollar share of brand *i*
p_{it}	Average price per 16-oz equivalent of brand *i* paid by the consumers at time *t*
Y_t	Total expenditure spent on all brands of canned tuna in the market area at time *t*
$FEATURE_{it}$	Percent of incremental volume sales for brand *i* sold in the presence of feature advertising only and no display at time *t*
$DISPLAY_{it}$	Percent of incremental volume sales for brand *i* sold in the presence of display only and no feature advertising at time *t*
$FEATURE\&DISPLAY_{it}$	Percent of incremental volume sales for brand *i* sold in the presence of feature and display at time *t*
$REDUCTION_{it}$	Percent of incremental volume sales for brand *i* sold in the presence of price reduction only during at time *t*

i = Starkist, Bumble Bee, Chicken of the Sea, and *Allother* variable is endogenous because it is determined by prices and total expenditure. Prices of all package sizes and types of canned tuna (such as tuna in water and tuna in oil) of brand *i* are aggregated and weighted into the average price per 16-oz. equivalent of brand *i*.

Explanatory variables

The total expenditure (Y_t) is the total dollar expenditure spent on all brands of canned tuna in the market area during time *t*. According to the LA/AIDS, the total expenditure in equilibrium is equal to a cost function (budget) of a utility-maximizing consumer. The utility function associated with the LA/AIDS is weakly separable. Weak separability allows for partitioning individual items into groups, which is consistent with two-stage budgeting. That is, given weak separability, the consumers allocate income to various groups and given the allocation to subgroups, choices are made among the elements of the subgroups. With respect to canned tuna, the consumer is envisioned as allocating expenditure to canned tuna and given the allocation, decides how much of the various brands to buy. Therefore, the total expenditure on the canned tuna in the market is predetermined and set as exogenous variable. The other exogenous variables are promotion-activity variables including the percent of incremental volume sales with the presence of feature only (*FEATURE*), the percent of incremental volume sales with the presence of display only (*DISPLAY*), the percent of incremental volume sales with feature and display (*FEATURE&DISPLAY*), and the percent of incremental volume sales with the presence of price reduction (*PREDUCTION*).

IRI collected and calculated each brand's total volume sales, which are comprised of base sales and incremental sales. Base sales are calculated by IRI using a proprietary model, which factors out promotional effects primarily by projecting volumes during non-promotional periods versus promotional periods. Incremental sales are those sales which actually represent the effects of promotional activities. Each brand's promotional activities are assumed exogenous for the relatively short time period considered here. However, incremental sales from promotional activities of a brand are also included in the brand market share, which is an endogenous variable. As a result, promotion-activity variables may have an endogeneity problem. One remedy is to create dummy variables that indicate whether promotional activities are conducted or not. However, this is not possible here because some canned tuna brands such as *Starkist* and *Allother* have promotional activities in at least one supermarket every week of the sample period. Another alternative is to drop the variables that cause the problem. But this can cause another problem of omitted variable bias and model identification for the simultaneous equations and, therefore, should not be used here. Several studies have used promotion-activity variables collected by IRI as exogenous variables in their estimations (Cotterill, 1994; Haller, 1994; Vickner and Davies, 1999, and Cotterill *et al*, 2000). Because of the limitations of the available data and practically empirical difficulties, the promotion-activity variables are treated as exogenous variables.

A Feature is a retailer print advertisement that is used to promote a specific product or group of products. Field auditors (supermarkets) record features appearing in newspapers, circulars and flyers. The percent of incremental volume sales for brand *i* sold in the presence of feature advertising only and no display during time t is calculated as:

$FEATURE_{it}$, = (Incremental volume sales of brand *i* in stores with feature only / Total volume sales of brand *i*) x 100.

A display is a temporary secondary location for a product in a store (i.e., in addition to its normal stocking location). Displays are recorded by field auditors (supermarkets) who identify each display by its location and the UPCs that are in the display. Field auditors monitor and record display activity in sample stores on a weekly basis. The general rule is that a secondary stocking unit must have at least 18 units of product in order to be considered a display. The percent of incremental volume sales for brand *i* sold in the presence of display only and no feature advertising during time *t* is calculated as:

$DISPLAY_{it}$ = (Incremental volume sales of brand *i* in stores with display only / Total volume sales of brand *i*) x 100.

The percent of incremental volume sales for brand *i* sold in the presence of feature and display during time *t* is recorded by field auditors when features appearing in newspapers, circulars, flyers, and display activity are both conducted in the same week. This variable is calculated as:

$FEATURE\&DISPLAY_{it}$, = (Incremental volume sales of brand *i* in stores with feature and display / Total volume sales of brand *i*) x 100.

Price reduction is a retailer promotional activity that is used to promote a specific product or group of products. Prices of the products promoted are reduced below their regular prices and that it is monitored and recorded by field auditors on a weekly basis. The percent of incremental volume sales for brand i sold in the presence of price reduction only during time t is calculated as:

$REDUCTION_{it}$ = (Incremental volume sales of brand i in stores with price reduction only / Total volume sales of brand i) x 100.

Econometric Methodology

This section starts with the estimation of the simultaneous equations that contain the LA/AIDS and price reaction functions. Next, partial own- and cross-price elasticities are calculated using the estimated parameters from the LA/AIDS. Then, followship demand elasticities and observed price elasticities of demand for each brand are calculated. Finally, the *RI*, *OI*, and *CQ* are estimated to measure the degree of market power of the canned tuna industry in Knoxville.

Estimating Simultaneous Equations

To estimate the LA/AIDS model, the Stone index and the Corrected Stone index time series must be generated. This study first uses the corrected Stone index in the process of estimating the degree of market power. Then, the traditional Stone index is used later with the same process for comparison. The corrected Stone index suggested by Moschini (1995) is specified as:

$$\log P_t^* = \sum_{i=1}^{n} w_{it} \log\left(\frac{p_{it}}{p_i^0}\right), \tag{3.1}$$

and the traditional Stone index is specified as:

$$\log P_t = \sum_{i=1}^{n} w_{it} \log p_{it}\ , \tag{3.2}$$

where

p_{it} = the price of the *i*th brand at time *t*,

p_i^0 = the average price of the *i*th brand over the time period,

w_{it} = the share of the *i*th brand at time *t*, and

subscript i = *Starkist*, *Chicken of the Sea*, *Bumble Bee,* and *Allother*.

Next, the expenditure (Y_t) on all brands at time *t* weighted by the corrected Stone index at time *t* is calculated. In the estimation of the LA/AIDS, the weighted expenditure (Y_t^*) is treated as a predetermined variable. Blanciforti and Green (1983) noted the use of the price index considerably simplifies the estimation procedure but not without some cost. If the Stone index is not treated as exogenous, the dependent variable, w_{it}, will appear on both sides of the LA/AIDS and the resulting estimators will not necessarily possess desirable sampling properties. However, if the Stone index was not treated exogenously, the possible bias would be small because the term w_{it} was weighted by $\log(\frac{p_{it}}{p_i^o})$, which is a fraction. Following Deaton and Muellbauer (1980), all previous studies that used the Stone index in their LA/AIDS estimations ignored this econometric problem and treated the Stone index exogenously in obtaining parameter estimates. In addition, each price variable is normalized by its mean. Asche and Wessells (1997) noted that if prices are normalized to one, the use of the elasticity formula suggested by Chalfant (1987), and Green and Alston (1990) is valid in both the AIDS and LA/AIDS.

In equation (2.12), demand shift variables (D_{it}), such as promotional effects, can be incorporated into the model (Heien and Pompelli, 1988; and Asche, Bjorndal, and Salvanes, 1998) by allowing the intercept (α_i) to be a function of them, that is $\alpha_i^* = \alpha_i + \delta_{ki} D_{it}$.

By including demand shift variables and normalizing all prices, the LA/AIDS can be written as:

$$w_{it} = \alpha_i^* + \sum_{j=1}^{4} \gamma_{ij} \log \frac{p_{jt}}{p_j^0} + \beta_i \log\left(\frac{Y_t}{P_t^*}\right) + \omega_{it}, \tag{3.3}$$

and the price reaction function is specified as:

$$\log p_{it} = \mu_{i0} + \sum_{i \neq j, j=1}^{4} \phi_{ij} \log \frac{p_{jt}}{p_j^0} + \lambda_{mi} C_{it} + \nu_{it}, \tag{3.4}$$

where

$\alpha_i, \delta_{ki}, \gamma_{ij}, \phi_{ij}, \lambda_{mi},$, and β_i = parameters to be estimated,

p_{jt} = the price of brand j at time t,

C_{it} = a vector of supply shift variables of brand i at time t,

p_j^0 = the mean value of the j^{th} price series,

Y_t = the total expenditure on canned tuna in the market weighted by the corrected stone index at time t, and

i and j = *Starkist, Chicken of the Sea, Bumble Bee,* and *Allother*.

There are three sets of restrictions implied by economic theory imposed on the parameters of the system (in the LA/AIDS):

Adding up: $\sum_{i=1}^{4} \alpha_i^* = 1$, $\sum_{i=1}^{4} \gamma_{ij} = 0$, and $\sum_{i=1}^{4} \beta_i = 0$ (3.5)

Homogeneity: $\sum_j \gamma_{ij} = 0 \quad \forall \; j$ (3.6)

Symmetry: $\gamma_{ij} = \gamma_{ji} \quad \forall \; i \neq j$. (3.7)

The adding up condition of the LA/AIDS model is satisfied by the data since $\sum w_i = 1$ (Asche, Bjorndal, and Salvanes, 1997). Therefore, for four demand equations only three demand equations of the leading firms (*Starkist, Chicken of the Sea,* and *Bumble Bee*) are estimated, and then the parameter estimates for the fourth equation (*Allother*) are generated from them. Thus, in this study the simultaneous equations include three demand equations and four price reaction functions with seven endogenous variables.

The LA/AIDS and the price reaction functions are estimated simultaneously with brand market shares (w_i) and prices (p_i) as endogenous variables. The demand shift vector D_i captures brand *i* retail promotion activities. These activities include the percent of incremental volume sales with the presence of display only (*DISPLAY*), the percent of incremental volume with feature only (*FEATURE*), the percent of incremental volume sales with the presence of both feature and display (*FEATURE&DISPLAY*), and the percent of incremental volume with the presence of price reduction (*REDUCTION*). That is $D_i \equiv \{FEATURE_i, DISPLAY_i, FEATURE\&DISPLAY_i, REDUCTION_i\}$.

Several assumptions are made in order to estimate the price reaction functions. No change in the cost structure of both manufacturers and retailers is assumed to have occurred over the three year period. No change in production technology among canned tuna processors is assumed to have taken place. In addition, changes in the prices of inputs for the production of canned tuna affect firms similarly. Finally, no principal-agent problem between the food producers and the retailers is assumed to exist, implying that the manufacture-retail price margin was constant for each firm. Consequently, all variations in price were attributed to brands' pricing strategies. The shift variables (C_i) in the price reaction functions include total expenditure (Y), brand *i's* market share (w_i) and its promotional activities (D_i).

The simultaneous system contains three demand equations and four price reaction equations. The simultaneous system is identified by both order and rank conditions. Since the demand and price equations are assumed to take place simultaneously based on the Bertrand competition assumption, correlations of the disturbances across equations could be present; therefore the three-stage least squares method (3SLS) is selected to estimate the simultaneous equations.

With respect to 3SLS, the first stage starts with the regression of each endogenous variable on the right hand side of each equation on all predetermined variables in the model and obtains the estimated values of the endogenous variables. For the second stage, the structural model is estimated using ordinary least squares method and the endogenous variables on the right hand side of the model are replaced by the estimated values obtained from the first stage. The third stage takes into account the correlation of the disturbances across equations. A variance-covariance matrix is obtained by using the two-stage least squares residuals from the second stage. Then, the Aitken generalized least squares (GLS) estimation is applied to the structural equations using the variance-covariance matrix.

The simultaneous equations are able to be estimated using 3SLS based on the assumption that the structural error terms are homoskedastic and not autocorrelated. However, when the observations are collected over time, the error terms are likely to be autocorrelated. Blanciforti, Green and King (1986) found evidence of serial correlation in the AIDS models of aggregate food groups. Yen and Chern (1992) estimated a flexible demand system with correction for autocorrelation and compared results with those obtained from the Translog and AIDS models. They concluded that correcting serial correlation in demand system modeling was important. Heteroskedasticity is normally encountered when dealing with micro economic data "but not when dealing with aggregates observed over time unless the time period covered is very long" (Kmenta, 1986). Because the scanner data used in this study were collected in the same geographical area and for the same supermarkets over the three-year period, heteroskedasticity might be encountered. Residuals that violate the assumption of no autocorrelation and homoskedasticity are called *nonspherical*. Estimation of models with nonsperical residuals yields estimated variances that are inconsistent. As a result, the standard tests of significance and confidence intervals are not valid. Therefore, it is important to test the autocorrelation and heteroskedasticity problems for each equation in the system.

The Breusch-Pagan test is employed to test heteroskedasticity, and the sample correlogram and Ljung-Box statistics (L-B statistics) are used to test for autocorrelation.

Specifically, the L-B statistics tests whether autocorrelation exists, and the sample correlogram approximately indicates the order of autocorrelation.

If heteroskedasticity and/or autocorrelation are found, the simultaneous equations are estimated using an improved estimation method called *weighted three-stage least squares* (W3SLS). The W3SLS method can remedy the autocorrelation and heteroskedasticity problems. The method is asymptotically efficient and gives consistent estimates of both estimated parameters and their variance-covariance matrix (Kmenta, 1986). The procedures of the W3SLS are as follows.

Step 1: Each regression equation is estimated using the two-stage least squares method in order to obtain the regression residuals. All explanatory variables are used as instrumental variables.

Step 2: The regression residuals are tested for autocorrelation using sample correlogram and Ljung-Box statistics (L-B statistics) and for heteroskedasticity using the Breusch-Pagan test.

Step 3: If autocorrelation and/or heteroskedasticity are found, each equation is weighted by a transformation matrix. Each equation's transformation matrix is constructed based on the Aitken generalized least squares (GLS) method. In other words, if a variance-covariance matrix (Ω) of an equation is not equal to $\sigma^2 I$, that is E($e_i e_j$) = σ_{ij}, i and j = 1, 2,…, n, a transformation matrix (P) can be constructed such that $P'P = \Omega^{-1}$ or $P\Omega P' = I$.

Step 4: Each regression equation is pre-multiplied (i.e., weighted) by its transformation matrix in order to get a transformed equation.

Step 5: All transformed equations are then estimated simultaneously using 3SLS.

Calculating Demand Elasticities

The parameter estimates obtained from the LA/AIDS are used to calculate partial own- and cross-price elasticities, whereas price-response elasticities are obtained directly from the parameter estimates from the price-reaction functions. The formula of the partial own- and cross-price elasticities of demand (η_{ij}) suggested by Chalfant (1987), and Green and Alston (1990) is:

$$\eta_{ij} = \frac{d\ln Q_i}{d\ln P_j} = -\delta_{ij}^k + \frac{\gamma_{ij}}{w_i} - \frac{\beta_i}{w_i} w_j , \tag{3.11}$$

where δ_{ij}^k is the Kronecker delta ($\delta_{ij}^k = 1$ for $i = j$; $\delta_{ij}^k = 0$ for $i \neq j$), w_i and w_j are average market shares of brand i and j, and γ_{ij} and β_i are parameters estimated from the LA/AIDS (i, j = *Starkist, Chicken of the Sea, Bumble Bee,* and *Allother*). Alston, Foster, and Green (1994) conducted Monte Carlo experiments to investigate the appropriate formula to compute elasticities from the LA/AIDS. They found that the formula in equation (3.11) is quite accurate relative to alternatives since it is a reasonably good approximation to the true AIDS.

Following Chalfant (1987) and Cotterill (1994), standard errors of the partial own- and cross-price elasticities, $SE(\eta_{ij})$, are computed based on the standard errors of the estimated parameters and the average budget shares that are treated as nonstochastic. The standard errors are computed as:

$$SE(\eta_{ij}) = \frac{SE(\gamma_{ij})}{w_i} - \frac{SE(\beta_i)}{w_i} w_j , \tag{3.12}$$

where $SE(\gamma_{ij})$ and $SE(\beta_i)$ are standard errors of the estimated parameters from the LA/AIDS, and w_i and w_j are average market shares of brand *i* and *j*.

Calculating Followship Demand Elasticities and Observed Demand Elasticities

After obtaining partial own- and cross-price elasticities, the fully collusive elasticity and the observed demand elasticity of each brand are calculated. The fully collusive elasticity of brand *i*, η_i^F, can be obtained by adding up its partial own-price elasticity (η_{ii}) and all cross-price elasticities ($\eta_{ji, j\neq i}$) assuming that all price-response elasticities are equal to one (full collusion), $\eta_i^F = \eta_{ii} + \sum_{i\neq j}^{n} \eta_{ij}$. The observed demand elasticity of brand *i*, η_i^0, is defined as $\eta_i^0 = \eta_{ii} + \sum_{i\neq j}^{n} \eta_{ij}\varepsilon_{ji}$, where ε_{ji} represents rivals' price-response elasticity or the conjectural price-response of firm *j* with respect to firm *i*'s price *(i≠j)*. The non-followship demand elasticity of brand *i* is its partial own-price elasticity (η_{ii}).

Calculating Measures of the Degree of Market Power

The degree of market power of brands in the canned tuna industry is measured by the *Rothschild* and *O indices*, and the *Chamberlin Quotient*. Fully collusive elasticities and observable demand elasticities are used to calculate these measures.

The *Rothschild Index (RI)* is specified as: $$RI_i = \frac{\eta_i^F}{\eta_{ii}} \qquad (3.13)$$

where η_i^F represents the fully collusive elasticity of brand *i,* and η_{ii} represents the non-followship demand elasticity of brand *i* or its own-price elasticity.

The *O Index* is specified *(OI)* as: $$OI_i = \frac{\eta_i^F}{\eta_i^0}, \qquad (3.14)$$

where η_i^0 represents the observable elasticity of demand for brand *i*.

The *Chamberlin Quotient (CQ)* is specified as: $$CQ_i = 1 - \frac{RI_i}{OI_i}. \qquad (3.15)$$

Re-estimating Using the Stone Index

In order to see the empirical magnitude of the corrected version of the Stone index, this study re-estimates the simultaneous equations using the Stone index in the LA/AIDS, and then calculates the *RI*, *OI*, and *CQ* to compare the differences.

Chapter Four

Estimation and Results

This chapter starts with a statistical description of the scanner data for the canned tuna industry used in the estimation. Building on the empirical model developed in the previous chapters, it presents the estimation of the simultaneous equations with the corrected Stone index in the LA/AIDS and remedies autocorrelation. Weighted three-stage least squares are used for the final estimates of the model. The estimated parameters obtained from the LA/AIDS are used to calculate partial own- and cross-price elasticities. Next, the *RI*, *OI*, and *CQ* are calculated to measure the degree of market power of each brand using the partial own-price and cross-price elasticities, and price-response elasticities obtained from the estimation. The estimated price-reaction functions are analyzed for strategic price responses among brands in the industry. Finally, the process of estimating the degree of market power is repeated with the use of the traditional Stone index in the LA/AIDS, and the results are compared.

Data Description

Weekly scanner data for canned tuna industry were collected by IRI for 157 weeks over the period of January 4, 1998 to December 31, 2000 from 134 supermarkets in Knoxville, Tennessee. There are four brands, *Starkist*, *Chicken of the Sea*, *Bumble Bee*, and *Allother*. Descriptive statistics for all variables and brands are presented in Table 4.1.

Table 4.1 Descriptive Statistics for Canned Tuna: 1998 – 2000 (157 weekly observations)

Variable	Mean	Standard Deviation	Min	Max
Share (w_i):				
Starkist	0.666	0.059	0.415	0.823
Chicken of the Sea	0.146	0.036	0.071	0.316
Bumble Bee	0.048	0.015	0.023	0.144
Allother	0.139	0.048	0.061	0.343
Price (P_i):				
Starkist	0.915	0.081	0.633	1.126
Chicken of the Sea	0.987	0.146	0.487	1.248
Bumble Bee	0.963	0.167	0.428	1.288
Allother	0.686	0.060	0.450	0.798
% Volume in Feature Ads only (*$Feature_i$*):				
Starkist	8.533	10.712	0.067	48.046
Chicken of the Sea	3.526	10.258	0.037	73.875
Bumble Bee	5.012	13.183	4.018	64.099
Allother	8.723	17.107	0.864	70.108
% Volume on Display only (*$Display_i$*):				
Starkist	15.242	9.980	0.499	50.009
Chicken of the Sea	2.350	4.826	0.727	32.264
Bumble Bee	6.137	9.432	0.100	49.273
Allother	14.959	14.082	0.666	63.366
% Volume on Feature and Display (*Feature and $Display_i$*):				
Starkist	10.291	12.127	1.347	62.497
Chicken of the Sea	3.614	10.222	2.089	54.276
Bumble Bee	3.922	14.191	7.107	80.696
Allother	7.413	15.193	0.880	65.874
% volume on Price Reduction (*$Reduction_i$*):				
Starkist	7.635	5.807	0.809	33.629
Chicken of the Sea	13.464	11.606	0.185	54.854
Bumble Bee	17.347	15.808	0.012	63.536
Allother	11.154	12.401	0.053	49.954
Total Expenditure (Y_t)	28845.11	4372.3	15973.69	50266.57

Starkist, *Chicken of the Sea*, and *Bumble Bee* are the three leading brands, which had average combined market shares of about 86 percent of the canned tuna sales in Knoxville area. *Starkist*'s average market share was 66.6%, the highest in the industry. For *Chicken of the sea*, *Bumble Bee* and *Allother*, their market average shares were 14.6%, 4.8%, and 13.9% respectively. *Chicken of the Sea* had the highest average price per unit ($0.99/unit), whereas the average price of *Allother* was the lowest ($0.69/unit).

Table 4.2 compares the canned tuna market shares between Knoxville market and the U.S. market in 2000. The three leading brands' market share (CR3) at the national level was 82 percent lower than those in Knoxville market (85%). *Starkist* seemed to be a popular brand in Knoxville market since its market share was 64 percent compared to only 40% at the national level; however it was the leader in both market levels. Interestingly, *Bumble Bee* had higher market share (22%) than *Chicken of the Sea* (20%) at the national level, whereas its market share in Knoxville (5%) was lower than those of *Chicken of the Sea* (16%). The market share of *Allother* in Knoxville (15%) was very close to those for the whole country (16%).

Table 4.2 Comparing Market Shares between Knoxville and U.S. markets in 2000

Brand	Knoxville Market	U.S. Market*
Starkist	64	40
Chicken of the Sea	16	20
Bumble Bee	5	22
Allother	15	16

*Source: US Business Reporter, available at http://www.activemedia-guide.com/mrksh_profile.htm

With respect to promotional activities, *Starkist* was the most successful brand in the presence of feature advertising and display. It had the highest average percentage of total volume sales in the presence of display (15.24%), and display and feature together (10.29%). *Starkist* was the only brand that offered price reductions every week during the observation period in at least one supermarket. However, its average percentage of total sales in the price reduction category was only 7.64%. *Bumble Bee* had the highest average percentage of total sales (17.35%) when it reduced its price. However, to analyze how successful a brand was when it had a price reduction, the brand's price elasticity of demand should be taken into account. Finally, the average total expenditure spent on all canned tuna brands within a week in Knoxville market was $28845.11.

Estimation Results

Simultaneous Equations

The simultaneous equations in this dissertation contain the LA/AIDS and price-reaction functions. The LA/AIDS is specified as:

$$w_{it} = \alpha_i + \delta_{ki} D_{it} + \sum_{j=1}^{4} \gamma_{ij} \log \frac{p_{jt}}{p_j^0} + \beta_i \log\left(\frac{Y_t}{P_t^c}\right) + \omega_{it}\,, \qquad (4.1)$$

and the price reaction function is:

$$\log p_{it} = \mu_{i0} + \sum_{i \neq j, j=1}^{4} \phi_{ij} \log \frac{p_{jt}}{p_j^0} + \lambda_{mi} C_{it} + \nu_{it}\,, \qquad (4.2)$$

where

w_{it} = the market share of good *i* at time *t*,

p_{it} and p_{jt} = the price of brand *i* and *j* at time *t*,

p_j^0 = the mean value of the j^{th} price series,

$\log P_t^c = \sum_{i=1}^{n} w_{it} \log\left(\frac{p_{it}}{p_i^0}\right)$ = the corrected Stone index,

Y_t = the total expenditure on the canned tuna in the market weighted by the corrected stone index at time *t*,

D_{it} = a vector of demand shift variables of brand *I* at time *t* ≡ {*FEATURE_i*, *DISPLAY_i*, *FEATURE&DISPLAY_i*, *REDUCTION_i*},

C_{it} = a vector of supply shift variables of brand *i* at time *t* ≡ { w_i , Y , and D_i},

$\alpha_i, \delta_{ki}, \gamma_{ij}, \phi_{ij}, \lambda_{ki,}$, and β_i = parameters to be estimated, and

i = *Starkist, Chicken of the Sea, Bumble Bee,* and *Allother*.

The LA/AIDS contains three equations (the demand equations of *Starkist, Chicken of the Sea,* and *Bumble Bee* with the demand equation of *Allother* being dropped) and four price reaction equations.

Testing for Heteroskedasticity

The Breusch-Pagan test is employed to detect heteroskedasticity for each equation. The test is based on the assumption that the variance (σ^2) of each disturbance term, ε_i, is a linear function of some explanatory variable. Therefore, it is not constant over time depending on the variation of the related explanatory variable. The explanatory variables in this dissertation include total expenditure, and promotional activities, which are collected from 134 supermarkets. Although there are differences in size of supermarkets, the data are aggregated and collected from the same supermarkets during the time period. The data are treated like a representative supermarket. Thus, the regression variances seem to be constant over the time period. Nonetheless, tests for heteroskedasticity are conducted to be sure that there is no such problem involved in the estimation. According to the Breusch-Pagan test, explanatory variables that are suspected to cause heteroskedasticity are selected. In this study, the total expenditure variable (Y_t), which represents consumers' total budgets spent on all canned tuna brands, is selected. The test is done as follows.

1. Regress each equation using 2SLS in order to obtain its regression residuals (e_t).
2. Calculate a maximum likelihood estimator of σ^2, $\hat{\sigma}^2$, where $\hat{\sigma}^2 = \Sigma e_t^2 / n$.
3. Construct a variable f_t such that $f_t = e_t^2 / \hat{\sigma}^2$.
4. Estimate equation $f_t = b_1 + b_2 Y_t$ to obtain the sum square of regression (SSR).
5. The null hypothesis of homoskedasticity is tested based on the Chi-square statistic. That is Q^{BP} = SSR/2 ~ χ_1^2 (degree of freedom = 1).

The test results are shown in Table 4.3. The null hypotheses of homoskedasticity for all equations in the system cannot be rejected at the 1% level of significance. The test results imply that heteroskedasticity is not likely to occur in the estimation.

Table 4.3 Heteroskedasticity Test Results

Equation	Q^{BP}	[Prob (χ_1^2 > **6.64**) = 0.01]
Demand $_{\text{Starkist}}$	1.68	
Demand $_{\text{Chicken of the Sea}}$	3.60	
Demand $_{\text{Bumble Bee}}$	0.01	
Price reaction $_{\text{Starkist}}$	6.25	
Price reaction $_{\text{Chicken of the Sea}}$	3.02	
Price reaction $_{\text{Bumble Bee}}$	2.89	
Price reaction $_{\text{Allother}}$	3.95	

Testing for Autocorrelation

Since the observations comprise a time series, the residuals of each equation in the model are potentially autocorrelated. The process of testing for autocorrelation is started by regressing each equation using the 2SLS method in order to obtain regression residuals. Each equation's residuals are tested for autocorrelation by using a sample correlogram and Ljung-Box statistic (L-B statistic). The L-B statistic tests whether autocorrelation exists and the sample correlogram approximately indicates the order of autocorrelation. The results from the L-B test indicate that all seven equations have autocorrelation. According to sample correlograms, six out of seven equations are suspected to be first-order autoregressive (AR1), whereas one equation (*Chicken of the Sea's* price reaction function) is likely to be second-order auto regressive (AR2).

The regression residuals of each equation are then regressed on their lagged values. The residuals of *Chicken of the Sea's* price reaction function are regressed on their two period lags, whereas those of the other equations are regressed on their one period lag. Mathematically, $e_{it} = \sum_{s=1}^{2} \rho_{is} e_{it-s} + u_{it}$, where e_{it} is the residual of equation i at time t, $t = 2, \ldots, n$, s = number of time lagged, $s = 1$ and 2, and u_{it} are interdependent and identically distributed with zero mean and variance σ_u^2. The estimated coefficients (ρ_{is}) are presented in Table 4.4. All the estimated coefficients are statistically significant. Therefore, it can be concluded that all equations are AR1 except for the price reaction function of *Chicken of the Sea* that is AR2. The estimated autoregressive coefficients shown in Table 4.4 are used to form a transformation matrix for use in W3SLS.

Estimation of W3SLS

According to Table 4.4, each equation in the simultaneous model is found to have autocorrelation. This study uses W3SLS to correct the problem. The estimated

Table 4.4 Estimated Autoregressive Coefficients

Equation	ρ_1	ρ_2
Demand $_S$	0.263^{***}	-
Demand $_C$	0.507^{***}	-
Demand $_B$	0.306^{***}	-
Price reaction $_S$	0.282^{***}	-
Price reaction $_C$	0.419^{***}	0.1936^{**}
Price reaction $_B$	0.282^{***}	-
Price reaction $_A$	0.308^{***}	-

*** Significance at the 1% level, *** significance at the 5% level.
Subscript: S = *Starkist*, C = *Chicken of the Sea*, B = *Bumble Bee*, and A = *Allother.*

coefficients (ρ_{is}) in Table 4.4 are used to form a transformation matrix for each regression equation. After pre-multiplying each equation by its transformation matrix, the transformed equations are estimated simultaneously using 3SLS. The estimated parameters of the LA/AIDS are reported in Table 4.5. Significant estimated parameters in Table 4.5 are used to calculate own- and cross-price elasticities of demand for each brand.

According to the adding up condition, only three demand equations of *Starkist*, *Chicken of the Sea*, and *Bumble Bee* are estimated, and then the parameter estimates for the *Allother* demand equation (γ_{AA} and β_A) are generated from them. The effect of each brand's price on its share is negative and statistically significant. Prices of *Chicken of the Sea* and *Allother* have positive effects on *Starkist*'s market share. Prices of *Starkist* and *Allother* also have positive effects on *Chicken of the Sea*'s market share, but only the price of *Allother* has positive effects on *Bumble Bee*'s market share. The positive effect of a brand's price on another brand's market share is reasonable. When a brand increases its price and the other brands do not follow, consumers may switch to buy a substitute, resulting in an increase in the substitute brand's market share. *Bumble Bee*'s price in both *Chicken of the Sea*'s and *Starkist*'s equations is not statistically significant implying that a change in *Bumble Bee*'s price has no effect on those two brands' shares. Total expenditure weighted by the corrected Stone index is statistically significant and has negative effects on *Starkist'* and *Bumble Bee*'s market shares. With respect to *Starkist*'s promotional activities, DISPLAY, FEATURE, and DISPLAY&FEATURE are statistically significant and have positive effects on *Starkist*'s share, even though the magnitudes are

Table 4.5 Estimation of the LA/AIDS model

	$Share_{Starkist}$	$Share_{Chicken\ of\ the\ Sea}$	$Share_{Bumble\ Bee}$
Intercept	1.526	0.015	0.284
	$(0.307)^{**}$	(0.163)	$(0.064)^{**}$
$P_{Starkist}$	-0.503	0.196	0.010
	$(0.072)^{**}$	$(0.025)^{**}$	(0.013)
$P_{Chicken\ of\ the\ Sea}$	0.196	-0.261	-0.001
	$(0.025)^{**}$	$(0.024)^{**}$	(0.007)
$P_{Bumble\ Bee}$	0.010	-0.001	-0.035
	(0.013)	(0.007)	$(0.014)^{**}$
$P_{Allother}$	0.297	0.065	0.026
	$(0.064)^{**}$	$(0.030)^{*}$	$(0.014)^{*}$
Y/P*	-0.088	0.015	-0.023
	$(0.030)^{**}$	(0.016)	$(0.006)^{**}$
DISPLAY	0.002	-0.002	0.000
	$(0.000)^{**}$	$(0.000)^{**}$	(0.000)
FEATURE	0.001	0.000	0.000
	$(0.000)^{**}$	(0.000)	(0.000)
DISPLAY& FEATURE	0.001	-0.001	0.001
	$(0.000)^{*}$	$(0.000)^{**}$	$(0.000)^{**}$
PRICE REDUCTION	-0.001	-0.001	-0.000
	(0.000)	$(0.000)^{**}$	(0.000)

Adjusted R^2 = 0.6684, Standard errors in parentheses,

* = Significance at 5% level, and * * = significance at 1% level

According to the adding up condition, γ_{AA} = -0.388 and β_A = 0.096.

not high. DISPLAY&FEATURE and PRICE REDUCTION have significant negative effects on *Chicken of the Sea*'s market share.

The homogeneity and symmetry restrictions are imposed in the estimation:

Homogeneity: $\sum_j \gamma_{ij} = 0 \quad \forall \; j$, and (4.3)

Symmetry: $\gamma_{ij} = \gamma_{ji} \quad \forall \; i \neq j$. (4.4)

The restrictions of homogeneity and symmetry are tested using an *F* test. This test is based on the null hypothesis that the sample information is consistent with the imposed restrictions. In other words, if the null hypothesis cannot be rejected, it implies that the error structure of the respective unrestricted model do not differ from that of the restricted model. If the null hypothesis is rejected, it implies that the imposed restrictions are not supported by sample information. The computed *F* statistic of the imposed restrictions are presented in Table 4.6

The computed *F* in Table 4.6 shows that the null hypotheses of the homogeneity restrictions on *Starkist* and *Chicken of the Sea* demand equations cannot be rejected at 1%. The null hypothesis of symmetry restriction between *Starkist* and *Bumble Bee* demand equations cannot be rejected at 1% level of significance. For the other two symmetry restrictions, the null hypotheses are rejected. The results imply that the data used in this dissertation seem to be consistent with the homogeneity restrictions; however the data support only one symmetry restriction. Several studies of food demand have also rejected the symmetry restriction. A list of studies in food demand that imposed homogeneity and symmetry restrictions in the LA/AIDS is shown in Table 4.7. Deaton and Muellbauer (1980) estimated the LA/AIDS on eight nondurable goods using annual

Table 4.6 Test Results for Imposed Restrictions

Property	Restriction	Computed F statistic
Homogeneity	$\sum_{j=1}^{4}\gamma_{Sj}$	0.02
Homogeneity	$\sum_{j=1}^{4}\gamma_{Cj}$	0.01
Homogeneity	$\sum_{j=1}^{4}\gamma_{Bj}$	22.39^{**}
Symmetry	$\gamma_{SC} = \gamma_{CS}$	27.11^{**}
Symmetry	$\gamma_{SB} = \gamma_{BS}$	4.90
Symmetry	$\gamma_{BC} = \gamma_{CB}$	26.94^{**}

**Significance at the 1% level, subscript: S = *Starkist*, C = *Chicken of the Sea*, B = *Bumble Bee*, and A = *Allother*. *j* = *Starkist*, *Chicken of the Sea*, *Bumble Bee*, and *Allother*.

Table 4.7 Listing of Research on Food Product That Imposed Restrictions on the LA/AIDS

Auther (Published year)	Homogeneity	Symmetry
Deaton and Muellbauer (1980)	Rejected	Rejected
Blanciforti and Green (1982)	Rejected	-
Blanciforti and Green (1983)	Rejected	-
Chalfant (1987)	Not reported	Not reported
Green, Carman, and McManus (1991)	Rejected	Rejected
Cotterill (1994)	Not reported	Not reported
Richards, Kagan, and Gao (1997)	Not rejected	Not rejected
Vickner and Davies (1999)	Rejected[a]	Rejected[a]
Cotterill, Putsis, and Dhar (2000)	Not reported	Not reported

- means the restriction was not imposed. [a] partially rejected in the EC3SLS

British data and found that symmetry restriction was rejected. Green, Carman, and McManus (1991) found that homogeneity and symmetry conditions were strongly rejected in the estimation of demand on dried fruits. Satyanarayana *et al* (1999) found rejection of symmetry in the estimation of demand for malt using the LA/AIDS. Vickner and Davies (1999) estimated the degree of market power in the spaghetti sauce industry and found that in their error-components 3SLS (EC3SLS) estimation six of the ten symmetry restrictions on the LA/AIDS were rejected. However, they used the parameter estimates from model with the imposed restrictions. Since the results from testing the restrictions are consistent with those found in previous studies, the estimated results from the LA/AIDS in this study are reported with the restrictions imposed.

Partial Own- and Cross- Price Elasticities

Before calculating the *RI*, *OI*, and *CQ*, partial own- and cross-price elasticities, and price-response elasticities are needed. The parameter estimates obtained from the LA/AIDS shown in Table 4.5 are used to calculate partial own- and cross-price elasticities of demand for each brand, and price-response elasticities are obtained directly from the parameter estimates from the price-reaction functions of the simultaneous model.

The partial own- and cross-price elasticities of demand are shown in Table 4.8. The partial own- and cross-price elasticities of demand for brand *Allother* in Table 4.8 are calculated using parameter estimates derived from the adding up restrictions. Therefore, the tests of significance for these elasticities are not shown in the Table. The own-price elasticity of demand for each brand is found along the diagonal of the Table. All brands'

Table 4.8 Partial Own- and Cross-Price Elasticities

	% Δ Price			
	Starkist	*Chicken of the Sea*	*Bumble Bee*	*Allother*
Starkist	-1.67***	0.31***	0.02	0.46***
Chicken of the Sea	1.27***	-2.80***	-0.01	0.43**
Bumble Bee	0.51**	0.06	-1.71***	0.61**
Allother	1.68	0.37	0.15	-3.89

Elasticities are read from left to right;
*** Significance at the 1% level, ** significance at the 5% level.

own-price elasticities are negative and elastic. The partial own-price elasticity of demand for *Starkist* is -1.67, meaning that a 1% increase in the price of *Starkist* causes a 1.67% decrease in its quantity sold. *Allother*'s partial own-price elasticity is the most elastic. A brand's elastic demand implies that if the brand raises its price and no other brands follow, its revenue will decline. However, the brand is able to maintain or increase its revenue and market share when it increases price, even though it faces an elastic demand, if it has enough market power that can influence its rivals to follow.

The elastic demand of the canned tuna industry can be explained two ways. First, although the products are differentiated by brand, they are substitutes. Consumers can switch and buy an alternative brand if they consider an increase in price of a brand too high. Second, canned tuna is a durable good. Consumers can stockpile their favorite brands when prices are low. In this case each brand is an inter-temporal substitute for itself (Tirole, 1988).

The cross-price elasticities are found off the diagonal of Table 4.8. Six out of nine cross-price elasticities are statistically significant (not including those derived from the adding up restriction). The significant cross-price elasticities of demand for all other brands are positive, meaning that they are substitutes. The cross-price elasticity of demand for *Chicken of the Sea* with respect to *Starkist*'s price is 1.27, which is elastic and statistically significant, meaning that a 1% increase in the price of *Starkist* leads to a 1.27% increase in *Chicken of the Sea*' s quantity sold. *Chicken of the Sea* and *Allother* seem to be good substitutes for *Starkist* because their cross-price elasticities with respect to *Starkist*'s price are high and elastic. On the other hand, the cross-price significant elasticities of demand for *Starkist* with respect to the *Chicken of the Sea* and *Allother*'s prices are inelastic. This suggests that consumers consider *Starkist* less substituTable than those brands in the market. The cross-price elasticity of demand for *Bumble Bee* with respect to *Starkist*'s price is 0.51 and statistically significant implying that *Bumble Bee* can be a substitute for *Starkist*, even though it is not as good as *Chicken of the Sea* and *Allother*.

Price-response Strategies

To calculate the *RI*, *OI*, and *CQ*, price-response elasticities of firms in the canned tuna market are required. The parameter estimates from price reaction functions are shown in Table 4.9. Due to the double-log specification, the estimated ϕ_{ij} parameter in equation (3.4) represents the price-response elasticities of firm i with respect to firm j's price. According to the existence of a Bertrand-Nash equilibrium, firms' prices are supposed to have a positive relationship. However, price-response elasticities in this

Table 4.9 Estimated Price Reaction Functions

	P_{SK}	P_{CS}	P_{BB}	P_{AO}
Intercept	2.652	0.138	2.975	-0.680
	(0.548)***	(0.881)	(1.043)***	(0.763)
P_{SK}	-	0.667	-0.363	0.190
		(0.174)***	(0.198)*	(0.205)
P_{CS}	0.319	-	-0.261	-0.066
	(0.046)***		(0.078)***	(0.057)
P_{BB}	0.010	-0.002	-	0.032
	(0.025)	(0.041)		(0.038)
P_{AO}	0.382	0.252	0.040	-
	(0.102)***	(0.136)*	(0.160)	
Y/P	-0.163	0.048	-0.253	0.069
	(0.051)***	(0.084)	(0.097)***	(0.074)
SHARE	-1.531	-3.622	-6.219	0.450
	(0.167)***	(0.348)***	(-3.60)**	(0.356)
DISPLAY	0.002	-0.007	-0.001	-0.002
	(0.001)***	(0.001)***	(0.001)	(0.000)***
FEATURE	0.002	-0.000	-0.004	-0.002
	(0.001)**	(0.001)	(0.001)***	(0.000)***
DISPLAY&	0.001	-0.004	-0.004	-0.004
FEATURE	(0.001)	(0.001)***	(0.001)***	(0.001)***
REDUCTION	-0.001	-0.006	-0.003	-0.002
	(0.001)	(0.001)***	(0.001)***	(0.000)***

Parameter estimates for each equation are read by column.
Adjusted R^2 = 0.654, standard errors in parentheses,
* = Significance at 10% level, * * = significance at 5% level, *** = significance at 1% level
Subscript: SK = *Starkist*, CS = *Chicken of the Sea*, BB = *Bumble Bee*, and AO = *Allother*.

study are found to have both positive and negative relationships. An interpretation is that positive price-response elasticities imply tacit collusion among brands, and negative price-response elasticities imply price war. The price-response elasticity of *Starkist* with respect to *Chicken of the Sea*'s price is 0.32 and statistically significant, meaning that if *Chicken of the Sea* raises price by 1%, *Starkist* will raise its price by 0.32%. The price-response elasticity of *Chicken of the Sea* with respect to *Starkist*'s price is 0.67 and statistically significant. This asymmetry leads to an inference that a change in price of *Starkist* has high influence on the price of *Chicken of the Sea*, but a change in price of *Chicken of the Sea* has less influence on the price of *Starkist.* The price-response elasticities of *Bumble Bee* with respect to prices of both *Starkist* and *Chicken of the Sea* are negative and statistically significant. This implies that instead of tacitly colluding in price with its rivals, *Bumble Bee* conducts a price war. For example, when *Starkist* increases price by 1%, *Bumble Bee* decreases its price by 0.36%. According to the cross-price elasticity of demand for *Bumble Bee* with respect to *Starkist*'s price (0.51) in Table 4.8, *Bumble Bee* seems to be a substitute for *Starkist*, but the degree of substitution is not as close as for *Chicken of the Sea* and *Allother* (1.27 and 1.68, respectively). Therefore, *Bumble Bee*'s strategy is to cut its price, in order to gain more sales in the market. The price-response elasticities of *Chicken of the Sea* and *Starkist* with respect to *Bumble Bee*'s price are not statistically significant. It implies that the two leading brands do not respond to Bumble Bee's price strategy. On the other hand, they positively respond to the price set by *Allother* because their price-response elasticities with respect to *Allother*'s price are statistically significant. Since the results lead to the inference that none of the canned tuna brands in the market follow *Bumble Bee*'s price strategy, while

Bumble Bee can maintain its market share with a high price in the market, its market power is not derived from coordinated market power or tacit collusion. These results can be confirmed by considering the measures of market power in the next section. Twelve of the 16 promotion-activity variables are statistically significant. Ten of the twelve promotion activities of *Chicken of the Sea, Bumble Bee* and *Allother* have negative effects on their respective prices and they are statistically significant. This implies that when a promotional campaign is conducted, a brand tends to decrease its price. These results are reasonable and easily explained. Since one of the objectives for conducting promotional activities is to increase a brand's revenue, and because those brand's own-price elasticities are elastic (Table 4.8), a decrease in price results in an increase in their revenues. Interestingly, *Starkist*'s DISPLAY and FEATURE variables have positive impacts on its price (Table 4.9) and share (Table 4.5) and they are statistically significant. This leads to an inference that *Starkist* may have market power because it is able to increase both price and market share when it uses such promotional activities. This inference is supported by considering the measures of market power in the next section.

Measures of the Degree of Market Power

The degree of market power of brands in the canned tuna industry is measured by the *RI, OI, and CQ.* Estimated non-followship, fully collusive, and observed demand elasticities are used to calculate these measures. Brand *i*'s partial own-price elasticity (η_{ii}) represents the brand's non-followship demand elasticity. The fully collusive elasticities and the observed demand elasticities of brand *i* are calculated using the partial own- and cross-price elasticities, and price-response elasticities shown in Table 4.8 and 4.9.

The fully collusive elasticity of brand i , η_i^F , is defined as $\eta_i^F = \eta_{ii} + \sum_{i \neq j}^{n} \eta_{ij}$. The observed demand elasticity of brand *i*, η_i^0 , is defined as $\eta_i^0 = \eta_{ii} + \sum_{i \neq j}^{n} \eta_{ij} \varepsilon_{ji}$, where η_{ij} is the cross-price elasticity of demand for firm *i* with respect to a change in price of firm *j*, and ε_{ji} represents rivals' price-response elasticity or the conjectural price-response of firm *j* with respect to a change in price of firm *i* *(i≠j)*.[2]

The estimated elasticities and measures of market power are shown in Table 4.10. The first row in Table 4.10 contains each brand's non-followship demand elasticity (from Table 4.8). The non-followship demand elasticity can be interpreted as a unilateral measure of market power because it measures the responsiveness in quantity purchased a brand experiences when it raises price but no rivals follow. *Starkist*, the largest brand in the market, has the highest unilateral market power since its non-followship demand elasticity is the lowest elasticity in absolute value. It means that when *Starkist* raises its price, consumers change their quantities demanded less than they do when the other brands change their prices. The aggregated small brands, *Allother*, seem to have the least ability to maintain their unilateral market power because they have the highest elastic demand in absolute value. This is reasonable since each brand in *Allother* possesses small market share and has no power in the market. If it raised its price, its quantity

[2] This dissertation uses all significant *and* insignificant parameter estimates to calculate the fully collusive and observed demand elasticities. This is consistent with the way other research in this area has been done.

Table 4.10 Elasticities and Measures of Market Power

	Starkist	*Chicken of the Sea*	*Bumble Bee*	*Allother*
Non-followship Elasticity (η_{ii})	-1.667	-2.802	-1.706	-3.887
Observed Elasticity (η_i^0)	-1.377	-2.423	-1.682	-3.148
Fully Collusive Elasticity (η_i^F)	-0.869	-1.106	-0.532	-1.690
$RI_i = \dfrac{\eta_i^F}{\eta_{ii}}$	0.522	0.395	0.312	0.435
$OI_i = \dfrac{\eta_i^F}{\eta_i^0}$	0.631	0.457	0.316	0.537
$CQ_i = 1 - \dfrac{RI_i}{OI_i}$	0.174	0.137	0.014	0.190

demanded would considerably decrease.

The observed demand elasticities are shown in the second row of Table 4.10. These elasticities take into account the effect of coordinated market power, which is the sum of the product between cross price elasticities and price-response elasticities among brands in the market. Each brand's observed demand elasticity is less elastic than its non-followship demand elasticity in absolute value because of the positive effect from coordinated market power.

Each brand's fully collusive elasticity shown in the third row of Table 4.10 is calculated based on the assumption that the brand's price-response elasticities equal one, meaning that if the brand increases its price, all rivals will raise their prices at the same rate. The fully collusive elasticities are useful in measuring the degree of market power of each brand. The higher the market power a brand has, the farther is the brand's observed elasticity from its non-followship elasticity, and the closer to its fully collusive elasticity.

The degree of market power of a brand in this study means that the brand is able to set a high price without losing its market share. (According to Table 4.1, the average price per unit (16 oz. equivalent) for the three leading canned tuna brands was 0.95 cents, whereas the average price per unit for *Allother* was only 0.68 cents.) A brand's market power is derived from two sources. First, it arises from the brand characteristics such as image and product differentiation including promotional activities such as display and features. These factors construct the brand's unilateral market power, and the *RI* represents such power. Second, the brand's market power is derived from tacit collusion. Because firms in oligopoly are interdependent, they take into account their rivals' strategies and try to respond in order to maximize their profits. A brand's market power due to tacit collusion means that the brand can influence its rivals to follow its strategy (e.g., a price increase). The *OI* and *CQ* typically represent this kind of market power.

The *RI* shown in the fourth row of Table 4.10 measures a unilateral degree of market power of each brand. It compares a brand's fully collusive elasticity with non-followship elasticity. The value of *RI* ranges from zero to one. The closer the RI is to one, the greater the degree of market power. The results show that *Starkist* has the highest unilateral degree of market power with the *RI* equal to 0.522. The *RI* of *Chicken of the Sea*, *Bumble Bee* and *Allother* is 0.395, 0.312 and 0.435, respectively.

Since the observed elasticity takes into account both unilateral market power and coordinated market power, it is crucial to investigate the results of the *OI*. The fifth row in Table 4.10 presents the values of this index. Not surprisingly, *Starkist*, the biggest brand in the market, has the highest degree of market power with its *OI* equal to 0.631. According to the results, the degree of market power seems to be consistent with market shares. A firm with high market share has a high degree of market power. The *OI* of *Allother*, *Chicken of the Sea*, and *Bumble Bee*'s *OI* are 0.537, 0.457, and 0.316, respectively. The *RI* and *OI* of *Allother* are slightly higher than those of *Chicken of the Sea* and *Bumble Bee*. Note that the *Allother*'s market share (13.90 %) is aggregated from many small competitive firms and the estimated coefficients from the aggregated market-share equation are used to calculate the own-price and cross-price elasticities. Therefore, it is possible that the high value of *RI* and *OI* of *Allother* is affected by the aggregated market share. For this reason, it might not be appropriate to compare *Allother*'s degree of market power with those of the three leading brands.

The last row in Table 4.10 shows the values of the *CQ*. The *CQ* measures the fraction of market power of the observed demand due to tacit collusion. Basically, the *CQ* of brand i is defined as $CQ_i = 1 - \frac{RI_i}{OI_i} = 1 - \frac{\eta_i^0}{\eta_{ii}}$. By simplifying the term on the right hand side, CQ_i becomes $-\frac{\sum_{j \neq i} \eta_{ij} \varepsilon_{ji}}{\eta_{ii}}$. It can be seen that the *CQ* of brand i measures the portion of its coordinated market power ($\sum_{i \neq j} \eta_{ij} \varepsilon_{ji}$) with respect to its non-followship elasticity. The higher coordinated market power due to tacit collusion a brand has, the higher the brand's *CQ*. The results from Table 4.10 show that *Starkist* derives approximately 17.4% of its market power from tacit price collusion. *Chicken of the Sea* obtains about 13.6% of its market power from tacit collusion.[3] Interestingly, although *Bumble Bee* can maintain its market power at third place (among the three leading brands), its market power is derived less from the coordinated market power due to tacit collusion because its *CQ* is only 1.4%. Bumble Bee's *CQ* has confirmed the results of price-response elasticities in Table 4.9 such that none of the canned tuna brands in the market follows *Bumble Bee*'s price strategy. The *CQ* of *Allother* is 19.0% meaning that *Allother* derives about 19% of its market power from tacit collusion. The coordinated market power exists when a firm can influence its rivals to follow its strategy. Because the average price per unit of *Allother* is the lowest in the market, when *Allother* increases its price, the other brands are willing to cooperate by increasing their prices slightly in order to gain more revenue from substitution.

Table 4.11 presents the findings from previous studies comparing with those found in this study. Cotterill (1994) estimated the degree of market power in the domestic carbonated soft drink industry. Vickner and Davies (1999) analyzed market power in the domestic spaghetti sauce industry. Elasticities, *RI*, *OI*, and *CQ* are shown in average values. The carbonated soft drink industry in the Cotterill study has the lowest non-followship and observed elasticities on average compared to those obtained in this study and in the Vickner and Davies study. Brands in the carbonated soft drink industry in the Cotterill study seem to have high unilateral and coordinated market power since the

[3] When only significant parameter estimates are used to calculate the measures of market power, qualitatively, the results are unaltered with the exception of the *CQ*. Chicken of the Sea's *CQ* (0.145) is higher than *Starkist*'s *CQ* (0.125), meaning that *Chicken of the Sea*'s market power derived from tacit collusion is higher than that of *Starkist*.

Table 4.11 Comparing Average Elasticities and Measures of Market Power

	Canned Tuna	Carbonated Soft Drink	Spaghetti Sauce
Non-followship Elasticity (η_{ii})	-2.52	-1.53	-4.97
Observed Elasticity (η_i^0)	-2.16	-1.45	-4.03
Fully Collusive Elasticity (η_i^F)	-1.05	-0.94	-1.43
$RI_i = \dfrac{\eta_i^F}{\eta_{ii}}$	0.42	0.67	0.28
$OI_i = \dfrac{\eta_i^F}{\eta_i^0}$	0.49	0.72	0.34
$CQ_i = 1 - \dfrac{RI_i}{OI_i}$	0.11[a]	0.15[b]	0.32[b]

[a]Average value for the three leading brands in the market
[b]Average value for the two leading brands in the market

industry's *RI* and *OI* on averages are very high (0.67 and 0.72 respectively). The average *RI* and *OI* found in this study are less than those found in the Cotterill study but more than those found in the Vickner and Davies study. The average fully collusive elasticity obtained in this study (-1.05) is close to that found in the Cotterill study (-0.94). The average *CQ*s shown in Table 4.11 are comparable to those obtained from the two leading brands in carbonated soft drink market (Cotterill, 1994) and in the spaghetti sauce market (Vickner and Davies, 1999), and from the three leading brands in this study. The average *CQ* found in the Vickner and Davies study is the highest (0.32). This leads to the inference that market power of the two leading brands in the spaghetti sauce market was derived more from tacit price collusion.

Summary of Results

This part estimates the degrees of market power and price-response strategies of four canned tuna brands: *Starkist*, *Chicken of the Sea*, and *Bumble Bee*, and *Allother*. The LA/AIDS and price reaction functions are estimated simultaneously using W3SLS. The corrected Stone index is used in the LA/AIDS. The results can be summarized as follows.

- According to the test of restrictions imposed in the LA/AIDS, one of the three homogeneity restrictions and two of the three symmetry restrictions are rejected. The estimated results are reported with restrictions imposed.
- There is a significant negative relationship between market share and price in the canned tuna industry.
- The significant partial own-price elasticities of demand for all brands are negative and elastic. *Starkist* has the lowest own-price elasticity in absolute value, and *Allother* has the highest own-price elasticity in absolute value.
- *Chicken of the Sea* and *Allother* are better substitutes for *Starkist* than *Bumble Bee*.
- *Starkist*, *Chicken of the Sea*, and *Allother* are cooperative in their price strategies, whereas *Bumble Bee* conducts price war against *Starkist* and *Chicken of the Sea*.
- *Starkist*, the highest market-share brand, has the highest market power both unilateral and coordinated market power due to the lowest own-price elasticity and highest *RI, OI and CQ*.
- *Starkist* and *Chicken of the Sea* can maintain their market power derived from both unilateral and coordinated market power, whereas *Bumble Bee* can maintain its market power without tacit collusion.

Estimating Results Using the Stone Index

This dissertation uses the corrected Stone index as was suggested by Moschini (1995) to improve the estimation of the LA/AIDS in the simultaneous equations. In order to estimate the effects of differences between the two indices, the LA/AIDS was also estimated along with the price-reaction functions. The results are used to calculate the *RI*, *OI*, and *CQ*. Two changes have been made in the simultaneous equations. First, the total expenditure variable is weighted by the calculated traditional Stone index. Second, all price series estimated in the simultaneous equations are not normalized by their means. The latter is made in order to allow the use of the elasticity formula suggested by Chalfant (1987), and Green and Alston (1990).

The simultaneous equations with the Stone index in the LA/AIDS are estimated using the W3SLS method with correction for autocorrelation. The estimated parameters from the LA/AIDS using the traditional Stone index and corrected Stone index are shown in Table 4.12. The results show that parameter estimates from the two versions of indices have the same sign and the differences are very small. Moreover, the standard errors of each pair of estimated coefficients are very close. For example, the estimated coefficient of *Starkist*'s price on its market share (γ_{SS}) from the use of the corrected Stone Index is equal to -0.503, whereas the estimated coefficient obtained from the use of Stone index is -0.475 and both coefficients have very close standard errors (0.072 and 0.070, respectively).

Table 4.13 displays the partial own- and cross-price elasticities of demand calculated from estimated coefficients, which are obtained from the LA/AIDS using the

Table 4.12 Comparing Estimated Parameters from the LA/AIDS

Parameter	Estimate using Corrected Stone Index	Estimate using Stone Index
γ_{SS}	-0.503^{***} (0.072)	-0.475^{***} (0.070)
γ_{SC}	0.196^{***} (0.025)	0.191^{***} (0.024)
γ_{SB}	0.010 (0.013)	0.010 (0.012)
γ_{SA}	0.297^{***} (0.064)	0.273^{***} (0.062)
γ_{CC}	-0.261^{***} (0.024)	-0.255^{***} (0.023)
γ_{CB}	-0.001 (0.007)	-0.001 (0.007)
γ_{CA}	0.065^{**} (0.030)	0.064^{**} (0.029)
γ_{BB}	-0.035^{**} (0.014)	-0.033^{**} ((0.014)
γ_{BA}	0.026^{*} (0.014)	0.023 (0.014)
γ_{AA}	-0.388 (-)	-0.360 (-)
β_S	-0.088^{***} (0.030)	-0.097^{***} (0.029)
β_C	0.015 (0.016)	0.008 (0.015)
β_B	-0.023^{***} (0.006)	-0.024^{***} (0.006)
β_A	0.096 (-)	0.113 (-)

*** Significance at the 1% level, ** significance at the 5% level, * significance at the 10% level.
Subscript: S = *Starkist*, C = *Chicken of the Sea*, B = *Bumble Bee*, and A = *Allother.*
(-) indicates that the parameters were derived using the adding up restrictions.

corrected Stone index and the traditional Stone index. Table 4.14 shows the price-response elasticities for the two indices. Vuong (1989) proposed some new tests for model selection and non-nested hypotheses based on likelihood-ratio statistics. However, the tests were more suitable for cross-section than time series data. Since this study uses time series data, the tests suggested by Voung are impropriate. However, the results from both versions in Table 4.13 and 4.14 are calculated in ratios for relative comparisons and are shown in Table 4.15 and 4.16. All ratios comparing between the two versions for the partial own- and cross-price elasticities of demand shown in Table 4.15 are very close to 1 with the difference no more than 0.2. The ratios of the two versions for the price-response elasticities are shown in Table 4.16. The ratios calculated from the significant

Table 4.13 Comparing Partial Own- and Cross-Price Elasticities

	Index	*Starkist*	*Chicken of the Sea*	*Bumble Bee*	*Allother*
Starkist	Corrected Stone Index	-1.67***	0.31***	0.02	0.46***
	Stone Index	-1.62***	0.31***	0.02	0.43***
Chicken of the Sea	Corrected Stone Index	1.27***	-2.80***	-0.01	0.43**
	Stone Index	1.27***	-2.75***	-0.01	0.43**
Bumble Bee	Corrected Stone Index	0.51**	0.06	-1.71***	0.61**
	Stone Index	0.54**	0.06	-1.66***	0.55**
Allother	Corrected Stone Index	1.68	0.37	0.15	-3.89
	Stone Index	1.42	0.34	0.13	-3.70

Elasticities are read from left to right;
*** Significance at the 1% level, ** significance at the 5% level

Table 4.14 Comparing Price-response elasticities[1]

	Index	Starkist	Chicken of the Sea	Bumble Bee	Allother
Starkist	Corrected Stone Index	-	0.32^{***}	0.01	0.38^{***}
	Stone Index	-	0.32^{***}	0.02	0.35^{***}
Chicken of the Sea	Corrected Stone Index	0.67^{***}	-	-0.002	0.25^{*}
	Stone Index	0.66^{***}	-	-0.004	0.25^{*}
Bumble Bee	Corrected Stone Index	-0.36^{*}	-0.26^{***}	-	0.04
	Stone Index	-0.35^{*}	-0.27^{***}	-	0.01
Allother	Corrected Stone Index	0.19	-0.07	0.03	-
	Stone Index	0.18	-0.07	0.03	-

[1]Elasticities are read from left to right;
*** Significance at the 1% level, * significance at the 10% level

Table 4.15 Ratios Comparing Partial Own- and Cross-Price Elasticities

	Starkist	*Chicken of the Sea*	*Bumble Bee*	*Allother*
Starkist	0.95^{*}	1.00^{*}	1.00	1.07^{*}
Chicken of the Sea	1.00^{*}	1.02^{*}	1.00	1.00^{*}
Bumble Bee	0.94^{*}	1.00	1.06^{*}	1.20^{*}
Allother	1.18^{*}	1.08	1.15	1.05

Each ratio = result from the use of the corrected Stone index / result from the use of the traditional Stone index.
* Calculated from significant parameter estimates

Table 4.16 Ratios Comparing Price-Response Elasticities

	Starkist	*Chicken of the Sea*	*Bumble Bee*	*Allother*
Starkist	-	1.00*	0.50	1.08*
Chicken of the Sea	1.01*	-	0.50	1.00*
Bumble Bee	1.03*	0.96*	-	4.00
Allother	1.05	1.00	1.00	-

Each ratio = result from the use of the corrected Stone index / result from the use of the traditional Stone index.
* Calculated from significant parameter estimates

coefficients are close to one, indicating a small difference between the two versions.

The *RI*, *OI*, and *CQ* calculated from both versions are shown in Table 4.17. The ratios of the measures are shown in Table 4.18. The scanner data used in this study seem to be consistent with both price indices because their results are similar. For example, the *RI* of *Starkist* estimated from the use of the corrected Stone index is 0.522, whereas those estimated from the use of the Stone index is 0.530 with the ratio of 0.98. *Starkist*'s *OI* estimated from the use of the corrected Stone index is 0.631, whereas those estimated from the use of the corrected Stone index is 0.638 and the ratio is 0.99.

The empirical results in this dissertation lead to a conclusion that there only is a slight difference from the use of the corrected Stone index and the traditional Stone index in the LA/AIDS. However, these results are estimated from time- series scanner data in a single local market covering a short time period. Moreover, the only product analyzed is canned tuna. Therefore, it cannot be generalized that there is no difference between the use of the two versions of the Stone index applied to other products or to other data. Further studies will be needed to clarify this issue.

Table 4.17 Comparing Measures of Market Power

	RI		*OI*		*CQ*	
	Corrected Stone Index	Stone Index	Corrected Stone Index	Stone Index	Corrected Stone Index	Stone Index
Starkist	0.522	0.530	0.631	0.638	0.174	0.169
Chicken of the Sea	0.395	0.385	0.457	0.447	0.137	0.139
Bumble Bee	0.312	0.305	0.316	0.309	0.014	0.012
Allother	0.435	0.489	0.537	0.582	0.190	0.159
Average	0.416	0.426	0.485	0.494	0.128	0.120

Table 4.18 Ratios Comparing Measures of Market Power

	RI	*OI*	*CQ*
Starkist	0.98	0.99	1.03
Chicken of the Sea	1.02	1.02	0.98
Bumble Bee	1.02	1.02	1.16
Allother	0.89	0.92	1.18
Average	0.98	0.98	1.06

Chapter Five

Conclusions

The first part of this dissertation estimated the degree of market power of brands in the \$2.1 billion canned tuna industry. The study investigated brands' behaviors at the local level and Knoxville, Tennessee was chosen as a representative local market. Scanner data of prices, quantity sold, and promotional activities were collected weekly by the IRI for 157 weeks over the period of January 4, 1998 to December 31, 2000 from 134 supermarkets in Knoxville. The canned tuna market was highly concentrated because the highest three-firm market shares over the study period were more than 80 percent of the total sales. There are four canned-tuna brands in this study; *Starkist*, *Chicken of the Sea*, and *Bumble Bee*, and *Allother*.

A brand's market power is derived from two sources. First, it comes from the brand's product differentiation such as advertising, packages, and image. These factors construct the brand's unilateral market power. Second, the brand's market power is derived from tacit collusion (coordinated market power) meaning that the brand can influence its rivals to follow its price strategy. Three measures of market power are employed in this study, the *Rothschild and O Indices*, and the *Chamberlin Quotient*.

In order to calculate a brand's *RI*, *OI*, and *CQ*, the brand's partial own- and cross-price elasticities, and price-response elasticities are needed. Therefore, simultaneous equations including both demand and supply equations are constructed. On the demand side, the LA/AIDS is employed, whereas price-reaction functions are applied on the supply side. The assumption of Bertrand competition with differentiated products is set such that price is the strategic variable and that brands make their decisions at the same time period.

Previous empirical studies (Cotterill, 1994 and Vickner and Davies, 1999) estimated the degree of market power in carbonated soft drink and spaghetti sauce markets using the Stone index in the LA/AIDS. However, some studies found that the use of the Stone index in the LA/AIDS causes estimated parameters to be biased and inconsistent (Pashardes, 1993 and Moschini, 1995). This dissertation uses the corrected Stone index suggested by Moschini (1995) in the LA/AIDS estimation in order to disentangle the problems.

The simultaneous equations with three demand equations and four price reaction functions are estimated using W3SLS with a correction of autocorrelation. The parameter estimates obtained from the LA/AIDS are used to calculate partial own- and cross-price elasticities of demand for each brand, whereas price-response elasticities are obtained directly from the parameter estimates from the price reaction functions. All brands' partial own-price elasticities are consistent with the law of demand, and found elastic. The own-price elasticity of demand for *Starkist* is the least elastic. All canned tuna brands in the market are substitutes since their cross-price elasticities are positive. The estimated price-response elasticities represent strategic-price responses among brands in the market. The results show that *Starkist* and *Chicken of the Sea* are cooperative, whereas *Bumble Bee* conducts price war. When *Starkist* or *Chicken of the Sea* raises their prices, *Bumble Bee* responds by cutting its price.

The degree of market power of a canned tuna brand is measured by the *RI*, *OI*, and *CQ*. A brand with high degree of market power can not only set a high price and maintain its level of market share, but also influence its rivals to follow its price strategy. The *RI* measures the degree of unilateral market power of a brand. The *OI* measures both the degree of unilateral and coordinated market power. The *CQ* measures percentage of market power derived from tacit collusion. The results show that *Starkist*, the biggest brand in the market, can maintain its market power at the highest level with the highest *RI*, *OI* and *CQ*. Both *Starkist'* and *Chicken of the Sea*'s market power is derived from both unilateral and coordinated market power. *Bumble Bee*, the third leading firm in the market, however, can maintain its unilateral market power without tacit collusion.

Finally, this study re-estimates the simultaneous equations with the use of the traditional Stone index in the LA/AIDS. The parameter estimates from the estimation using the Stone index are compared to those of the first version. The results from both versions are found very close giving the interpretation of market power in the same fashion.

PART 2: INVESTIGATING PRICE-RESPONSE STRATEGIES: A DYNAMIC APPROACH

Chapter One

Introduction

In the first part of this study, strategic-price responses among firms were investigated using the price-response elasticities obtained from the estimated price-reaction functions. It was assumed that the canned tuna market was characterized by Bertrand competition with differentiated products such that price was the strategic choice variable, and firms made their decisions during the same time period. The findings indicated that *Bumble Bee* conducted a price war against *Starkist* and *Chicken of the Sea*. However, both *Starkist* and *Chicken of the Sea* did not respond to the *Bumble Bee* price strategy during the same time period. The price-response results obtained from the first part provide evidence only on static price behavior and do not describe any dynamic price behavior. Vickner and Davies (2000) commented that current studies are not sufficient to supply firms in the food industry "with practical, empirical procedures for estimating strategic price response."

A dynamic or supergame theory is able to explain strategic price response (Tirole, 1988). The supergame theory characterizes multiple outcomes. Cartwright *et al.* (1989) examined the advantages and disadvantages of the static and dynamic price-correlation tests and concluded that an application of a dynamic model such as a Granger-causality test is a useful supplement to test price correlations. Multivariate-time series modeling techniques, mainly as applied in macroeconomic analyses, support statistical concepts that improve the study of dynamic price-response criteria.

This part extends the static model of part one to a dynamic approach. The Bertrand-competition assumption is dropped in this part, and a firm is assumed to set its price depending on its own past prices and those of rivals. A vector autoregressive (VAR) model is employed and its applications are used to investigate the price relationships. The Granger-causality test, the impulse response function (IRF) analysis, and the forecast error variance decomposition (FEVD) analysis are applied to the VAR. The Granger-causality test examines not only whether dynamic price-response relationships exist, but also for types of strategic-price relationships such as price leadership or price war. The IRF analysis graphically reveals the direction of the effect of a one-time shock to one of the innovations on future values of the endogenous variables, whereas the FEVD analysis measures proportions of a brand's price variation that can be explained by shocks to its own price and it rivals' prices for each forecast horizon.

The results obtained from this part disentangle a problem encountered from the first part. Although *Starkist* and *Chicken of the Sea* do not respond *Bumble Bee*'s price strategy during the same time period, the Granger-causality results show that both *Starkist* and *Chicken of the Sea* respond negatively to *Bumble Bee*'s past price. This means that both *Starkist* and *Chicken of the Sea* also conduct price war but in a dynamic way. The results from the IRF and FEVD analyses also support the Granger-causality test results for the three-leading canned-tuna brands' relationships.

With respect to previous research in strategic-price relationships, Vickner and Davies (2000) estimated strategic-price response between two leading brands in the canned pineapple industry using the VAR and vector error correction model. The

Granger causality test and the IRF analysis were applied to investigate the price relationships. However, confidence intervals were not included in the Vickner and Davies IRF results. Confidence intervals are useful in determining the statistically significant regions of the IRFs. Failing to include confidence intervals may affect the interpretation of their estimated results. This dissertation improves on the analysis by including the confidence intervals in the IRF analysis. Moreover, this dissertation includes the FEVD analysis, which was not used in Vickner and Davies' work, to investigate firms' price variations affected by their rivals' price innovations.

The remainder of this part is structured as follows. Chapter Two presents the econometric modeling approach and literature review. Chapter Three introduces the econometric methodology used for the estimation. Chapter Four reports the findings, and Chapter Five presents a conclusion. Further information on the data can be found in part one.

Chapter Two

Econometric Modeling Approach and Literature Review

This chapter presents a framework for analysis of the strategic price responses among brands in the canned tuna industry based on a dynamic system of equations. A vector autoregressive (VAR) model is developed to investigate dynamic-strategic price responses. The chapter begins with the empirical model and then provides a review of the relevant literature. The empirical tools are presented first to facilitate an understanding of the applied literature.

Econometric Modeling Approach

Bertrand competition assumes each firm simultaneously sets its profit-maximizing price given the current prices other firms charge. The price-reaction functions in equation (3.4) presented in the first part used only static information on price behaviors among firms. They did not allow for the possibility of dynamic price behavior. In practice, it is not necessary that firms' decisions be based on prices during the same time period. A firm's price strategy can possibly depend on its past prices or its rivals' past prices. To investigate the potential for a dynamic strategic-price response, the Bertrand-competition assumption used in the first part is dropped. A firm is assumed to set its price depending on its own past prices and those of rivals. A dynamic, or supergame, theory is able to explain strategic price response (Tirole, 1988). The supergame theory characterizes multiple outcomes. Multivariate-time series modeling techniques provide statistical concepts for the study of competitive price responses as a dynamic adjustment process.

The modeling approach starts with the formulation of a general vector autoregressive (VAR) model (Sims, 1980). The VAR model is specified as:

$$P_t = \sum_{i=1}^{k} A_i P_{t-i} + u_t , \qquad (2.1)$$

where P_t is a column vector of n variables at time *t,* $P_t = [p_t^1, p_t^2, \ldots, p_t^n]'$, A_i is an (n x n) matrix of parameters with no zero elements, *i* represents a time lag, for *i* = 1, 2,.., *k*, and u_t is a column vector of random errors which are assumed to be contemporaneously correlated but not auto-correlated. Equation (2.1) is different from the structural-equations approach, such as the price-reaction functions used in the first part, because no zero restrictions are imposed on the model, meaning that there is no price variable excluded from any equation of the model, and only endogenous variables are included (Charemza and Deadman, 1997). Therefore, the model in equation (2.1) is called an *unrestricted* VAR model. A firm in the canned tuna market is assumed to set its price depending on its own past prices and those of rivals so the unrestricted VAR model in equation (2.1) can be used to investigate firms' pricing behaviors.

Gujarati (1995) summarized advantages and disadvantages of using VAR models. The advantages of VAR are as follows.

(1) The method is simple to use. Because all variables in VAR are endogenous, one does not have to worry about determining which variables are endogenous and which variables are exogenous.

(2) Estimation is simple. The OLS methods can be used to each equation separately.

(3) In many cases, the forecasts obtained from VAR are better than those obtained from the more complex simultaneous equation models.

Problems with VAR models are noted below.

(1) A VAR model is said to be *a-theoretic*, because it is not based on formal theory, unlike the model of part one.

(2) VAR models are less suited for policy analysis, since policy parameters do not explicitly appear.

(3) If the order of appropriate lag length is high, there will be many parameter estimates. This may limit the degrees of freedom for hypothesis testing.

(4) All variables in the VAR model must be stationary. If the model contains a mix of stationary and non-stationary variables, transforming the data will not be easy.

When dealing with dynamic time series data, the majority of recent empirical studies found that the data are non-stationary because the means, variances, and covariances of the variables are not constant over time (Charemza and Deadman, 1992). Often, differencing a time series can lead to stationarity. For example, suppose that a time series variable for brand 1, p_t^1, is non-stationary and is generated by

$$p_t^1 = p_{t-1}^1 + e_t^1, \tag{2.2}$$

where e_t^1 represents an error term series of identically distributed stationary variables and is $iid \sim (0, \sigma^2 I)$. By differencing p_t^1 by p_{t-1}^1 from both sides of the equation, the series becomes stationary. That is

$$p_t^1 - p_{t-1}^1 = e_t^1, \qquad (2.3)$$

In this case, p_t^1 is said to be integrated of order 1, *I(1)*. A non-stationary series is said to be integrated of order *d*, *I(d),* if it can be transformed to a stationary series by differencing *d* times (Charemza and Deadman, 1992).

Dickey and Fuller (1979) have proposed a simple test for the order of integration of p_t in equation (2.2), called the DF test. The objective of the DF test is to test $\rho = 1$ in the autoregressive equation:

$$p_t^1 = \rho p_{t-1}^1 + e_t^1, \qquad (2.4)$$

The DF test, also known as the unit root test, is a test of the null hypothesis that in equation (2.4) $\rho - 1 = 0$ from the equivalent regression equation to (2.4), that is:

$$\Delta p_t^1 = \delta p_{t-1}^1 + e_t^1, \qquad (2.5)$$

where $\delta = \rho - 1$, and $\Delta p_t^1 = p_t^1 - p_{t-1}^1$.

If the null hypothesis is rejected, and the alternative $\delta < 0$ can be accepted, the series p_t^1 is stationary and $p_t^1 \sim$ *I(0)*. But if the null hypothesis cannot be rejected, it implies that the series p_t might be integrated of order 1 or higher or might not be integrated at all. Therefore, the next step would be to test whether the order of integration is one. If $p_t^1 \sim$ *I(1)*, then $\Delta p_t^1 \sim$ *I(0)*. Hence we can repeat the test replacing p_t^1 with Δp_t^1. In practice, we can continue the process until we found an order of integration for p_t^1 (Charemza and

Deadman, 1992). The DF test can also be used with drift and/or a linear deterministic trend. The DF equation with drift and a linear deterministic trend is specified as:

$$\Delta p_t^1 = \mu + \theta t^d + \delta p_{t-1}^1 + e_t^1, \tag{2.6}$$

where μ is a constant or intercept representing drift and t^d is a linear deterministic trend.

The DF test can be used only if there is no autocorrelation. In the case that the error term e_t^1 is autocorrelated, the DF test can be modified to include enough lagged difference terms so that the error terms are serially independent. The modified DF test is called augmented Dickey-Fuller (ADF) test. The ADF equation with drift can be specified as

$$\Delta p_t^1 = \mu + \delta\ p_{t-1}^1 + \sum_{i=1}^{j} \phi_i \Delta p_{t-i}^1 + v_t^1 \quad , \tag{2.7}$$

where

$\Delta p_{t-i}^1 = p_{t-i}^1 - p_{t-i-1}^1$,

i represents a time lag, for *i* = 1, 2,.., *j*, and

v_t represents an error term series of identically distributed stationary variables and is *iid* ~ $(0, \sigma^2 I)$.

The null hypothesis is still that $\delta = 0$ or $\rho = 1$, that is, there exists a unit root in p_t series. Note that the ADF test can also be used with an inclusion of a linear deterministic trend. The ADF test is extensively used in empirical research (e.g., Charemza and Deadman, 1992; Benson *et al.*., 1995; Masih and Masih, 2000; Vickner and Davies, 2000). However, it is necessary to use the ADF test with care. Charemza and Deadman (1992) commented that the choice of augmentation terms (the lagged difference terms) in the ADF equation was important, but it was neglected in the literature. Too many augmentations may cause a decrease in the power of the test, resulting in not rejecting the null hypothesis too often. On the other hand, too few augmentations may affect the size of the test, resulting in rejecting the null hypothesis of unit root too often.

An alternative test for a unit root is developed by Phillips and Perron (1988), called The Phillips-Perron test or the PP test. The PP test generalizes the DF test to situations that allow for fairly mild assumptions concerning the distribution of the errors. That is, it is possible to test a unit root even though the error terms are not $iid \sim (0, \sigma^2 I)$. The PP test starts with the following regression equations:

$$p_t^1 = \alpha + \rho p_{t-1}^1 + \varepsilon_t^1, \qquad (2.8)$$

where the error term ε_t^1 has zero mean.

There is no requirement that the error term is serially uncorrelated or homogeneous. Unlike the DF assumptions of non-autocorrelation and homogeneity, the PP test allows the disturbances to be weakly dependent and heterogeneously distributed (Enders, 1995). Phillips and Perron (1988) characterized the distribution and derived test statistics that can be used to test the coefficients ρ under the null hypothesis that a unit root in the series exists. Critical values for the PP statistics are the same as those given for the ADF tests.

Choi (1992) conducted Monte Carlo experiments to study how the ADF and PP tests for a unit root perform. They used data generated by aggregating-subinterval data rather than the subinterval data themselves. The study concluded that for the aggregated subinterval data the PP test was more powerful than the ADF test in finite sample.

Specifically, for the aggregate data the PP test has greater power to reject a false null hypothesis of a unit root. However, Choi and Chung (1995) found in their Monte Carlo experiments that for data with high sampling frequency, the PP test appears to be less powerful than the Dickey-Fuller test in finite samples. Enders (1995) notes that, when the true model has negative moving average terms, the ADF test is preferable; however, when the true model has positive moving average terms, the PP test is more appropriate. In practice, it is difficult to choose the most appropriate test because the true data-generating process is never known. Therefore, both types of unit-root tests should be used. If they support each other, one can have confidence in the results. If they do not support each other, one of the two results has to be chosen. Additional analysis of the type of data, the sample time period, or economic theory might be useful in considering the most appropriate test (Enders, 1995).

If the variables in the vector P_t in equation (2.1) are found to be non-stationary, the estimation of the VAR will give spurious results (Gujarati, 1995). There are two ways to solve the problem. One way is to regress the unrestricted VAR on first differences of all variables (if all variables are found to be *I(1)*). This process can eliminate the non-stationarity from the variables; however it is not the best solution (Patterson, 2000) and may involve a misspecification (Enders, 1995). The reason is that valuable information about long-run relationships among variables would be lost from taking the first differences.

Another way arises when the non-stationary variables are co-integrated. It is possible that some linear combination of a set of non-stationary time series is stationary, i.e., the set of series is co-integrated. If two or more variables have long-run equilibrium relationship(s) or share common trend(s) or give a stationary linear combination, they are said to be co-integrated (Masih and Masih, 2000). The presence of a co-integrating relation forms the basis of a restricted VAR or a vector error correction (VEC) model. The VAR model of *k*-th order in equation (2.1) can be re-parameterized in a VEC form as:

$$\Delta P_t = \Pi P_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \Delta P_{t-i} + u_t , \tag{2.9}$$

where

$\Gamma_i = -(A_{i+1} + A_{i+2} + \ldots + A_k)$, $i = 1, \ldots, k-1$,

$\Pi = -(I - A_1 - A_2 - \ldots - A_k)$,

I is an identity matrix of order *n*,

and Δ denotes first differences.

A VEC model is a restricted VAR model designed for use with non-stationary time series that are found to be co-integrated. The VEC model has co-integrating relations constructed into the specification so that it restricts the long-run behavior of the endogenous variables to converge to their co-integrating relationships, while allowing for dynamic adjustment. According to the VEC model in equation (2.8), the co-integration effects are represented by ΠP_{t-1}. The Π matrix $(n \times n)$ can be written as two $(n \times r)$ matrices α and β, $(1 \leq r \leq n - 1$ = the number of co-integrated vectors), such that $\Pi = \alpha\beta'$. The matrix β contains r co-integrating vectors representing long-run relationships among P_{t-1}. The matrix α consists of the parameters measuring the speed of adjustment of each stationary co-integrating combination. The short-run dynamic responses are explained by the elements in Γ_i.

Applications of the VAR Analysis

Sims (1980) and Enders (1995) recommended that the goal of VAR analysis be to investigate the interrelationships among the variables, not the parameter estimates. There are (n + kn^2) terms to be estimated in a VAR model, where n is the number of variables and k is the number of lags. Because the models are over-parameterized, it is difficult and not useful to interpret the relationships between variables from the coefficients in the estimated VAR models. For this reason, researchers in this area have used the VAR applications to study interrelationships among variables instead. Several applications of the VAR analysis are used in this study. First, the VAR model allows the use of the Granger causality test to clarify the relevant information. One may want to know whether an increase of a brand's price results in an increase in other brands' prices when they would not have changed otherwise, or whether the relationship works in the opposite direction. Charemza and Deadman (1992) addressed the definition of Granger causality in a simplified way that "x is a Granger cause of y, if present values of y can be predicted with better accuracy by using past values of x rather than by not doing so, other information being identical." Assume that a firm in the canned tuna market sets its price depending on its own past prices and those of rivals. Granger causality can be applied to test such dynamic price reactions. Specifically, the Granger-causality test gives information about strategic-price responses between a pair of firms. If firm i's pricing strategy depends on firm j's past price, but it is not true in the opposite direction, theoretically, firm j will be defined as a price leader, and firm i will be defined as a price follower. If both firms' price strategies depend on each other's past prices, it can be interpreted that they conduct warfare (Vickner and Davies, 2000).

The VAR model can be used to forecast the signs of the short-run responses of variables by means of an impulse response function (IRF) when there is an exogenous shock on one of the variables. Gujarati (1995) noted that the individual coefficients in the estimated VAR models were often difficult to interpret so the researchers often used IRF analysis instead. In the literature, a unitary change in a variable or an error term is called a variable shock or innovation. An IRF allows a graphical representation of the effect of a one-time shock to one of the innovations on future values of the endogenous variables. If the innovations between equations are contemporaneously uncorrelated, interpretation of the impulse response function is simple. A change in innovation of a firm by one unit at time t is simply a shock to its own future price. With respect to equation (2.1), a change in innovation of a firm by one unit at time t is equivalent to a change in the firm's price by one unit at time t (because all lag variables on the right hand side of the VAR are predetermined), and because the error terms are contemporaneously correlated, it not only can affect the firm's price in the future, but can also be transmitted to the other firms' prices over time. IRFs can be derived by mathematically transforming a VAR model into a vector-moving average (VMA) model. IRFs are matrices of coefficients in a VMA model, in which its error terms are orthogonal, i.e., they are not contemporaneously correlated (Charemza and Deadman, 1992, p. 161-164). In empirical work, the process that transforms error terms to be orthogonal in order to identify impulse responses is called a Choleski decomposition.

It is helpful to understand the properties of the forecast errors to reveal interrelationships among variables in the system. Enders (1995) suggested that it is convenient to describe the properties of the forecast errors from the VAR in terms of the error sequence. It is possible to decompose the *t*-step (period) ahead forecast error variance due to each one of the shocks. The forecast error variance decomposition (FEVD) measures the proportion of the variation in a variable that is explained by its own innovation as well as by the innovations in the other variables. Each step or time period is called forecast horizon. If all variables of interest are endogenous, the forecast errors variance of each error sequence will be explained by shocks at all forecast horizons (Enders, 1995). In empirical research, it is normal for a variable to explain almost all of its forecast error variance at short horizons, and smaller proportions at longer horizons. Like IRF analysis, the Choleski decomposition is a necessary tool to identify FEVD. Both IRFs and FEVDs are computed by most econometric packages which incorporate VAR and VEC analysis. Therefore, the study of strategic-price response can be characterized by the use of IRFs and FEVDs.

In sum, the VAR and VEC models can be applied to investigate the dynamic interrelationships among price series in two ways. The first way is to use the Granger causality test for firms' price-response relationships such as leader-follower relationship or warfare. The second way is to see when there is a unitary exogenous shock on a brand's price, how the other brands respond over time after the shock occurred. The IRF analysis tells us about the direction in which a price series responds to shocks. The FEVD analysis examines the proportions of the movements in a series due to its own shocks and shocks from the other variables.

Literature Review

An econometric technique based on dynamic time-series methodology has been emphasized in macroeconomic and monetary research since the early 1980s (Sims, 1980; Litterman and Weiss, 1985; Friedman and Kuttner, 1993; and Thoma, 1994). Later, dynamic time-series techniques, such as VAR and VEC models, were widely used in applied microeconomic fields, e.g., energy economics, agricultural economics analysis and industrial organization. A list of some of the studies that have used the time series analysis in applied microeconomic fields is shown in Table 2.1.

Dynamic time series models, such as VAR and VEC, have been used to analyze markets and pricing conduct. The VAR model proved to have high performance in forecasting a price movement in agricultural-marketing products (Park, 1990, and Gjolberg and Bengtsson, 1997).

The VAR applications such as the Granger-causality test, the IRF analysis, and the FEVD analysis are used in this part. The Granger-causality test is employed to investigate the price-response relationships among canned tuna brands in the market. Several studies used the Granger-causality test to estimate relationships among variables of interest. Cartwright *et al.* (1989) suggested that a dynamic time-series application, such as the Granger-causality test, was a useful supplement to the price-correlation analysis. Giot *et al.* (1999) investigated market leadership in European markets for imported off-season fresh apples and grapes. With the use of the Granger-causality test, they found that the major import market of Rotterdam significantly led the wholesale markets in France and Germany for apples. Tiffin and Dawson (2000) examined the

Table 2.1 Listing of Research in Applied Microeconomics using Time Series Methods

Auther (Published year)	Objective
Cartwright *et al.* (1989)	Examining price correlation to determine the relevant product and geographic market
Park (1990)	Comparing the VAR performance to alternatives
Vogelvang (1992)	Investigating long-run relationships of coffee prices
Vany and Walls (1993)	Investigating long-run relationships of natural gas spot prices in the U.S.
Benson *et al.* (1995)	Examining long-run relationships for market delineation
Gjolberg and Bengtsson (1997)	Comparing the VAR performance to alternatives
Urga (1999)	Estimating inter-fuel substitution in U.S.
Ramanathan (1999)	Estimating short- and long-run price and income elasticities of gasoline demand in India
Giot *et al.* (1999)	Testing market leadership in the European fresh fruit market
Vany and Walls (1999)	Investigating long-run relationships of electricity spot prices in the U.S.
Tiffin and Dawson (2000)	Investigating producer-retail price relationship in the UK lamb market
Vickner and Davies (2000)	Estimating strategic price-response in the canned pineapple industry in the U.S.
Pagan *et al.* (2001)	Investigating the impact of advertising expenditures on citrus sales from the Texas Rio Grande Valley
Kaufmann and Cleveland (2001)	Investigating oil production in the U.S.

relationships between the retail price and the producer price of lamb in England. They found that lamb prices in the retail market significantly affected the producer prices but not in the opposite direction. Pagan *et al.* (2001) analyzed the impact of advertising expenditures on citrus sales from the Texas Rio Grande Valley. They found that advertising expenditures Granger-caused increases in citrus sales, but it was not true in the opposite direction.

The other useful applications of the VAR model are the IRF and FEVD analyses. Benson *et al.* (1995) suggested that the multivariate time series techniques offer new insights regarding antitrust market delineation. IRF and FEVD analyses were employed in their research to analyze the speed and strength with which a price series responds to shocks occurring in other series. Pagan *et al.* (2001) used the IRF and FEVD analyses as additional tools to support the results obtained from the Granger-causality test. They found that the IRF and FEVD findings were consistent with those obtained from the Granger-causality test.

The previous research which is closely related to this part is that of Vickner and Davies (2000). They estimated strategic price response in a product-differentiated oligopoly, the canned pineapple industry, using national-level weekly scanner data from June 1994 to October 1996. Two canned pineapple firms in the U.S., Del Monte and Dole, were investigated. The study started with the ADF test to examine stationarity of each firm's price series and found that the price series of both Dole and Del Monte were stationary with the deterministic time trend included without controlling for seasonality, but only one of the two was stationary with the deterministic time trend included after controlling for seasonality. However, without controlling for the time trend, a unit root was found in the price series of both firms, and the study concluded that each price series, without a time trend, was an integrated process of order 1 or *I(1)*. The stationary price series with the deterministic trend included was estimated using the VAR model. The non-stationary price series without controlling the time trend was tested for co-integration and estimated using the VEC model. They found that a linear combination between price series of Dole and Del Monte existed that was stationary. The results from the unrestricted VAR and VEC models were compared and found to be supported by each other. The hypothesis of price leadership was tested using Granger causality. In addition, the pricing relationships were analyzed by the IRF analysis. The results from the Granger causality test showed that Dole was the leader in determining price in the market, whereas Del Monte followed Dole's pricing decisions. The results, in fact, confirmed the price leadership hypothesis. The IRF analysis also supported the price leadership hypothesis. Finally, the study suggested that an empirical time series analysis may be used to support industrial organization theorists when studying dynamic games.

This part is different from the Vickner and Davies study in two ways. First, it improves the price-response study by including confidence intervals in the IRF results, which were not included in Vickner and Davies' IRF analysis. Second, it includes the FEVD analysis, which was not used in the Vickner and Davies study, to rigorously investigate pricing relationships. The FEVD results can give additional information to the IRF and Granger-causality results in estimating price-response effects.

In sum, the strategic-price responses among canned tuna brands can be investigated using the VAR applications, including the Granger-causality test, the IRF analysis, and the FEVD analysis. The Granger-causality test examines whether the dynamic price-response relationships exist. The IRF analysis graphically reveals the direction of the effect of a one-time shock to one of the innovations on future values of the endogenous variables, whereas the FEVD analysis measures proportions of a brand's price variations that can be explained by shocks to its own price and it rivals' prices for each forecast horizon.

Chapter Three

Econometric Methodology

An objective in this part is to estimate strategic price responses among canned tuna brands based on a dynamic approach. The Bertrand-competition assumption is dropped and replaced by the assumption that a firm in the market sets its price depending on its own past prices and those of rivals. This chapter starts with testing for unit roots and the order of integration for each price series using the ADF and PP test. Several lag length criteria are presented within the estimation of the VAR model. Presented next are applications of the VAR model including pairwise Granger-causaltity tests and the analysis of IRFs and FEVDs to investigate the dynamic price-response relationships. Finally, the four price series are used. Further information on the data can be found in part one.

Testing for Unit Root and Order of Integration

The four price series (*Starkist*, *Chicken of the Sea*, *Bumble Bee*, and *Allother*) used in the first part are tested for unit roots and the order of integration. Empirical research that uses a structural model based on a static approach typically ignores non-stationarity and assumes that the time series are stationary (Gujarati, 1995). However, the use of non-stationary variables in a dynamic time series regression gives spurious results (Gujarati, 1995); therefore, testing for stationarity is a necessary process in estimating dynamic time series models. The most efficient test, which is extensively used in empirical research, is the ADF test. The ADF test can be used by including drift and/or a linear deterministic trend. The ADF test for a price series p_t used in this study is specified as:

$$\Delta p_t = \mu + \delta \; p_{t-1} + \sum_{i=1}^{j} \phi_i \Delta p_{t-i} + v_t \quad , \tag{3.1}$$

where

p_t represents the observed price series,

$\Delta p_t = p_t - p_{t-1}$,

$\Delta p_{t-i} = p_{t-i} - p_{t-i-1}$,

i represents a time lag, for *i* = 1, 2,.., *j*,

μ is a constant or intercept representing drift , and

v_t represents an error term series of identically distributed stationary variables and is *iid* ~ $(0, \sigma^2 I)$.

The ADF *t*-statistics is based on

$$ADF_t = (\hat{\delta} \; - 1) / \hat{\sigma}_{\hat{\delta}} , \tag{3.2}$$

where $\hat{\sigma}_{\hat{\delta}}$ is the usual least squares estimated error of $\hat{\delta}$.

The null hypothesis is that δ = 0, that is, there exists a unit root in p_t meaning that the series is non-stationary. The ADF test includes enough lagged difference terms so that the error term is serially independent, and that can be checked during the process.

The PP test is also a powerful test for a unit root and, therefore, is employed. The PP test is based on an initial least squares fit of the regression

$$p_t = \alpha + \rho p_{t-1} + \varepsilon_t . \qquad (3.3)$$

Equation (3.3) is non-parametric because there is no assumption that the error term ε_t is white noise. Let p_t be generated by $\Delta p_t = \varepsilon_t = \psi(L)\varepsilon_t$, where $\psi(L)$ is a power series in the lag operator L and ε_t, the residual from equation (3.3), is zero-mean white noise with variance σ_ε^2.

The PP *t*-statistic is specified as

$$PP_t = [(\hat{\gamma}_0 / \hat{\lambda}^2)^{1/2}\{(\hat{\rho}-1)/\hat{\sigma}_{\hat{\rho}}\} - 1/2T\{\hat{\lambda}^2 - \hat{\gamma}_0)/\hat{\lambda}\}]/\{\sum_{t=2}^{T}(p_{t-1} - \overline{p}_{-1})^2\}^{1/2}, \qquad (3.4)$$

where $\hat{\gamma}_0$ and $\hat{\lambda}^2$ are consistent estimators of the short- and long-run variances defined as $\gamma_0 = E(\varepsilon_t^2); \lambda^2 = \sigma_\varepsilon^2\{\psi(1)\}^2$, and $\overline{p}_{-1} = \sum_{t=2}^{T} p_t / (T-1)$ (Leybourne and Newbold, 1999). The coefficient ρ is tested under the null hypothesis that there exists a unit root in the series.

Both the ADF and PP test are done using the EView software package. If all price series are stationary, the dynamic-price reactions will be estimated using the VAR model. If all price series are non-stationary, the dynamic-price reactions will be estimated using the VECM and co-integration analysis.

Selecting for Lag Length

A proper lag length must be selected before the VAR model is utilized so that the error terms of each equation in the model are not serially correlated. The VAR model used in this study is specified as:

$$P_t = \theta + \sum_{i=1}^{k} A_i P_{t-i} + u_t \, , \qquad (3.5)$$

where

P_t is a column vector of price series of *Starkist, Bumble Bee, Chicken of the Sea* and *Allother*,

θ and A are unknown parameters to be estimated,

i represents a time lagged, for i = 1, 2,.., k, and

u_t is a column vector of random errors which are assumed to be contemporaneously correlated but not auto-correlated at an appropriate lag length *k*.

The selection process uses a general-to-specific method. The maximum lag is assumed and tested, and then the number of lags is decreased and tested until the appropriate lag length is found. There are several criteria used to select the lag length. These criteria are described as follows:

i) *The Likelihood ratio test* (LR)

Starting from the maximum lag, the LR tests the null hypothesis that the coefficients on lag *k* are jointly zero using the χ^2 statistic, and the number of lags is decreased one at a time until the null hypothesis is rejected. The χ^2 distribution has degrees of freedom equal to *k*-1. The Likelihood ratio test is specified as:

$$LR = (T - c)\{\log|\Omega_{k-1}| - \log|\Omega_k|\} \, , \qquad (3.6)$$

where T = number of observations, k = lag length,

c = the number of parameters per equation under the alternative, and

$|\Omega_k|$ = determinant of the estimated residual variance-covariance matrix obtained from the VAR(k) model.

ii) The Akaike Information Criterion (AIC)

The AIC is calculated to select the model which has the minimal loss of information or the smallest AIC. The AIC is specified as:

$$\text{AIC }(k) = T\log|\Omega_k| + 2N, \tag{3.7}$$

where N = total number of parameters estimated in all equations.

iii) The Schwarz Bayesian Criterion (SC)

$$\text{SC }(k) = \log|\Omega_k| + N\log(T). \tag{3.8}$$

The SC is derived for the case of normally and independently distributed residuals and is the result of a Bayesian procedure of seeking the most appropriate model. The order k of lag length is chosen so that AIC or SC criterion is minimized.

In this study, all three criteria are used to select the appropriate lag length for the VECM estimation. To be sure that the selected lag length is appropriate and there is no autocorrelation in the model, a test for autocorrelation based on the Lagrange multiplier statistics (LM test) is performed. The LM test for k-th order autocorrelation requires two-step estimation under the null hypothesis that there is no autocorrelation. The first step is to estimate each equation in the VAR model in equation (3.5) and obtain the regression residuals (u_t) for t = 1, … , T. In the second step, an auxiliary regression is estimated with the tth residual, $\hat{u}_t$, regressed on the original set of regressors and $\hat{u}_{t-1},\ldots,\hat{u}_{t-k}$. The test is the joint significance of $\hat{u}_{t-1},\ldots,\hat{u}_{t-k}$ in the auxiliary regression. The LM test statistic is LM (k) = $(T-k)(R_a^2)$, where R_a^2 is the R^2 obtained from the auxiliary regression and k is the order of lag length. The LM test is asymptotically distributed as $\chi^2(k)$ distribution.

The VAR Estimation

With the appropriate lag length (k), the VAR model in equation (3.5) can be estimated if all price series are stationary [*I(0)*]. Since the right hand side of equation (3.5) contains only predetermined variables and the error terms are assumed to be serially correlated with constant variance (asssuming the appropriate lag length is chosen), each equation can be estimated using ordinary least squares (OLS). Moreover, OLS estimates are consistent and asymptotically efficient. The estimation of the VAR model in equation (3.5) is done using the EView software package. There are three applications of the VAR analysis employed in this study in order to investigate the price-response relationships among canned tuna brands. They are the Granger-causality test, impulse response function (IRF) analysis, and forecast error variance decomposition (FEVD) analysis.

Testing for Granger-Causality

The VAR model is employed in this study to test the assumption that a firm in the market sets its price depending on its prices and rivals' prices from the past periods. Such an assumption can be tested using Granger-causality tests. According to the price-response elasticities obtained from the price-reaction functions in the first part (Table

4.9), *Bumble Bee's* price does not affect price strategies of *Starkist* and *Chicken of the Sea* during the same time period. Since *Bumble Bee* is one of the three leading brands in the market, it is interesting to test whether its past strategy affects the other two brands' strategies. In other words, it can be tested that *Bumble Bee's* price Granger-causes *Starkist*'s and *Chicken of the Sea's* price, and vice versa.

It is difficult and not useful to interpret the relationships between variables from the coefficients in the estimated VAR models because the VAR models are over-parameterized. Therefore, Granger-causality test results obtained from the estimated VAR are the key solutions here. For each equation in the VAR, the joint significance of each of the other lagged endogenous variables in that equation is tested based on the Chi-square (Wald test) statistics. The Wald test calculates the test statistic by estimating the unrestricted regression without imposing the coefficient restrictions specified by the null hypothesis. The null hypothesis is that P_j does not Granger-cause P_h, where P_j is the lag of an endogenous variable j on the right hand side of an equation and P_h is the endogenous variable h on the left hand side of that equation (j and h are *Starkist, Chicken of the Sea, Bumble Bee,* and *Allother*). The Wald statistic measures how close the unrestricted estimates come to the restrictions under the null hypothesis. If the restrictions are true, then the unrestricted estimates should not be different from those without restrictions. A dynamic relationship between two brands can be classified into three types. For example, a pair of price series between *Starkist* and *Bumble Bee* is tested. If the null hypothesis that the lags of *Starkist*'s price do not Granger-cause *Bumble Bee*'s price is rejected, whereas the null hypothesis that the lags of *Bumble Bee*'s price do not Granger-cause *Starkist*'s price cannot be rejected, it can be interpreted that

Starkist is a price leader and *Bumble Bee* is a price follower. If both null hypotheses are rejected, it can be interpreted that the two firms conduct warfare (Vickner and Davies, 2000). However, if both null hypotheses cannot be rejected, it can be concluded that they are not interdependent in a dynamic way, i.e. they do not take into account each other's past price strategies.

Impulse Response Function and Forecast Error Variance Decomposition Analyses

To investigate pricing relationships rigorously, the IRF and FEVD analysis are employed. If there is a unitary change in a brand's price at time *t*, the IRFs will give information about whether the brand's price and its rivals' prices respond to the shock in a positive or negative direction at time t+1, t+2, etc. The IRF analysis reveals the direction of the relationships graphically between variables from a shock of one variable, whereas the FEVDs measure proportions of the forecast error variance of a brand's price that can be explained by shocks to its own price and its rivals' prices. Theoretically, if none of the forecast error variances in a brand's price at all forecast horizons can be explained by innovations on the other brands' prices, the inference is the brand's price series is exogenous. If all price series are endogenous, the forecast error variance in a brand's price can be explained by shocks on its price and the other brands' prices at all forecast horizons. The effects from shocks are reported as percentages. For example, if 50 percent of the three-period-ahead error variance in *Bumble Bee*'s price can be explained by innovations to *Starkist*'s price, then *Starkist*'s price has a large influence on the progress of Bumble Bee's price. The results from the IRF and FEVD analyses can serve as a way to confirm the dynamic price-relationship results obtained from the

Granger-causality tests. Both IRFs and FEVDs are constructed from the VAR model with orthogonal residuals using the Choleski decomposition.

Chapter Four

Estimation and Results

The strategic price-response relationships among canned tuna brands in the Knoxville market are analyzed using a VAR model. The analysis starts with unit root tests for all price series using the ADF and PP tests. Next, the lag length in the VAR model is selected using the LR, AIC and SC criteria. Then, the VAR model with the appropriate lag length chosen is estimated. Brands' price-response relationships are examined by applications of the VAR analysis including Granger causality, IRF, and FEVD analyses.

Testing for Unit Root and Order of Integration

The observed canned-tuna price series for *Starkist, Chicken of the Sea, Bumble Bee,* and *Allother* for 157 consecutive weeks are depicted in Figure 4.1. The data descriptions are shown in Table 4.1 (chapter 4) of the first part. All the prices seem to fluctuate around no trend (horizontal) lines. However, more than a plot is needed to confirm stationarity. Therefore, all price series are tested for unit roots and order of integration using the ADF test (equation (3.1)) and the PP test (equation (3.3)). First, each price series is tested for a unit root using the original data. If the estimated ADF or PP test statistic is greater than its respective critical value, it can be concluded that the price series is stationary. If the null hypothesis that there exists a unit root in the series cannot be rejected, the series will be tested again with its first differences. The tests are

Figure 4.1 Observed Price Series of Canned Tuna Brands

continued until a stationary series is found. The results from the ADF and PP tests are shown in Table 4.1. The ADF test results indicate that the price series of *Starkist, Bumble Bee* and *Allother* are stationary at their level [*I(0)*], whereas the price series of *Chicken of the Sea* has a unit root and becomes stationary for the first differences [*I(1)*]. Charemza and Deadman (1992) suggested that the choice of number of augmentation terms (the lagged difference terms) included in an ADF equation was important and should be such that error terms in the equation are not auto-correlated. The test results shown in Table 4.1 are based on the ADF equations that include 4 lagged differences. The ADF tests with 2, 3, and 5 lagged differences in each ADF equation are also tested

Table 4.1 The ADF and PP Test Results on Price Series

Price Series	ADF Test Result [Level]	ADF Test Result [First Difference]	PP test Result [Level]
Starkist	Stationary (-3.56)	_	Stationary (-9.52)
Chicken of the Sea	Non-stationary (-1.37)	Stationary (-8.69)	Stationary (-4.35)
Bumble Bee	Stationary (-4.30)	_	Stationary (-7.82)
Allother	Stationary (-3.37)	_	Stationary (-8.77)

All test equations include 4 lagged differences. (ADF and PP *t*-statistics are in parentheses)
The tests are based on the 5% level of significance with MacKinnon Critical Values = – 2.88.

for a unit root, and the results are not different from those in Table 4.1. On the contrary, when 6 lagged differences or more are used, the results are changed in favor to accepting the null hypothesis in all price series. However, the coefficients of the 5th and 6th lagged-difference variables in the ADF equation with 6 lagged-difference terms are not statistically significant. Moreover, Charemza and Deadman (1992) suggested that too many augmentation terms may cause a decrease in power of the test, too often resulting in the failure to reject the null hypothesis. Therefore, the ADF equations with more than 4 lagged differences included may not be appropriate.

The ADF test results from Table 4.1 cause a problem here. If all variables are stationary, a VAR model can be used to estimate the dynamic-price responses. A VEC model can be used when all variables are not stationary but are co-integrated. It may not be appropriate to estimate a VAR model with three stationary variables and one non-stationary variable because the estimated results will be spurious (Gujarati, 1995). In addition, the VEC model with the use of co-integration cannot be used in this situation.

However, the results obtained from the ADF test are not the only ones that can be used, since there is the PP test, which can also be used to test for a unit root of a time series.

The PP test results are also shown in Table 4.1. All price series are found stationary at the 5% level of significant. In addition, the PP tests with 2, 6, and 8 lagged differences included are also tested and inferences for the test results are the same as those shown in Table 4.1. Choi (1992) conducted Monte Carlo experiments to study the effects of data aggregation on the power of the ADF and PP tests for a unit root. Choi concluded that for the aggregate data the PP test was more powerful than the ADF test in finite samples. Since the scanner data used in this study were aggregated and collected for a short time period, all price series are considered to be stationary based on the PP test results.

Selecting for Lag Length

Since all price series are stationary, the unrestricted VAR model specified in equation (3.5) can be used. However, the appropriate lag length of the VAR must still be selected. The appropriate lag length is chosen using the LR, AIC and SC tests and autocorrelation is also detected based on the Lagrange multiplier statistics (LM test). Table 4.2 summarizes the lag length selection from the LR, AIC, and SC, and the test results for autocorrelation from the LM test (at the 5 % level of significance). The results from the LR and AIC indicate that $k = 5$ is appropriate, whereas the SC selects $k = 2$ as a proper lag length. Vickner and Davies (2000) noted that AIC and SC may be biased toward shorter lag structures. Therefore, the test for autocorrelation can be an additional

Table 4.2 Lag Length Criteria and Autocorrelation Test Results

Criteria	Number of lag length (k) selected	LM Test for Autocorrelation [H_0: No Autocorrelation]
The Likelihood ratio test (LR)	5	Not rejected
The Akaike Information Criterion (AIC)	5	Not rejected
The Schwarz Bayesian Criterion (SC)	2[a]	Rejected

[a]When k = 3 and 4 are selected, the null hypothesis of no auto-correlation was also rejected.

indicator for the lag length selection. The LM test results in Table 4.2 show that autocorrelation exists when k = 2 is selected. In addition, auto-correlation is tested and found when k = 3 and k = 4, but there is no autocorrelation found when k = 5. Therefore, this study chooses k = 5 as an appropriate lag length.

The VAR Estimation

The four price series are estimated using the VAR model in equation (3.5) with 5 lags for each series. The estimated results are shown in Table 4.3. The correlogram for 60 weeks of lags indicated that none of the estimated-residual series has autocorrelation. For example, p-values for the Q-statistics in weeks 26 and 52 reported in Table 4.3 surpass the 10% threshold, meaning that there is no autocorrelation up to these weeks. The model seems to be over-parameterized since there are 84 terms estimated and many of the non-significant coefficients should be excluded from the model. Note that the objective here is to investigate dynamic strategic-price responses or interrelationships among the canned tuna brands. Enders (1995) suggested that "improperly imposing zero restrictions may waste important information." Sims (1980) and Enders (1995)

Table 4.3 Parameter Estimates from the Vector Autoregressive Model

	Dependent Variable: P			
Variable	SK	CS	BB	AO
C	0.538**	0.278	0.955**	0.190
	(2.741)	(1.179)	(2.737)	(1.329)
$P_{SKt\text{-}1}$	0.187*	-0.052	-0.303*	-0.024
	(2.200)	(-0.514)	(-2.009)	(-0.392)
$P_{SKt\text{-}2}$	0.075	-0.029	0.200	0.066
	(0.922)	(-0.289)	(1.308)	(1.058)
$P_{SKt\text{-}3}$	0.111	0.151	0.170	-0.017
	(1.279)	(1.451)	(1.100)	(-0.273)
$P_{SKt\text{-}4}$	0.107	0.127	-0.600**	0.005
	(1.225)	(1.208)	(-3.865)	(0.081)
$P_{SKt\text{-}5}$	0.042	-0.134	0.402*	0.141*
	(0.474)	(-1.242)	(2.522)	(2.165)
$P_{CSt\text{-}1}$	0.046	0.435**	-0.048	0.002
	(0.627)	(5.071)	(-0.384)	(0.041)
$P_{CSt\text{-}2}$	-0.004	0.067	0.016	-0.127*
	(-0.053)	(0.747)	(0.123)	(-2.328)
$P_{CSt\text{-}3}$	0.071	0.136	-0.329 *	0.081
	(0.956)	(1.514)	(-2.474)	(1.492)
$P_{CSt\text{-}4}$	-0.150	0.273**	0.167	-0.044
	(-1.953)	(2.959)	(1.224)	(-0.787)
$P_{CSt\text{-}5}$	-0.070	-0.009	-0.086	0.050
	(-0.230)	(-0.098)	(-0.657)	(0.933)
$P_{BBt\text{-}1}$	-0.032	-0.103	0.566**	0.048
	(-0.687)	(-1.796)	(6.665)	(1.382)
$P_{BBt\text{-}2}$	-0.032	0.163**	-0.265**	-0.081*
	(-0.689)	(2.664)	(-2.943)	(-2.212)

Table 4.3 Parameter Estimates from the Vector Autoregressive Model (Continued)

	Dependent Variable: *P*			
Variable	SK	CS	BB	AO
P_{BBt-3}	0.022	-0.095	0.176	0.035
	(0.427)	(-1.561)	(1.957)	(0.944)
P_{BBt-4}	0.061	0.070	-0.260**	0.013
	(1.215)	(1.151)	(-2.906)	(0.357)
P_{BBt-5}	-0.123**	-0.037	0.159	-0.011
	(-2.673)	(-0.684)	(1.954)	(-0.339)
P_{AOt-1}	0.126	0.067	-0.026	0.307**
	(1.069)	(0.485)	(-0.128)	(3.667)
P_{AOt-2}	0.130	0.143	-0.307	0.164
	(1.077)	(0.985)	(-1.434)	(1.869)
P_{AOt-3}	0.003	-0.183	0.254	-0.059
	(0.023)	(-1.238)	(1.162)	(-0.658)
P_{AOt-4}	0.044	-0.140	0.158	-0.050
	(0.369)	(-0.978)	(0.748)	(-0.579)
P_{AOt-5}	-0.220	-0.241	-0.013	0.182*
	(-1.895)	(-1.724)	(-0.062)	(2.153)
Model Diagnostics				
Adj. R^2	0.13	0.61	0.40	0.18
AIC	-2.17	-1.81	-1.03	-2.81
SC	-1.76	-1.39	-0.61	-2.39
p-value of Q Statistic (Week 26)	0.96	0.85	0.27	0.64
p-value of Q Statistic (Week 52)	0.92	0.95	0.66	0.21

(-) t-statistics are in parentheses
*Significance at 5%level, **significance at 1% level
Subscript: SK = *Starkist*, CS = *Chicken of the Sea*, BB = *Bumble Bee*, AO = *Allother*

recommended that the goal of VAR analysis is to investigate the interrelationships among the variables, not the parameter estimates. Moreover, the lags of each variable are likely to be highly collinear, so that the *t*-statistics on estimated coefficients may not be reliable guides to determine the relationships. Therefore, Granger-causality test results obtained from the VAR analysis are more reliable for the investigation.

Granger-Causality test Results

The Granger-causality test results in terms of *p*-values based on the Chi-square statistics are reported in Table 4.4. The test results can be summarized as follows. All price series Granger-cause themselves implying that each brand considers its past prices in determining its present price strategy. *Starkist* Granger-causes *Bumble Bee*, and *Bumble Bee* also Granger-causes *Starkist*. This implies that the strategic-price response between *Starkist* and *Bumble Bee* represents a price war. *Chicken of the Sea* and *Bumble Bee* also Granger-cause each other indicating that these two brands conduct warfare. *Starkist,* and *Chicken of the Sea* do not Granger-cause each other, meaning that they are not inter-dependent with respect to dynamic-pricing behavior. In other words, they do not consider the past prices of one another in their price strategies. Interestingly, *Allother* Granger-causes *Chicken of the Sea*, but it is not true in the opposite direction. Vickner and Davies (2000) suggested the evidence of price leadership when there was unidirectional Granger causality. However, their conclusion about price leadership was also based on the IRF-analysis results, which showed a positive relationship between the leader and the follower. Therefore, the price-response relationship between *Chicken of the Sea* and *Allother* is analyzed with the results from IRF analysis.

Table 4.4 Granger-Causality Test Results

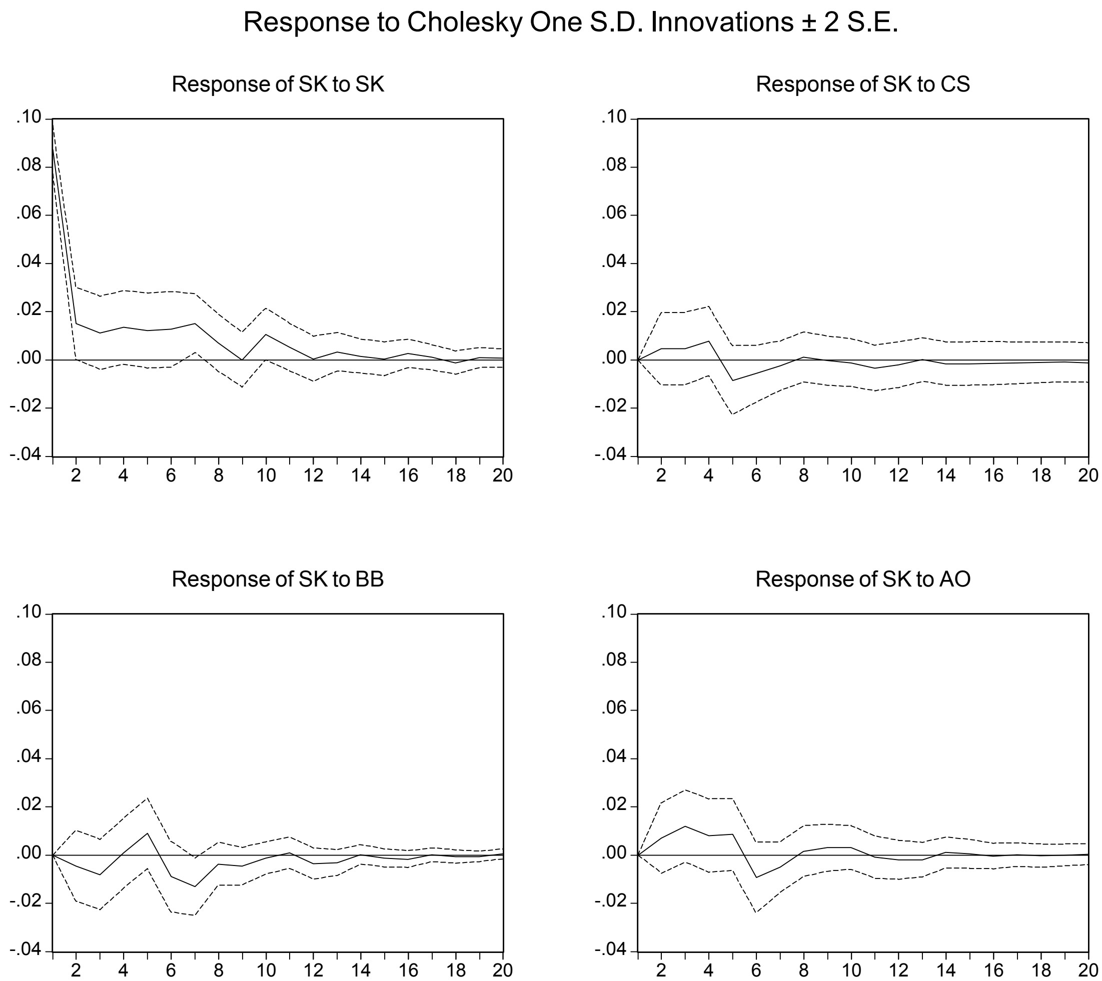
Equation	*p*-value of Chi-square statistics P_{SK}	P_{CS}	P_{BB}	P_{AO}
P_{SK}	0.010***	0.428	0.083*	0.202
P_{CS}	0.407	0.000***	0.061*	0.095*
P_{BB}	0.000***	0.031**	0.000***	0.603
P_{AO}	0.263	0.193	0.265	0.000***

*Significance at the 10% level, **significance at 5% level, and ***significance at 1% level
The null hypothesis is that the column variables do not Granger-cause the row variables.

The Granger-causality test results give additional information on the results obtained from (static) simultaneous equations in the first part. *Starkist*'s and *Chicken of the Sea*'s prices significantly affect *Bumble Bee*'s price strategy both in static and dynamic approaches. *Bumble Bee*'s price does not affect *Starkist*'s and *Chicken of the Sea*'s price strategies during the same time period, but its past price does.

Impulse Response Function Analysis

IRF analysis is an application of VAR analysis to characterize dynamic price-response strategies among canned tuna brands in the market. When there is a one-unit increase of a brand's price due to an exogenous shock (such as sudden changes in input prices or tuna quantity) during period *t*, it may affect the brand's future prices and those of rivals. An IRF of a brand reveals the direction of the brand's price response in the future periods due to a shock of a variable during period *t*. The cumulative IRFs for 20 periods are computed and graphically presented in Figures 4.2 to 4.5, shown on the following pages. Figure 4.2 depicts the time path of *Starkist*'s price series response to a

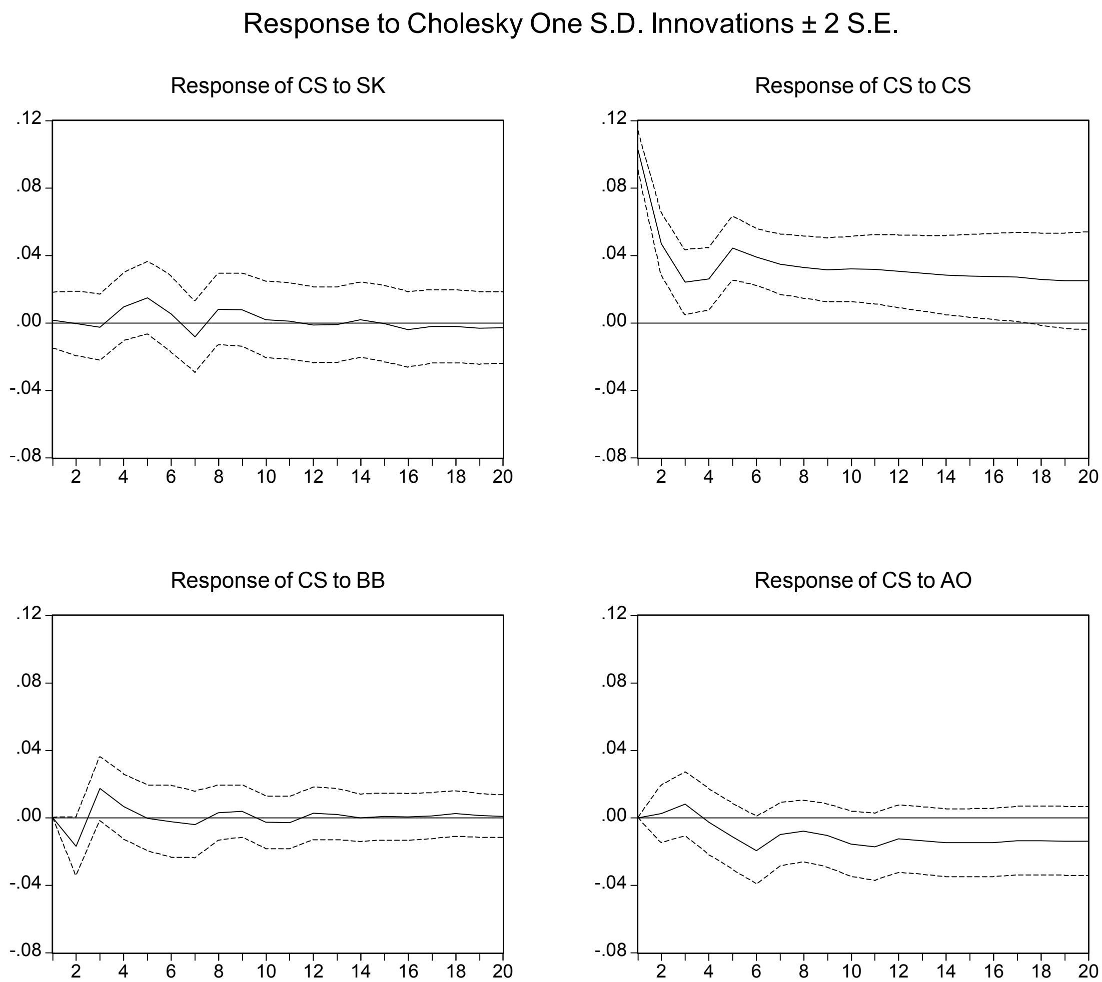


SK = *Starkist*, CS = *Chicken of the Sea*, BB = *Bumble Bee*, and AO = *Allother*

Figure 4.2 Impulse Response Functions of *Starkist*'s Price unit change in the innovations of itself and the other brands' prices. A price-series time path line is between its standard errors (the confidence interval) presented as dash lines. According to Figure 4.2, *Starkist* positively reacts to its own price shocks, and the response dies out rapidly in two weeks. *Starkist* does not react to the innovations of *Chicken of the Sea*'s and *Allother*'s prices. However, a unit shock on *Bumble Bee*'s price has a negative effect on *Starkist*'s price since its response during week 7 is statistically significant.

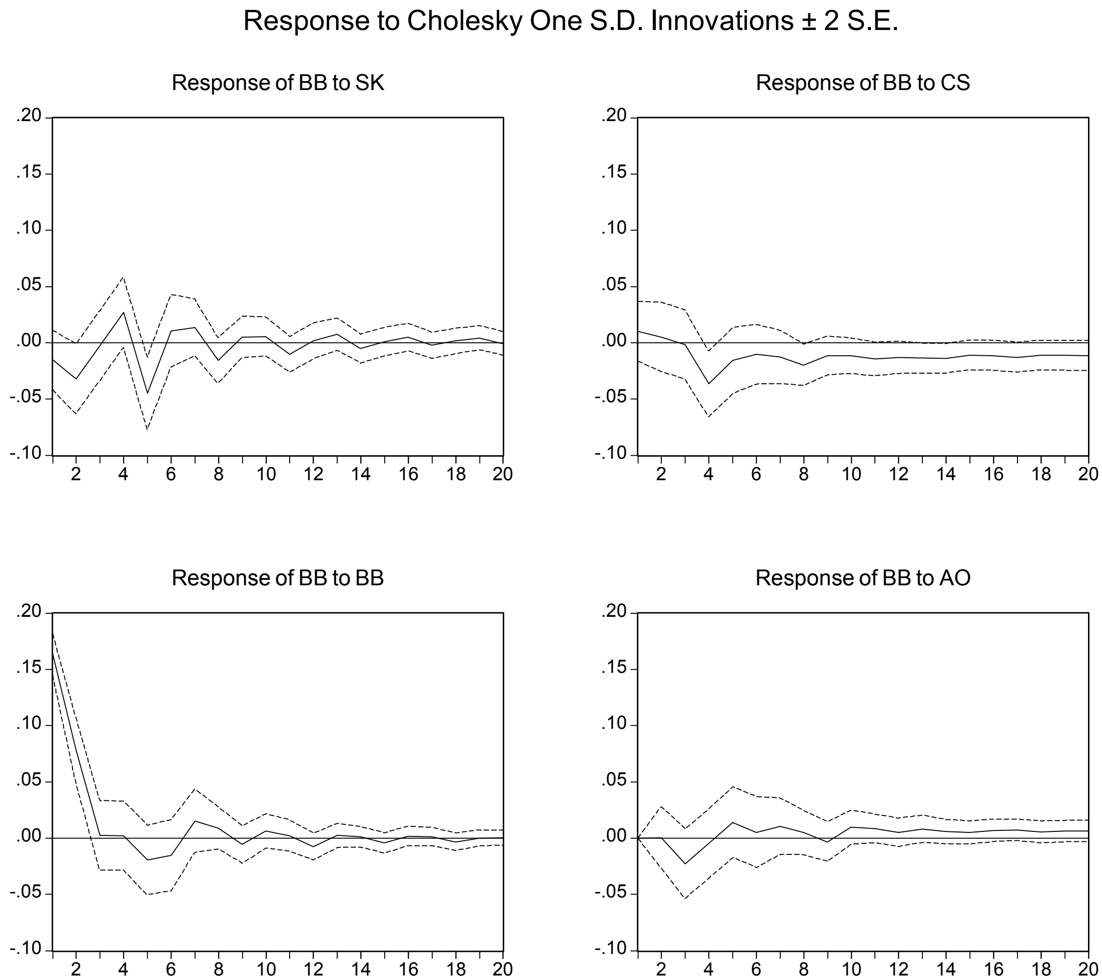
Chicken of the Sea's price responses are shown in Figure 4.3. *Chicken of the Sea* also positively reacts to its own shock. It takes approximately 16 weeks for *Chicken of the Sea*'s price shock to dissipate from its own shocks. *Chicken of the Sea* does not respond to innovations of *Starkist*. However, it responds negatively to shocks on *Bumble Bee*'s price for the first two weeks before adjusting to equilibrium. In addition, *Chicken of the Sea* responds negatively to shocks on *Allother*'s price because the cumulative IRF during week 6 is statistically significant.

According to Figure 4.4, *Bumble Bee* responds negatively to a unit shock on *Chicken of the Sea*'s price because its response during week 4 is statistically significant. These IRF results support the Granger-causality test results that *Bumble Bee* and *Chicken of the Sea* conduct warfare. With respect to a unit shock to *Starkist*'s price, *Bumble Bee* also responds negatively since the IRFs of week 2 and 5 are statistically significant. This interaction result also supports the results found from the Granger-causality test that *Starkist* and *Bumble Bee* conduct warfare because they respond to each other negatively. *Bumble Bee* reacts positively to its own shocks and adjusts quickly to equilibrium in about three weeks.



SK = *Starkist*, CS = *Chicken of the Sea*, BB = *Bumble Bee*, and AO = *Allother*

Figure 4.3 Impulse Response Functions of *Chicken of the Sea*'s Price



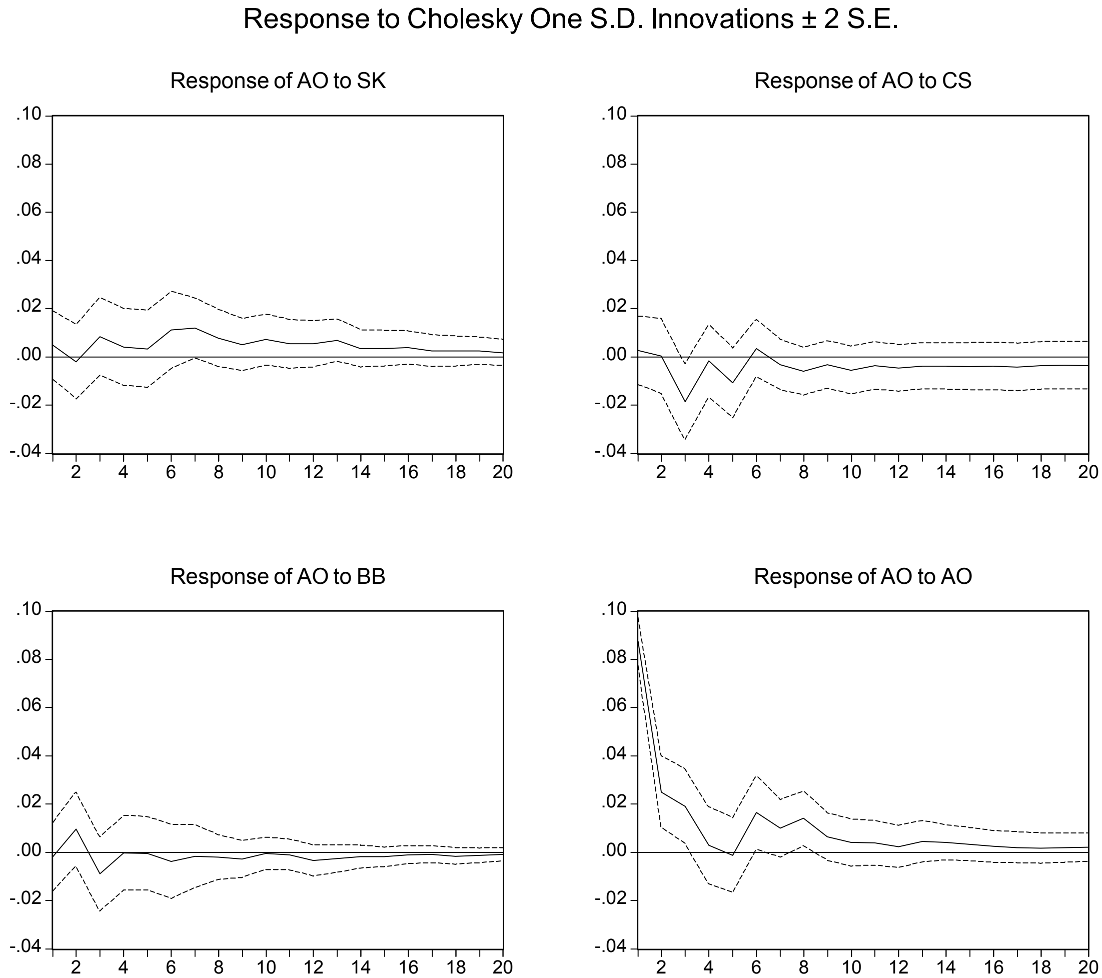
SK = *Starkist*, CS = *Chicken of the Sea*, BB = *Bumble Bee*, and AO = *Allother*

Figure 4.4 Impulse Response Functions of *Bumble Bee*'s Price

Figure 4.5 depicts *Allother*'s price which positively reacts to its own shocks and the price response decreases rapidly in two weeks. There is only a unit shock on *Chicken of the Sea*'s price to which *Allother* negatively responds.

The Granger-causality test results show a unidirectional causality between *Chicken of the Sea* and *Allother* such that *Allother*'s prices Granger-cause *Chicken of the Sea*'s prices. Vickner and Davies (2000) suggested the evidence of price leadership when there was unidirectional Granger causality. Vickner and Davies investigated the price-response relationship between two leading canned pineapple brands, Dole and Del Monte. They found that Del Monte followed Dole's pricing decisions. Their Granger-causality results were unidirectional. Their conclusion about price leadership was also based on the IRF-analysis results, which showed a positive relationship between the leader and the follower. In contrast, the IRF results shown in Figure 4.3 indicate that *Chicken of the Sea* responds negatively to a unit shock on *Allother*'s price. Therefore, it cannot be concluded that *Allother* is the price leader and *Chicken of the Sea* is the price follower. In addition, the IRF results from Figure 4.5 show that *Allother* responds negatively to a unit shock on *Chicken of the Sea*'s price. Therefore, the evidence of price war between the two brands is a more reasonable conclusion.

The IRF results reported in this part are different from those of Vickner and Davies. Confidence intervals in the Vickner and Davies IRF graphs were not shown. In other words, the level of significance was not considered in their IRF analysis. The confidence intervals in the IRF analysis are necessary to determine whether a shock on one variable significantly affects the other variable. For example, this part concludes that there is no dynamic price response between *Starkist* and *Chicken of the Sea* because



SK = *Starkist*, CS = *Chicken of the Sea*, BB = *Bumble Bee*, and AO = *Allother*

Figure 4.5 Impulse Response Functions of *Allother*'s Price

Starkist's IRF responding to *Chicken of the Sea*'s innovation (Figure 4.2) and *Chicken of the Sea*'s IRF responding to *Starkist*'s innovation (Figure 4.3) are not statistically significant. Their confidence intervals (represented as dash lines) cover zero levels for all time periods. Failing to take into account the confidence intervals, especially estimating VAR in levels, may lead to inaccurate conclusions.

Forecast Error Variance Decomposition Analysis

At each horizon (period), the FEVDs measure the percentage of the forecast error in a brand's price that is explained by its own innovation as well as by the innovations that have occurred from competitors' prices. The FEVD analysis is performed for 157 periods ahead in order to see the forecast effects from innovations during the observation period; however, only 1 to 4 (one month), 9 (two months), 26 (six months), 52 (one year), and 157 (three years) periods ahead are reported here. The FEVD results are shown in Table 4.5. Overall, the error variances in *Starkist*'s prices are generally accounted for by innovations to its own prices. The one-period-ahead error variance in *Starkist*'s price responds entirely to its own shock. After 9 periods ahead, innovations to *Starkist*'s price can be explained by its own shock (about 87.7%) and by shocks to *Bumble Bee*'s and *Allother*'s prices (about 4.9% and 5.1%, respectively). The shocks on the other brands' prices have small effects on *Starkist*'s price, and the proportions of error variances in the 9 periods ahead approximately represent the long-run FEVDs because the percentages of error variances are quite stable after that.

Table 4.5 Forecast Error Variance Decomposition Results

Period	S.E.	SK	CS	BB	AO
SK					
1	0.076	100.00	0.00	0.00	0.00
2	0.078	98.60	0.26	0.35	0.80
3	0.080	95.82	0.33	1.24	2.61
4	0.082	94.26	1.10	1.21	3.42
9	0.088	87.65	2.30	4.97	5.08
26	0.089	86.89	2.66	5.33	5.11
52	0.090	86.76	2.76	5.32	5.15
157	0.090	86.72	2.80	5.32	5.16
CS					
1	0.092	0.03	99.97	0.00	0.00
2	0.101	0.06	97.87	1.93	0.14
3	0.105	0.10	96.34	2.43	1.13
4	0.108	0.39	96.19	2.35	1.07
9	0.136	1.87	92.07	1.58	4.49
26	0.176	1.79	84.09	1.04	13.08
52	0.196	2.44	81.04	0.93	15.59
157	0.202	2.62	80.23	0.90	16.25
BB					
1	0.136	0.64	0.36	99.00	0.00
2	0.159	3.91	0.26	95.81	0.01
3	0.160	3.89	0.34	94.10	1.67
4	0.165	4.81	3.95	89.56	1.68
9	0.175	9.82	6.84	81.02	2.31
26	0.185	9.64	12.63	73.27	4.47
52	0.190	9.42	15.36	69.67	5.55
157	0.191	9.35	16.27	68.47	5.90
AO					
1	0.056	0.35	0.19	0.06	99.40
2	0.059	0.37	0.22	1.13	98.27
3	0.062	0.78	3.71	1.85	93.66
4	0.062	0.94	3.71	1.85	93.51
9	0.066	4.80	5.13	1.74	88.32
26	0.069	7.22	7.16	2.00	83.62
52	0.069	7.20	8.22	1.98	82.60
157	0.069	7.19	8.58	1.97	82.26

FEVDs are read from left to right. For each horizon, the error variance of a brand's price is explained in percentage by shocks on column variables.
SK = *Starkist*, CS = *Chicken of the Sea*, BB = *Bumble Bee*, and AO = *Allother*

Chicken of the Sea's price response is different from that of *Starkist*. During the first month ahead, about 96% of innovations to *Chicken of the Sea*'s price can be explained by shocks from its own price. In a longer time period (after 6 months ahead), approximately 13.1% of the forecast error variance of *Chicken of the Sea*'s price can be explained by shocks to *Allother*'s price, whereas shocks to *Starkist*'s and *Bumble Bee*'s prices have small effect to *Chicken of the Sea*'s price innovations. This result supports the IRF results in that *Allother* has a negative influence on *Chicken of the Sea*'s price.

Ninety-eight percent of the one-period-ahead error variance in *Bumble Bee*'s price can be explained shocks from its own prices. However, after about six months ahead shocks to the other brands' prices account for more than 26% of innovations to *Bumble Bee*'s price. Specifically, *Starkist* and *Chicken of the Sea* account for approximately 10% and 13%, respectively. These results support the IRF results in that the variability of *Bumble Bee*'s prices is affected by shocks to *Starkist*'s and *Chicken of the Sea*'s prices.

Allother price innovations are affected almost entirely by shocks to its prices in the short periods ahead (one month). After 6 months ahead shocks to *Starkist*'s and *Chicken of the Sea*'s prices account for approximately 7% of *Allother*'s price innovations. *Chicken of the Sea*'s price shocks have the highest influence on *Allother* price innovations in the long period. This also supports the IRF results in that *Chicken of the Sea* and *Allother* have negative effect to each other.

Overall, the IRF results are consistent with the Granger-causality test results in that *Starkist*'s and *Chicken of the Sea*'s price strategies negatively respond to *Bumble Bee*'s price strategy in a dynamic way. Moreover, the FEVD results support the IRF and Granger-causality test results in that both *Starkist*'s and *Chicken of the Se*a's past prices have high influence on *Bumble Bee*'s present price. Finally, there is no dynamic relationship between *Starkist*'s and *Chicken of the Sea*'s price strategies.

Summary of Results

The four price series of *Starkist, Chicken of the Sea, Bumble Bee*, and *Allother* are used to estimate strategic price-response relationships based on a dynamic approach using VAR analysis. The results are as follows.

- The ADF and PP tests are used to test for a unit root in each series. The results suggest all four price series are stationary.

- The LR, AIC and SC tests are employed to select the appropriate lag length and autocorrelation is tested for each equation in the VAR with the lag length selected by these criteria. The test results indicate that five lags are appropriate in the VAR estimation.

- A VAR model of order five with four price variables is estimated using OLS for each equation.

- Price-response relationships are analyzed by applications of VAR including Granger-causality, IRF, and FEVD analyses.

- The results from Granger-causality tests indicate that the price-response relationships between *Starkist* and *Bumble Bee* and between *Chicken of the Sea* and *Bumble Bee* are bidirectional meaning that both pairs of brands conduct warfare. The price-response relationship between *Chicken of the Sea* and *Allother* is unidirectional implying that the lags of *Allother*'s price affect Chicken of the Sea's price decision. In addition, the Granger-causality results show that no dynamic relationships occur among *Starkis*t, *Chicken of the Sea*, and *Allother*.

- With respect to the IRF results, *Starkist*'s price responds negatively to a unit shock from the *Bumble Bee* price and the reverse is also true. *Chicken of the Sea*'s and *Bumble Bee*'s prices respond negatively to a unit shock of price of each other, and so does the price relationship between *Chicken of the Sea* and *Allother*. The IRF results support the Granger-causality results (with the exception of the *Chicken of the Sea-Allother* relationship) in that all pairs of brands conduct price war. All brands' prices react to their own shock and revert to equilibrium in about three weeks with the exception of *Chicken of the Sea*'s price series that takes approximately 16 weeks to die out.

- The FEVD analysis is conducted for 157 periods ahead. Overall, all price series' forecast error variances are explained mainly by shocks to their own prices. However, 20% of forecast error variance in *Bumble Bee*'s price after 26-periods ahead is explained by shocks on *Starkist*'s and *Chicken of the Sea*'s price. The portion of error variance in *Bumble Bee*'s price from outside shocks is relatively high compared to those of the other brands.

- The IRF and FEVD results are consistent with the Granger-causality test results in that *Starkist*'s and *Chicken of the Sea*'s price strategies negatively respond to *Bumble Bee*'s price strategy in a dynamic way. In addition, both *Starkist*'s and *Chicken of the Se*a's past prices have high influence on *Bumble Bee*'s present price.

Chapter Five

Conclusions

The second part of this dissertation estimates strategic price-response among canned tuna brands in the Knoxville, Tennessee market. Unlike the first part, the Bertrand-competition assumption is dropped and replaced by the assumption that a firm in the market sets its price depending on its own past prices and those of rivals. A vector autoregressive (VAR) model is employed to investigate the dynamic-price relationships among the four price series of *Starkist*, *Chicken of the Sea*, and *Bumble Bee*, and *Allother*.

The first step of the analysis is to test whether each price series is stationary. The augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test are employed to test for stationary. The ADF test results show that *Chicken of the Sea*'s price series is not stationary, while the other price series are stationary. On the other hand, the PP test results indicate that all price series are stationary. This study concluded that all price series are stationary based on the PP test results because of the finding of Choi (1992) that the PP test was more powerful than the ADF test for the aggregate data in finite samples.

Since all price series are stationary, the unrestricted VAR model can be used for estimation. However, a proper lag length must be selected before the VAR model is estimated so that the error terms of each equation in the model are not serially correlated. The appropriate lag length is selected using the likelihood ratio (LR) test, the Akaike Information Criterion (AIC), and the Schwarz Bayesian Criterion (SC). To be sure that autocorrelation does not exist in each equation in the VAR of the order of the selected lag length, the Lagrange multiplier (LM) test is also performed. The test results conclude that the appropriate lag length is five.

The VAR model of order 5 is estimated. The interrelationships among the price series are analyzed by applications of VAR including the Granger-causality test, impulse response function (IRF) analysis, and forecast error variance decomposition (FEVD) analysis. Granger-causality tests examine pairs of brands' prices and tests whether a brand's past prices Granger-cause the other brand's price strategy. If both brands Granger-cause each other, it means that they conduct warfare. IRF analyses reveals graphically the direction of the relationships between price series from a shock of a brand's price, whereas the FEVD analysis measures proportions of error variance of a brand's price that can be explained by shocks to its own price and it rivals' prices for each forecast horizon.

The Granger-causality test results indicate that there are interrelationships between price strategies of *Starkist* and *Bumble Bee*, and between price strategies of *Chicken of the Sea* and *Bumble Bee*. Both of them conduct price war. There are no dynamic interrelationships between *Starkist* and *Chicken of the Sea*. *Allother* Granger-causes *Chicken of the Sea*, but it is not true in the opposite direction. All price-response relationships are investigated further using the IRF results. The price-response relationships found from Granger-causality tests are supported by the IRF analysis. The IRF results show graphically that when there is a unit shock on *Bumble Bee*'s price, at some point of the time, both *Starkist*'s and *Chicken of the Sea*'s prices respond negatively. Similarly, *Bumble Bee*'s price also responds negatively to a unit shock on either *Starkist*'s or *Chicken of the Sea*'s prices. The IRF results also show that *Chicken of the Sea* and *Allother* respond negatively to a unit shock of each other's price. The FEVD results also support these two brands' price relationships. This leads to the inference that they conduct price war. The FEVDs are estimated for 157 horizons ahead. Shocks on each brand's price mainly explain the error variance of the brand's price, especially up to the first-4-periods ahead. When the forecast time period is longer, the portion of error variance of each price series that can be explained by shocks on its own price is decreased gradually and the portions of error variance explained by shocks on the other brands' prices typically increase. After 26 periods ahead, the forecast error variance in *Bumble Bee*'s price has a relatively high portion (20%) attributed by shocks on *Starkist*'s and *Chicken of the Sea*'s prices.

Although the results from the first part indicate that *Starkist* and *Chicken of the Sea* do not respond to *Bumble Bee*'s price strategy during the same time period, the results from the Granger-causality test, the IRF and FEVD analyses show that both *Starkist* and *Chicken of the Sea* negatively respond to *Bumble Bee*'s past price. Moreover, both *Starkist*'s and *Chicken of the Se*a's past prices have high influence on *Bumble Bee*'s present price. Finally, there is no dynamic relationship between *Starkist*'s and *Chicken of the Sea*'s price strategies.

GENERAL CONCLUSIONS

General Conclusions

There are two main objectives of this dissertation. The first objective is to estimate the degree of market power in a product-differentiated oligopoly, in this instance the canned tuna industry at the local level. The second objective is to investigate strategic-price responses among firms in the industry based on the static and dynamic approaches. The weekly scanner data on the purchases of canned-tuna in Knoxville, Tennessee collected by Information Resources, Incorporated (IRI) from January 4, 1998 to December 31, 2000 were used for the estimation of the degree of market power and strategic-price responses. Four canned tuna brands are investigated including the three leading brands, *Starkist*, *Chicken of the Sea*, and *Bumble Bee*, and an aggregate of small-market share brands, *Allother*.

This study is composed of two parts. The first part is based on a static approach, and the second part is based on a dynamic approach. One of the main assumptions made in the first part is that the canned tuna market is operated as Bertrand competition such that price is a strategic variable, and firms make their price decisions during the same time period. The degrees of market power and strategic-price responses among firms are estimated in the first part. Measures of the degree of market power include the Rothschild index (*RI)*, the O index (*OI*) and the Chamberlin quotient (*CQ*). In order to calculate these measures, each firm's own-and cross-price elasticities and price-response elasticities are needed. These elasticities are estimated by the simultaneous demand-supply equations. Following Cotterill (1994), this study employs the linear approximate almost ideal demand system (LA/AIDS) proposed by Deaton and Muellbauer (1980) to estimate the demand for canned tuna in the market, and price-reaction functions are used to investigate strategic-price response among firms. The LA/AIDS uses the Stone price index. Previous studies employed the LA/AIDS to estimate the degree of market power in oligopoly markets (Cotterill, 1994, and Vickner and Davies, 1999). However, use of the Stone index in the LA/AIDS causes estimated parameters to be biased and inconsistent (Pashardes, 1993 and Moschini, 1995). One of the contributions in this dissertation is to use the corrected Stone index suggested by Moschini (1995) in the LA/AIDS estimation.

The degree of market power of a brand in this study means that the brand is able to set a high price without losing its market share. A brand's market power is derived from two sources. First, it arises from the brand's unilateral market power due to brand characteristics and product differentiation, and the *RI* represents such power. Second, the brand's market power is derived from tacit collusion meaning that the brand can influence its rivals to follow its strategy, such as a price increase. The *OI* and *CQ* typically represent this kind of market power.

The results of the measures of market power found in this dissertation are consistent with those of Cotterill (1994) and Vickner and Davies (1999) in that the leading firms which are able to maintain high price and market shares have high degrees of market power. *Starkist*, the highest-market share brand, has the highest degree of market power. The market power of *Starkist* and *Chicken of the Sea* is derived from both unilateral and coordinated market power, whereas that of *Bumble Bee* is derived from its own unilateral market power, not from coordinated market power. In addition, this dissertation re-estimates the simultaneous equations with the use of the traditional Stone index in the LA/AIDS, and the parameter estimates are compared to those of the corrected version. The results from both versions are found to be very close giving the interpretation of market power in the same fashion.

The strategic-price responses among brands are investigated through price-response elasticities obtained from the estimated price-reaction functions. *Starkist* and *Chicken of the Sea* have a positive effect on each other's price strategy. This positive relationship serves as a reason why the two leading firms have coordinated market power. *Starkist* and *Chicken of the Sea* have negative effects on *Bumble Bee*'s price strategy leading to an inference that *Bumble Bee* conducts price war against the two leading brands. On the other hand, *Bumble Bee* has no influence on *Starkist*'s and *Chicken of the Sea*'s price strategies. This also supports the findings of *Bumble Bee*'s degree of market power in that its degree of market power is mainly derived from unilateral market power without coordination from the other brands. However, *Bumble Bee* is one of the three leading brands in the canned tuna oligopoly market. Therefore, price strategies should be expected to be interdependent. Although *Starkist* and *Chicken of the Sea* do not respond to *Bumble Bee*'s price strategy during the same time period, they may consider *Bumble Bee*'s past price in their present decisions. This leads to an extension to the second part of this dissertation which is based on a dynamic approach.

With respect to the second part, the Bertrand-competition assumption is replaced by an assumption that a firm in the market sets its price depending on its own past prices and those of rivals. A vector autoregressive (VAR) model is employed, and its applications are used to investigate the dynamic price relationships. The VAR's applications are the Granger-causality test, the impulse response function (IRF) analysis, and the forecast error variance decomposition (FEVD) analysis. The Granger-causality test examines whether dynamic price-response relationships exist. The IRF analysis graphically reveals the direction of the effect of a one-time shock to one of the innovations on future values of the endogenous variables, whereas the FEVD analysis measures proportions of a brand's price variations that can be explained by shocks to its own price and it rivals' prices for each forecast horizon. Although the results from the first part indicate that *Starkist* and *Chicken of the Sea* do not respond *Bumble Bee*'s price strategy during the same time period, the Granger-causality results show that both *Starkist* and *Chicken of the Sea* respond negatively to *Bumble Bee*'s past price. Both leading brands conduct price war in a dynamic way. The findings from the second part actually clarify a question about why the two leading brands do not respond to Bumble Bee during the same time period. In addition, the second part finds that *Starkist* and *Chicken of the Sea* have no dynamic price relationships. The results from the IRF and FEVD analyses also support the Granger-causality test results for the three-leading canned-tuna brands' relationships.

Overall, the results from both parts of this dissertation provide helpful insights on the degree of market power and strategic-price responses among brands in the canned tuna market. This dissertation finds evidence of market power in the canned tuna market in Knoxville, Tennessee. The extent of the average *RI* and *OI* found in this study is less than those found in the carbonated soft drink industry (Cotterill, 1994), but higher than those found in the spaghetti sauce industry (Vickner and Davies, 1999). However, the average degree of market power derived from tacit collusion found in this study is the lowest compared to those found in the carbonated soft drink and the spaghetti sauce industries.

The results from the second part give additional information about firms' price strategies such that a short-run dynamic equilibrium exists. This can be explained by two reasons. First, there exists a price adjustment lag among firms. The time between when a firm desires to change price and when it can change price is longer than one observation period. The second reason occurs when firms switch their price strategies in different weeks. This strategy allows firms to avoid rigorous competition during the same time period. The long-run equilibrium is not discussed in this study because the observation period is short (three years), and firms' strategies can be changed in the longer period. Nonetheless, the study of strategic-price responses based on both static and dynamic approaches provides a significantly better understanding of firms' pricing behaviors.

Contributions, Limitations, and Extensions of this Research

Contributions of this research

This dissertation contributes to the empirical research in industrial organization in three ways. First, it improves the model specification in estimating the degree of market power developed by Cotterill (1994) and followed by Vickner and Davies (1999). In their studies, Cotterill (1994), and Vickner and Davies (1999) measured the degree of market power in the carbonated soft drink industry (Cotterill) and the spaghetti sauce industry (Vickner and Davies) by estimating the LA/AIDS model and price reaction functions simultaneously. In the LA/AIDS, they used the Stone price index suggested by

Deaton and Muellbauer (1980). In this study, the corrected Stone index suggested by Moschini (1995) was used in the LA/AIDS model.

Second, this study is the first to examine the degree of competitiveness of brands of a manufactured food product at the local level where competition may be most intense. Work to date on food manufacturers' degree of market power and pricing strategies has been conducted at the aggregate national level (Appelbaum, 1982; Schroeter, 1988; Baker and Breshnahan, 1985; Liang, 1989; Cotterill, 1994; and Vickner and Davies, 1999). These studies have not captured local market effects of pricing conduct and local demand. This dissertation provides information regarding the degree of competitiveness and price-response strategies among firms in a local market.

Third, this dissertation extends the analysis of brands' price-response strategies to a dynamic approach. A vector autoregressive (VAR) model and its applications are employed to investigate such relationships. The results obtained from the first part give information about price-response relationships in a static way. No price responses are found on *Starkist*'s and *Chicken of the Sea*'s price decisions against that of *Bumble Bee* during the same time period. However, the second part finds that both *Starkist* and *Chicken of the Sea* responded to Bumble Bee in a dynamic way. The second part contributes to the literature in that the study of firms' strategic-price responses based on both static and dynamic approaches is more representative of the real world.

Limitations of This Research

There are several limitations of this dissertation. The first limitation is due to the lack of brand-specific cost data. If these data are developed, better demand and price equations can be estimated. Second, there was a limitation in promotional-activity data. This study was not able to take into account the effects of the use of brands' coupons because IRI does not report the extent of their use. Third, the observation period is short. This may be a reason why there was no difference between the use of the Stone index and the corrected Stone index. The small number of observations may also affect the estimation of the dynamic price-response relationships in the second part. Generally, a price series is not stationary over time. The small sample size might be a reason why the four price series in this dissertation were found to be stationary. Finally, the price-response analysis in the second part investigates only whether the price relationships exist. The VAR's applications do not provide statistical magnitudes concerning the price relationships.

Extensions of This Research

This dissertation can be extended in several ways. The first way is to include store brands as key variables in the estimation of degree of market power and price-response strategies among the canned tuna brands in a local market. In this dissertation, store brands were included in *Allother*. However, store brands such as Kroger and BI-LO may have some effects on the national brands' demand and price strategies. Including store brands as key variables in the estimation should give better information about firms' pricing behaviors in a local market. The second extension is to apply this empirical method based on both static and dynamic approaches to the other markets or products. Another extension of this research is to find a way to include both static and dynamic information in the estimation of the degree of market power. Measures of the degree of market power need information of demand and price-response elasticities based on a static approach. Since this dissertation has shown that firms' price strategies are both static and dynamic, future studies might find a method to measure the degree of market power that is able to take into account both static and dynamic information in their investigations.

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