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I am submitting herewith a dissertation written by Scott Douglas Parrott entitled "An Investigation of the Effects of Seasonality on Marketing Linkages in Distribution Channels for Fresh Produce." I have examined the final 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 Agricultural Economics.

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AN INVESTIGATION OF THE EFFECTS OF SEASONALITY ON MARKETING LINKAGES IN DISTRIBUTION CHANNELS FOR FRESH PRODUCE

A Dissertation

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ABSTRACT

This study develops and tests an extension of an empirical description of price relationships between different levels in market distribution channels. The methodological procedures used in previous studies have placed unrealistic implicit and explicit restrictions on the parameter estimates. Also, the data used in most of the previous literature is not consistent with retailer or consumer planning horizons.

The new approach developed here incorporates seasonality and Shiller lags into the traditional procedure used to examine symmetry of price response between different market levels. Specifically, this study focuses on the vertical price linkages between the shipping point and retail levels in the fresh produce industry. Using an iterative Generalized Least Squares procedure, weekly store-level scanner data acquired from a retail chain are combined with data from shipping point sources to test the methodology.

Models were developed for three long-running fresh tomato retail series that differed by size and packaging. Results were similar for all three models. In each case, the retailer's length of adjustment time with respect to rising versus falling shipping point prices is the same. Also, the aggregate (long run) impact of a positive shipping point price change is not significantly different from a negative shipping point price change. Further, there was no difference in the chain's retail pricing behavior with respect to rising and falling prices within the same time period.

Results for all three models also indicated the retailer's highest response to shipping point price changes at the beginning of the shipping season occurred faster in the

price transmission process compared to the end of the season. It was also found that the retailer is much more sensitive to upstream price changes during periods of large tomato shipments relative to smaller levels.

All the results of this study point toward efficiency in price linkages for the shipping point to retail distribution channel for fresh tomatoes. This is likely due to the perishable nature of fresh tomatoes and how the retailer has adjusted to accommodate those demands.

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CHAPTER I

INTRODUCTION

Background and Importance

Fresh produce continues to be an important segment of food retailing and consumption. *Supermarket Business* estimates produce sales have increased from $29.3 billion in 1992 to $34.9 billion in 1996 (Howfrey). Changing lifestyles and diet/health concerns have helped to generate the increase in produce consumption. Supermarkets are responding by expanding the number of commodities and through expansion of the time they are available. Profitability concerns, reflected in Efficient Consumer Response, draw attention to produce and pricing efficiency.

Relatively short shelf lives and consumer interest in freshness and quality make fresh produce especially difficult to manage from the retailers' perspective. Fluctuations in the number of customers per day (or week) add to the complexity of providing sufficient quantities without stockouts or excessive spoilage. Consequently, better understanding of the price adjustment process from the farm gate to the consumer can be useful in providing foods that people want at competitive prices.

Price transmission refers to the way in which prices at one stage in the production process are related to prices at another. With respect to foods, this starts at the farm gate and continues to the consumer level. The highly perishable nature of fresh produce and little transformation of the products to the retail level result in price transmissions being a

key component of market structure for these commodities. Estimates of price linkages can provide insights into the efficiency of markets in the sense of how quickly they are transferred from one level to another as market clearing signals.

Problem Statement

One problem facing the fresh produce sector is that current empirical methods of assessing efficiency through price linkage analysis between market levels have not provided a realistic setting. There are three main reasons why they have not been appropriate.

First, most studies have used monthly data to assess the price linkages. This matches neither the time intervals used by channel participants to make pricing decisions nor consumer's planning horizons. Due to perishability, these decisions are taking place on a much more frequent basis.

Second, most estimation techniques that have been applied are inadequate or have placed unrealistic restrictions on the parameter estimates. For example, mainly due to the data inadequacies, many studies have neglected the use of polynomials to describe downstream price response to upstream price changes. This may constitute the absence of an important piece of a priori information. Those studies that have used polynomial approximations placed restrictions on the parameters that could bias the results. Also, the consequences of choosing the degree of the polynomial is not without undesirable statistical implications.

Third, the impacts of seasonal effects have been neglected in the literature on price linkage analysis. Traditional methods of accounting for seasonality are undesirable due to

losses in degrees-of-freedom. This problem is intensified in the presence of long data intervals. New approaches have been developed but do not consider the lagged effects of the independent variables.

Objectives

The goal of this study is to develop and test an extension of an empirical description of price relationships between different levels in the market distribution channel. Specifically, this study focuses on the vertical price linkages between the shipping point and retail levels in the fresh produce industry. Methodology and procedures are directed toward improving the current state of assessing market efficiency via price linkages by developing a more appropriate empirical model to describe the relationship between upstream and downstream prices. More specific objectives are to:

(1) assess whether the length of the adjustment time of retail prices is the same for both rising and falling shipping point prices,

(2) assess whether the sum of the price transmissions from rising shipping point prices is equal to the sum of the price transmissions from falling prices,

(3) assess whether on a period-to-period basis the coefficients of the rising prices are the same as those for falling prices,

(4) assess price responsiveness at the retail level with respect to rising and falling shipping point prices for different points in the shipping cycle, and

(5) assess how price responsiveness at the retail level with respect to rising and falling shipping point prices reacts to seasonal fluctuations in the shipping cycle.

Organization of the Study

This dissertation is composed of five chapters. The second chapter covers the literature review and builds the foundation for the extensions to the current methodology developed in chapter three. In addition to introducing the new methodology, chapter three provides a discussion of the basic theoretical assumptions underlying the empirical models. Chapter four presents the empirical results of the study. Finally, chapter five summarizes the results and presents conclusions and potential directions for future research.

CHAPTER II

REVIEW OF THE LITERATURE

Introduction

Price linkages (price transmissions) refer to relationships among prices as raw materials are transformed into the goods and services provided to consumers. With respect to foods, the transformation begins at the farm gate and entails the flow of foods through various levels of the food processing and distribution system. Studies of the linkages can be separated into two broad groups. One focuses on developing models of vertical price relationships. Various theoretical approaches are used to derive empirical models of pricing behavior. The other group is more pragmatic. Attention focuses on the empirical description of price linkages.

The present study is consistent with the second group. That is, it focuses on developing and testing an extension of an empirical description of price relationships for fresh produce between the different market levels in this distribution channel. Consequently, the literature review centers on those studies that are part of the second group. This review consists of two sections. The first concerns empirical analyses that have investigated the notion of symmetrical price responses at one level in a marketing channel with respect to rising and falling prices from other levels (above or below) for several different agricultural commodities. The second section deals with research that

has examined the effects of modeling economic relationships in light of seasonality in some variables.

Price Symmetry

Price adjustment within marketing channels has received the attention of many researchers. They have developed several interpretations for explaining the different markup pricing behaviors of channel participants. Different translations of market information among buyers, sellers, and consumers; market power; and institutional and technological constraints are but a few of the many examples mentioned in previous research (e.g., Kinnucan and Forker, 1987; Punyawadee, Boyd, and Faminow, 1991; Hansmire and Willet, 1993; and Mohamed, Arshad, and Hashim, 1995).

Much work has also been done in developing empirical tests to examine symmetrical price response. Houck (1977) improved on the earlier works of Tweeten and Quance (1969, 1971) and Wolframm (1971) by developing an approach to specify and estimate nonreversible functions which could more clearly test for the possibility of asymmetrical price changes. The hypothesis involved in examining asymmetry is that one-unit increases in an independent variable from period to period have a different absolute impact on the dependent variable than do one-unit decreases in the independent variable (Houck). Following Houck, this test is arranged mathematically as

$$\Delta Y_i = \beta_0 + \beta_1 \Delta X_i^{/} + \beta_2 \Delta X_i^{//} , \qquad (2.1)$$

for $i=1, 2, \ldots, t$, where

$$\Delta Y_i = Y_i - Y_{i-1} ,$$

$$\Delta X_i^{/} = X_i - X_{i-1} \text{ if } X_i > X_{i-1} \text{ , } = 0 \text{ otherwise ,}$$

and

$$\Delta X_i^{//} = X_i - X_{i-1} \text{ if } X_i < X_{i-1} \text{ , } = 0 \text{ otherwise .}$$

Other variables can also be added to this specification whether segmented into positive and negative changes versus a base period or not. Let X_0 be the initial value of X and Y_0 represent the initial value of Y. Equation (2.1) can be linked to the initial data value by noting that the value of Y at any time t is

$$Y_t = Y_0 + \sum_{i=1}^{t} \Delta Y_i \text{ ,} \tag{2.2}$$

for $i=1, 2, \ldots, t, t+1, \ldots, T$. T is the total number of observations beyond the initial value. The distinction between the initial and t^{th} value of Y is the sum of the period-to-period changes that have transpired. Mathematically, this can be expressed as

$$Y_t - Y_0 = \sum_{i=1}^{t} \Delta Y_i \text{ .} \tag{2.3}$$

By inserting equation (2.1) into (2.3), a nonreversible equation can then be specified as

$$Y_t^* = \beta_0 t + \beta_1 R_t^* + \beta_2 D_t^* , \qquad (2.4)$$

where

$$Y_t^* = Y_t - Y_0 ,$$

$$t = \text{time} ,$$

$$R_t^* = \sum \Delta X_i^{'} ,$$

and

$$D_t^* = \sum \Delta X_i^{''} .$$

R_t^*, the sum of all period-to-period increases, is always positive, and D_t^*, the sum of all period-to-period decreases, is always negative. Furthermore, if a positive (negative) net relationship exists between X and Y, both β_1 and β_2 are positive (negative). Houck further notes that expressing all variables as deviations from their initial values eliminates the problem of dealing with the intercept. Constructing the model equations using this procedure allows a formal test of the symmetry hypothesis: $\beta_1 = \beta_2$. Further discussion of this procedure will be addressed later in this chapter and in the next chapter.

Because fresh produce is highly perishable relative to other commodities, speculative inventories cannot be used as an explanation of asymmetrical response at the retail level (Powers, 1994). The short shelf life is a crucial distinction because it affects the need to clear markets quickly via the price adjustment mechanism. Therefore, this literature review focuses on fresh produce pricing studies and includes

other products to the extent they have implications for the model developed in this study.

Fresh produce

Heien (1980) developed a dynamic model of profit maximization that entailed markup pricing from the farm to retail levels. Tomatoes and lettuce were among the commodities included in the study. Monthly data for 1960-1976 were used to test the model. No evidence of asymmetrical price response relative to wholesale price changes was found.

Ward (1982) developed a similar model, but the inferences conflicted with those of Heien. Included in the study were carrots, celery, cabbage, corn, cucumbers, green peppers, and tomatoes. Using monthly data, Ward found that on average the retail price response to wholesale price decreases was greater than the response to increases and cited perishability as the likely cause. It was reasoned that retailers may be reluctant to raise price because turnover could be lowered thus increasing the incidence of spoilage.

Recently there have been improvements in understanding the retail supermarket function through better data. Using this knowledge, researchers have begun to place emphasis on weekly rather than monthly transactions. Powers (1994), using weekly data, investigated the retail-wholesale, retail-shipping point, and wholesale-shipping point pricing functions for iceberg lettuce from March 9, 1986 to August 30, 1992.

Powers, like Heien and Ward, considered price response in a dynamic sense. That is, they lagged the segmented independent variables in addition to using their

current period value thus improving Houck's specification. For example, Powers, applying the Houck procedure, expressed the wholesale-shipping point price linkage as

$$WP_t = \sum_{j=0}^{m1} \delta_{1,-j} SPR_{t-j} + \sum_{j=0}^{m2} \delta_{2,-j} SPF_{t-j} + \delta_3 HCR_t + \delta_4 HCF_t + e_t , \qquad (2.5)$$

where

$WP_t = W_t - W_0$ (wholesale price changes from period *0* to period t) ,

SPR = sum of all week-to-week increases in the FOB price from period *0* to period t ,

SPF = sum of all week-to-week decreases in the FOB price from period *0* to period t ,

HCR = sum of all week-to-week increases in truck hauling costs from period *0* to period t ,

HCF = sum of all week-to-week decreases in truck hauling costs from period *0* to period t ,

$m1$ = lag length for SPR ,

$m2$ = lag length for SPF , and

e_t is a random error term.

Hauling costs were not lagged because they varied little from week-to-week. With this formulation the symmetry hypothesis becomes

$$\sum_{j=0}^{m1} \delta_{1,-j} = \sum_{j=0}^{m2} \delta_{2,-j} .$$

Weekly retail, wholesale, and shipping point prices were obtained for four types of lettuce in twelve cities. Hauling costs between seven major California production regions and five cities were gathered for shipping point price transmissions, and hauling costs between the wholesale markets and twelve cities for wholesale to retail price transmissions were used. Missing hauling cost data necessitated using transportation costs from adjacent areas as proxies. Asymmetry was found in the retail-wholesale relationship in that retail prices were more responsive to wholesale price increases compared to decreases. Likewise, a comparable result was found in the retail-shipping point linkage. No difference was found in the wholesale price response to rising and falling shipping point prices.

Powers also found that for the retail-shipping point linkage, retail prices responded symmetrically to rising and falling hauling costs. It should be remembered, however, that missing hauling cost data to some cities used in the study were proxied, possibly affecting the symmetry inference.

A similar model was used by Mohamed, et al. in a study of eleven fresh vegetable varieties in Peninsular Malaysia. They used weekly data for the period January 1989-November 1992 and found results similar to Powers for the retail-wholesale linkage. An additional test was also used to examine whether the speed of adjustment is similar for price increases and decreases. Using equation (2.5), the hypothesis can be constructed as $\delta_{1,-0}=\delta_{2,-0}$, $\delta_{1,-1}=\delta_{2,-1}$, . . . , $\delta_{1,-m1}=\delta_{2,-m2}$ (Mohamed, et al.). Results indicated the speed of price adjustment was generally identical between the retail and wholesale levels.

Ward's finding that the retail sector was more responsive to wholesale price decreases than increases was opposite the findings of Powers and Mohamed, et al. concerning fresh vegetables. The difference can, perhaps, be explained by the composition of the data sets used. Observation periods longer than one week may bias results toward accepting symmetry (Pick, et al.1990 and Hansmire and Willet, 1993). This reasoning should be particularly relevant for products requiring a quick turnover.

The fresh fruit sector has also been a focus of investigation. Pick, et al. examined price responses in the marketing system for fresh lemons and naval oranges using weekly data from February 3, 1985 through June 1, 1987 and found short run (less than four weeks) retail prices to be more responsive to farm level increases than decreases. However, in the long run the responses tended to be more symmetric. Hansmire and Willet used monthly data from 1980-1990 and found similar results in the short run between the retail and wholesale levels in New York fresh apple markets.

Other agricultural commodities

Kinnucan and Forker analyzed retail level pricing relationships for four derivative products obtained from farm level fluid milk: retail fluid milk, butter, cheese, and ice cream. Using monthly data from 1971-1981, they found that retail level dairy prices adjust more fully to increases in the farm price of milk relative to decreases.

The authors contributed to the model methodology by developing a Chow-type test that examines the importance of retail level demand shifts since the basic markup model used in testing symmetrical price response implicitly assumes unidirectional

causality from wholesale to retail (if so specified). The procedure entails specifying an equation representing retail price as a function of price from a lower market level, a food-marketing cost index, and dummy variables expressing periods of significant retail demand shifts. Results indicated that retail demand shocks were unimportant in explaining the asymmetry observed in the study.

Boyd and Brorsen (1988) introduced the idea of testing for speed of adjustment in price responses since they noted previous work only considered aggregate effects. They applied this reasoning to the U.S. pork marketing channel using weekly data from 1974-1981 and found no evidence of asymmetrical price response in aggregate or in speed of adjustment.

Seasonality

Coefficients obtained from performing statistical procedures on data are normally assumed to be constant throughout the period of observation. For analyses of many products, this presumption is relevant. However, most agricultural commodities are seasonal in production. Also, from the retail side, consumers are often well aware of the quality of products entering the market and thus have varying consumption habits throughout the year (Hermann, et al. 1992). It would, therefore, be appropriate from a modeling standpoint to account for seasonality in the variables to capture changes in supply and demand. Traditional methods using intercept and slope shifters are often less desirable mainly due to losses in degrees-of-freedom (Lambregts and Capps, 1990). Researchers have responded by investigating methods to reduce parameterization and still account for seasonality.

Pesando (1972) applied "Almon type" polynomials (Almon, 1965) to describe seasonal variability in the acquisition of residential mortgages by life insurance companies. Based on quarterly data from 1957-1969, it was found that the model allowing seasonal variation was superior in terms of statistical properties and forecasting ability to another model which assumed seasonality to be constant.

Lambregts and Capps further endorsed the use of polynomial approximations in the presence of seasonality with their study of catfish, shrimp, and salmon in a Texas market. For their model, they noted that the parameters required for the polynomial approach were half in number compared to the traditional approach thus making polynomials much more practical for application.

A similar study was conducted by Hermann, et al. in the Japanese salmon market. They augmented a model used by a previous researcher (Kikuchi, 1987) to measure seasonality in Japanese salmon demand by fitting it with polynomial approximations for both the intercept and slope coefficients. Similar to Lambregts and Capps, they concluded that the use of polynomial approximations provides a substantial improvement over the traditional method for measuring seasonality.

Using equation (2.4) and ignoring for the moment the intercept and D_t^* terms, a simple example of the traditional and polynomial approximation (Almon) procedures can be illustrated following Lambregts and Capps and Hermann, et al. Assuming for simplicity the static current period case, a model specification of the traditional slope shifter type can be expressed as

$$Y_t^* = \beta_0 R_t^* + \beta_1[D_1 * R_t^*] + \beta_2[D_2 * R_t^*] + \ldots + \beta_{11}[D_{11} * R_t^*] , \qquad (2.6)$$

where $D_1=1$ if January, otherwise 0; $D_2=1$ if February, otherwise 0; . . . ; $D_{11}=1$ if November, otherwise 0.

For the polynomial approximation model, a vector j must be established and its elements defined (e.g., January=0, February=1, . . . , and December=11). Assuming a polynomial of degree two, the polynomial approximation model can be specified as

$$Y_t^* = \beta_0 R_t^* + \beta_1 j_t * R_t^* + \beta_2 j_t^2 * R_t^* . \qquad (2.7)$$

The advantage of the polynomial approximation approach can be observed by comparing equations (2.6) and (2.7) and noting the difference in parameters involved.

A comparison between the equations also reveals a difference in the marginal effect of R_t^* on Y_t^*. For the traditional specification, the marginal effect can be expressed as

$$\frac{\partial Y_t^*}{\partial R_t^*} = \beta_0 + \beta_m \qquad (2.8)$$

for $m=1, 2, \ldots, 11$. The marginal effect for the polynomial approach is

$$\frac{\partial Y_t^*}{\partial R_t^*} = \beta_o + \beta_1 j_t + \beta_2 j_t^2 . \qquad (2.9)$$

Depending on the signs and magnitude of β_1 and β_2, use of this procedure may result in the monthly values following a rising or falling trend thus causing the method to be less flexible compared to the traditional approach. The flexibility of the polynomial approach can be extended by the selection of alternative numbering schemes for *j*. For example, with weekly data, a u-shaped or n-shaped pattern can be accommodated by having *j* rise to 26 and then return to 1.

However there are other problems with the polynomial approximation technique (Fomby, et al., Greene, Judge, et al. (a) and (b), Kennedy, Kmenta, and Maddala). These include deciding the lag length of the independent variables, degree of the polynomial, and whether to constrain the polynomial endpoints.

Several methods exist for determining the lag length of independent variables. Examples include adjusted R^2, Akaike's Information Criterion (AIC) (e.g., Mohamed, et al.), and sequential F-tests. These methods often involve complicated pretesting schemes (Judge, et al. (b)). Further, underestimating (overestimating) the true lag length can result in biased (inefficient) estimates (Greene and Judge, et al. (a)). Many studies have handled this problem in an ad hoc fashion by specifying the lag length and then adding (deleting) variables until statistically insignificant (significant) lags are found (e.g., Kinnucan and Forker and Pick, et al.).

Methods for determining the appropriate degree of the polynomial also exist and usually depend on the chosen lag length. When the lag length is assumed known, sets of nested restrictions can be applied to construct likelihood ratio tests for finding the best polynomial degree (Judge, et al. (b)). Judge, et al. (b) also disclose a sequential

testing procedure based on F-tests that entail first selecting a polynomial degree equal to the lag length and then lowering it until the tests reveal the optimal degree.

When both the lag length and polynomial degree are unknown, researchers can apply a variety of methods. These include a two-step procedure consisting of estimating the lag length and then finding the optimal polynomial degree based on the first step, searching over all possible pairs of lag length and polynomial degree and comparing them to unrestricted OLS based on a weighted squared error loss function, and specification error tests (Judge, et al. (b)). Assuming the correct lag length is used, the disadvantages of these procedures are that overstating (understating) the polynomial degree results in inefficient (biased) estimates (Greene, and Judge, et al. (b)). As a final note, although the methods presented here allow for sample-based estimation of lag length and polynomial degree when they are not known a priori, the exact small sample properties of estimators resulting from these tests are unknown (Judge, et al. (b)).

Constraining the polynomial endpoints is another problematic feature of the polynomial approximation method. These constraints can be enforced by restricting the lag weights on the head and tail of the polynomial to be zero. Their purpose is to force the distributed lag to expire in a finite length of time. The original work by Almon, as well as a few subsequent studies (e.g., Kinnucan and Forker and Boyd and Brorsen), used these restrictions. Nevertheless, their use does pose some difficulties. For example, a polynomial model only has implications for weights inside the polynomial and makes no provision for information outside (Kmenta). In addition, endpoint

restrictions not only constrain the endpoints but also the polynomial weights in the model (Greene).

Shiller (1973) developed a procedure similar to Almon but less restrictive and problematic. Shiller believed researchers used the Almon approach because it produces a smooth and simple curve and not because the lag weights follow a polynomial (Judge, et al. (b) and Maddala). Rather than focusing on the shape of the lag structure, Shiller introduced the notion of "smoothness". That is, it was felt that prior information (e.g., lag structure) is better represented by allowing the lag weights to vary "around" but not exactly on the polynomial (Kennedy). Shiller showed this idea can be accomplished by permitting the means of the lagged coefficients to lie on a polynomial whereas the coefficients themselves are allowed to vary smoothly.

To illustrate, equation (2.4) without the intercept and D_t^* terms can be expressed dynamically as

$$Y_t^* = \sum_{i=0}^{n} \beta_i R_{t-i}^* + e_t , \qquad e_t \sim N(0,\sigma_e^2) \tag{2.10}$$

where n is the lag length. A way of imposing the lag weights to lie on a polynomial of degree q is to estimate (2.10) subject to $(n-q)$ constraints of the form

$$\Delta^{q+1}\beta_i = 0 \tag{2.11}$$

for $i=q+1, \ldots, n$ where Δ is the difference operator (e.g., $\Delta\beta_i = (1-L)\beta_i = \beta_i - \beta_{i-1}$). In contrast, the Shiller procedure requires estimating (2.10) subject to

$$\Delta^{q+1}\beta_i = w_i , \qquad w_i \sim N(0,\sigma_w^2) . \tag{2.12}$$

In Shiller's terminology, q is now the degree of the smoothness prior. Equation (2.12) indicates the restrictions are made stochastic rather than exact as in (2.11) and can thus be stated as probabilistic priors (Shiller). Therefore, σ_w^2 can be thought of as the degree of confidence in researchers' prior knowledge.

Shiller compared the new approach with OLS and the Almon procedure using quarterly data from 1955 to 1969. The four to six month prime commercial paper rate was used to explain variation in the Federal Reserve Board Aaa new issue yield series. All three methods were compared to known shapes of lag distributions. Results showed OLS exhibited a jagged portrayal of the known shape. Also, the known shape was inadequately represented by the Almon approach even when more freedom was given by increasing the degree of the polynomial. However, the Shiller estimates produced a smooth distribution that closely approximated the known shape.

Fomby (1979) applied the Shiller and Almon procedures as well as OLS to quarterly data from two previous studies. The data included capital expenditures and appropriations (1953-1967) as well as personal consumption and disposable income (1947-1961). For both data sets, Shiller's estimates were superior to OLS in terms of producing a lower Mean Squared Error (MSE). However, the Shiller and Almon procedures were not compared.

Venkateswaran, et al. (1993) investigated advertising carryover on New York City fluid milk sales using monthly data from 1971-1988. By using the Root Mean

Square Percent Error (RMS%E) test, the authors were able to compare OLS, Almon, and Shiller estimates. Results indicated the unrestricted OLS estimator is preferred under both MSE and RMS%E criteria in the absence of multicollinearity and autocorrelation. Under these circumstances, the Almon and Shiller estimates were almost equal in performance. When these estimation problems were present, however, the Almon and Shiller estimators may perform better than OLS in a MSE sense. The Shiller procedure was cited as being more desirable than Almon's approach mainly because the smoothness priors impose a less restrictive structure on the lag parameters thus affording an opportunity to obtain more precise estimates.

To date, there have been no extensions of the Shiller approach to incorporate seasonality. Such a model would be well-suited for empirical descriptions of price linkages within the distribution channel. The equations presented in this chapter can be altered to include other variables as well as dynamics and seasonality. In the next chapter, these alterations will be examined.

CHAPTER III

METHODOLOGY AND PROCEDURES

Introduction

Marketing services (marketing margins), which transform raw farm products into their final forms at the retail level, comprise the foundation of model methodologies used for investigating symmetry in price linkages. Model characteristics are derived from theoretical assumptions reflecting conjectured behavior of margin participants. In addition to the theoretical implications, many studies have extended these methodologies to consider other topics such as constraining the independent variables to lie on a polynomial (e.g., Ward and Kinnucan and Forker).

This chapter draws upon the extensive literature devoted to price linkage analysis, seasonality, and incorporation of prior information in regressions to develop a unique approach for modeling price relationships in fresh produce. It is comprised of four sections. First, the general price linkage model is presented, and its theoretical and empirical requirements are discussed. Next, the price linkage model is altered with respect to the polynomial approximation and Shiller methods discussed in chapter 2. Third, the procedures needed to estimate the new methodology are outlined and reviewed. Finally, the sources and assumptions of data used in this study are presented.

The Price Linkage Model

Several theoretical models have been proposed to explain vertical pricing behavior (e.g., Gardner, 1976 and Wohlgenant, 1989). However, since the goal of this study is to test an extension of the current methodology used to characterize the response of downstream prices to increasing and decreasing upstream prices, the markup pricing model employed by Kinnucan and Forker, Hansmire and Willet, and Powers among others is utilized.

Heien developed the theoretical underpinnings of the markup model. The model can be expressed as

$$R_i = b_{1,i}S_i + b_{2,i}Z_i \,, \tag{3.1}$$

where

R = retail price,

S = free-on-board (FOB) shipping point price, and

Z = marketing costs.

Following Powers, $b_{1,i}$ represents the number of units of the i^{th} vegetable at the shipping point level needed to have one unit at the retail level. Because fresh produce is perishable, $b_{1,i} > 1$. This coefficient also represents the amount the retail price changes based on a one unit change in the shipping price.

For an efficient market, the markup model seems appropriate because downstream prices should lag upstream prices. Retail price response to actual or anticipated shifts in supply or demand within the marketing system should only be modified by transportation

and storage. Lags in price linkages should, therefore, equal the amount of time necessary to move the produce from one level to the next, else price adjustment is inefficient (Powers). In addition to these considerations, the relationship specified in equation (3.1) is predicated on three assumptions.

First, retail level produce is marketed using fixed proportions of the shipping level commodities and marketing inputs, thus implying Leontif production technology. Support for this assumption is based on there being limited opportunity to substitute marketing inputs in response to changing factor prices, particularly in the short run. Also, the technology for distributing and marketing produce is predominantly fixed.

The second assumption is firms are operating under constant returns to scale, which implies constant marginal costs. The consequence of this assumption is the volume of product moving through the system has no effect on the price transmission process. Since fees for cooling, packing, and selling fresh produce remain constant throughout the year, this assumption appears relevant (Powers).

The final assumption of the markup model is that firms operate under competitive market structures. This may be the least defensible presumption since retailers represent the final link in the marketing system and are thus afforded significant advantages in market and price information. However, empirical evidence suggests food retailers behave competitively (Holloway, 1991). Holloway found that retail market departures from competitive conditions have been relatively insignificant from 1955-1983.

Empirically testing the markup model involves addressing the notions of causality, lags in price response, and asymmetry (Kinnucan and Forker). Equation (3.1) implicitly

assumes shipping point prices "cause" retail prices. Although methods exist for testing causal direction (e.g., Granger, 1969), they were not used in this study. Causality tests have been shown to be misleading and unreliable (Conway, et al., 1984). Furthermore, previous studies of vertical price linkages in fresh produce that used the markup model specified retail prices as functions of price movements at lower market levels (e.g., Ward, Pick, et al., Mohamed, et al. and Powers). Based on these findings, the direction of causality for the markup model used in this study is from shipping point to retail.

Lags in price response are believed to exist for many reasons. The time required to pack, store, and transport produce contributes to price response being less than instantaneous (Kinnucan and Forker). Retailers may also be slow to adjust their prices if they consider price changes at lower levels in the marketing channel to be transitory rather than permanent (Powers). Availability from alternative sources, including locally grown produce, could cause hesitation by retailers to change price when prices at lower, more distant levels change. Other reasons for lagged retail response include costliness of repricing (Heien) and differences in information use at various exchange points within the marketing system (Ward).

In the short run, retail prices may respond asymmetrically to rising and falling upstream prices under several conditions. Asymmetric response is predicted by theoretical models (e.g., Gardner) depending on whether upstream price changes are motivated by a shift in farm supply or retail demand. However, these shifts do not explain asymmetrical responsiveness under Leontif marketing technology and perfect elasticity of supply of marketing inputs which, in the short run, are reasonable for

retailers (Powers). Further, given the assumptions underlying the markup model, retail demand shifts should have little relevance in the short-run price linkage relationship.

Speculative inventories of a commodity may also explain asymmetrical price response. However, because of perishability, it cannot be assumed for fresh produce (Powers). Other factors possibly facilitating asymmetric responsiveness include market power (Ward, Kinnucan and Forker, Powers, and Mohamed, et al.); risk-averse firm behavior under conditions of profit uncertainty (Powers); and strategic pricing which recognizes the price-inelasticity of demand for food products.

In contrast to short run conditions, retail response to upstream price changes should be roughly symmetrical in the long run given the assumptions (Powers). However, equation (3.1) can be altered to allow for both short- and long-run adjustments, asymmetry, and lags in price response. This can be accomplished by using the Houck procedure discussed in chapter 2 and by including lags of increases and decreases in upstream price changes. Applying equations (2.1) through (2.4), equation (3.1) can be modified such that for the i^{th} commodity:

$$RP_{i,t} = \sum_{m=0}^{r} \delta_{1,i,m} SPR_{i,t-m} + \sum_{m=0}^{f} \delta_{2,i,m} SPF_{i,t-m} + e_{i,t} , \qquad (3.2)$$

where

RP = retail price changes from period 0 to period t,

SPR = sum of all week-to-week increases in the FOB shipping point price from period 0 to period t,

SPF = sum of all week-to-week decreases in the FOB shipping point price from period 0 to period t,

r = lag length for rising prices,

f = lag length for falling prices, and

e is a random error term.

Transportation costs have been used in previous studies of vertical price transmission (e.g., Powers). However, they are not used here. The retailer supplying the data purchases fresh produce from brokers and wholesalers in various locations, including those used in this study. Fresh produce transportation is part of the chain's distribution system, so transportation costs can be interpreted as fixed in the sense of no seasonal variation since warehouses, trucks, and drivers are part of the overhead (Eastwood, et al., 1997). Also, locally grown produce is not delivered directly to the chain's outlets.

From equation (3.2), the sum of the $\delta_{1,i,m}$'s and $\delta_{2,i,m}$'s represent the price transmission process. Should they sum to 1, the shipping point level prices are transmitted exactly to the retail level. The time required for the price adjustments to occur are reflected in r and f, and if they are equal, the transmission speeds are the same. As noted in chapter 2, a formal test of symmetry in price adjustment can be developed by constructing the hypothesis

$$\sum_{m=0}^{r} \hat{\delta}_{1,i,m} = \sum_{m=0}^{f} \hat{\delta}_{2,i,m} \,. \tag{3.3}$$

This null hypothesis can be assessed using an F-test composed of the sum of squared errors with and without the restriction (3.3). Also, the speed of adjustment can be tested by the null hypothesis

$$\hat{\delta}_{1,i,0} = \hat{\delta}_{2,i,0} \, , \; \hat{\delta}_{1,i,1} = \hat{\delta}_{2,i,1} \, , \; \cdots \, , \; \hat{\delta}_{1,i,r} = \hat{\delta}_{2,i,f} \, . \tag{3.4}$$

Similarly, an F-test using the sum of squared errors with and without the restrictions in equation (3.4) can be used to evaluate each of these equalities (Boyd and Brorsen). Because every variable appears as a deviation from its previous or initial value, equation (3.2) is estimated without an intercept.

With the exception of Griffith and Piggott (1994), no other study has examined seasonality within the framework mentioned above. Using the traditional slope shifter approach outlined in chapter 2 and monthly data, they found insignificant effects of seasonality in the Australian meat market. The popularity of fresh, perishable produce and proliferation of weekly data warrants a new approach for examining seasonality with this methodology. Also, the addition of Shiller lags can help overcome the problems previously encountered when using polynomial lags. These extensions will be developed in the next section.

Incorporating Seasonality and Shiller Lags

Seasonality

From chapter 2 (equation 2.7), the polynomial approximation approach for modeling seasonality was shown to be superior to the traditional intercept and slope shifter method in terms of conserving degrees of freedom. One of its limitations was the

marginal effects were likely to follow an upward or downward trend, depending on how the *j* vector is defined. Although the flexibility of the numbering scheme can be extended, it would not be rational to fix a particular yearly scheme to describe seasonality over several years, given the various exogenous factors affecting supply (e.g., varying weather patterns and planting conditions).

To account for the different yearly seasonal effects, *j* can be assigned arbitrarily based on variations in the data from year to year. Defining *j* in this manner can be interpreted as inserting a priori information into the estimation process, because weather patterns and other conditions affecting immediate production plans and harvest projections can be predicted with a fair amount of accuracy. Hence, this method can be of particular importance if economic forecasting is a goal.

To illustrate, consider the following example. The value of *j* is assigned

Date	**Shipments**	***j***
October 24	1,255,600	1
October 31	1,891,100	2
November 7	3,244,600	3
November 14	2,040,000	2

according to the level of shipments, which in this case is rounded to the nearest millionth digit. Once *j* is defined, it can then be incorporated directly into the regression model. This allows the constant returns to scale assumption to be relaxed, since the volume of shipments will now be a relevant variable in the price transmission process.

Equation (3.2), reflecting the information in j, can be rewritten as

$$RP_{i,t} = \sum_{m=0}^{r} \delta_{1,i,m}(j*SPR_{i,t-m}) + \sum_{m=0}^{f} \delta_{2,i,m}(j*SPF_{i,t-m}) + e_{i,t} \ . \tag{3.5}$$

The marginal effects of *SPR* and *SPF* on $RP_{i,t}$ for any time period *t-m* are

$$\frac{\partial RP_{i,t}}{\partial SPR_{i,t-m}} = \delta_{1,i,m}*j \tag{3.6}$$

and

$$\frac{\partial RP_{i,t}}{\partial SPF_{i,t-m}} = \delta_{2,i,m}*j \ . \tag{3.7}$$

Defined in this manner, the effects depend on the volume of shipments, which are, of course, seasonal in nature. Adjusting for dynamics, the sums of the marginal effects can be expressed as

$$\sum_{m=0}^{r} \frac{\partial RP_{i,t}}{\partial SPR_{i,t-m}} = \sum_{m=0}^{r} \delta_{1,i,m}*j$$

and

$$\sum_{m=0}^{f} \frac{\partial RP_{i,t}}{\partial SPF_{i,t-m}} = \sum_{m=0}^{f} \delta_{2,i,m}*j \ .$$

Alternatively, the marginal impact of j on $RP_{i,t}$ for any time period t-m is

$$\frac{\partial RP_{i,t}}{\partial j} = \sum_{m=0}^{r} \delta_{1,i,m} SPR_{i,t-m} + \sum_{m=0}^{f} \delta_{2,i,m} SPF_{i,t-m} \cdot \qquad (3.8)$$

Equation (3.8) indicates the impact of any particular j must be tracked over the lag periods for rising and falling prices. This ensures the seasonal effects are captured in both rising and falling prices and that their impacts are distributed over time.

Equations (3.6) and (3.7) offer two advantages over the methods employed by Lambregts and Capps and Hermann, et al. First, the j vector is allowed to vary from period to period without following a specific pattern. This may not be important for monthly (or longer) observations. However, for shorter time periods, this specification allows seasonal information to be considered that might not otherwise be permitted. For example, although Lambregts and Capps used weekly data, the weeks within each month were assigned the same j value. This implies every week within the month has the same marginal impact on the dependent variable, thus nullifying the additional detail afforded by weekly data.

Second, neither Lambregts and Capps nor Hermann, et al. considered dynamic adjustment in the dependent variable with respect to the independent variables. Allowing for dynamic adjustment is often necessary to understand economic relationships better, as has been noted earlier in this chapter. Altering the basic polynomial approach used by these authors to consider dynamic effects would necessarily imply increased parameterization. By applying equation (3.5), this problem can be avoided.

Shiller Lags

The Shiller procedure for estimating distributed lags was introduced in chapter 2 as an improvement over the more restrictive Almon method. Although the Almon approach has been successfully applied as a method of conserving degrees-of-freedom and mitigating multicollinearity, its limitations can potentially lead to difficulties in interpreting the small sample properties as well as drawing inferences from the parameters.

By allowing the means of the coefficients to lie on a given polynomial while the coefficients themselves vary smoothly, the Shiller approach offers two distinct advantages over Almon's procedure. First, the choice of degree of polynomial is replaced by a set of parameter restrictions that are stochastic (called smoothness priors). These stochastic restrictions constrain only the parameter means, instead of the parameters themselves. The implication is the problematic decision of choosing the polynomial degree is relaxed (Fomby). Second, as noted elsewhere (e.g., Shiller and Taylor, 1974), smoothness priors are felt to be better representations of prior information. This notion is reinforced in the presence of short data intervals. Since more detailed information is available, the likelihood of the data exhibiting a jagged portrayal over time is diminished.

Before applying the Shiller approach to equation (3.5), a brief review of estimating coefficients subject to polynomial restrictions is necessary. Intuitively, requiring the regression parameters of equation (3.5) to lie on a polynomial of degree q implies

$$\delta_{1,i,m} = \alpha_0 + \alpha_1 m + \ldots + \alpha_q m^q \ , \ \delta_{2,i,m} = \alpha_0^* + \alpha_1^* m + \ldots + \alpha_q^* m^q \ .$$

From equation (2.11) this is equivalent to estimating (3.5) subject to sets of linear constraints of the form

$$\Delta^{q+1}\delta_{1,i,m} = 0 \ , \ \Delta^{*q+1}\delta_{2,i,m} = 0 \ .$$

In applying the Shiller procedure (equation 2.12), the sets of linear constraints become stochastic such that

$$\Delta^{q+1}\delta_{1,i,m} = w_m \ , \ \Delta^{*q+1}\delta_{2,i,m} = w_m \ , \qquad w_m \sim N(0,\sigma_w^2) \ . \tag{3.9}$$

For the Shiller approach, q is now the degree of the smoothness prior. For simplicity, equation (3.9) can be written as

$$R^1\delta_{1,i,m} = w_m \ , \ R^2\delta_{2,i,m} = w_m \ , \qquad w_m \sim N(0,\sigma_w^2) \ , \tag{3.10}$$

where R^1 is a matrix of order $(r\text{-}q),(r+1)$, and R^2 is a matrix of order $(f\text{-}q),(f+1)$, which can be combined into R which has $(r\text{-}q)+(f\text{-}q)$ rows and $(r+1)+(f+1)$ columns. Because equation (3.5) consists of segmented variables, R is a set of restrictions applicable to all the independent variables. That is, the R matrix reflects information specific to the rising and falling segmented variables, respectively. The elements of R^i can be obtained by straightforward application of the difference operator (chapter 2). For simplicity, they can also be acquired from Pascal's triangle:

Degree of Smoothness Prior (q)

			1					
		1		-1				
	1		-2		1			1st
1		-3		3		-1		2nd

and so forth. Each element is the sum of the absolute values of the two closest elements above it. The signs in each row alternate from left to right beginning with positive.

To illustrate, let $r, f = 3$ and $q = 2$. The value of 2 for the smoothness prior indicates the third differences in the parameters are small or 0 on the average. The corresponding restriction matrices are $R^1_{1,4}$ and $R^2_{1,4}$. Combining $R^1_{1,4}$ and $R^2_{1,4}$ results in using the matrix $R_{2,8}$ to rewrite equation (3.10):

$$R\delta = w \tag{3.11}$$

where

$$R = \begin{bmatrix} 1 & -3 & 3 & -1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & -3 & 3 & -1 \end{bmatrix}$$

and

$$\delta = \begin{bmatrix} \delta_{1,i,0} \\ \vdots \\ \delta_{1,i,3} \\ \delta_{2,i,0} \\ \vdots \\ \delta_{2,i,3} \end{bmatrix}.$$

Alternatively, let $r = 3, f = 4$, and $q = 2$. In this case, the restriction matrices are $R^1_{1,4}$ and $R^2_{2,5}$ and equation (3.5) would be estimated subject to

$$\begin{bmatrix} 1 & -3 & 3 & -1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & -3 & 3 & -1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & -3 & 3 & -1 \end{bmatrix} * \begin{bmatrix} \delta_{1,i,0} \\ \vdots \\ \delta_{1,i,3} \\ \delta_{2,i,0} \\ \vdots \\ \delta_{2,i,4} \end{bmatrix} = w .$$

Applying the Shiller approach to equation (3.5) also has implications regarding the seasonal effects in the model. An interpretation of smoothness priors is that the estimated coefficients can deviate from any polynomial as long as they do so smoothly (Maddala). This implies the lagged seasonal effects in the model will vary smoothly over time (equations 3.6, 3.7, and 3.8). In cases of plentiful data or steady demand for products at the retail level, this could increase the efficiency of the parameters. Moreover, the inferences concerning short- and long-run adjustments and asymmetry in price response should be more coherent over time with smoothly varying seasonal effects.

Estimation of the Coefficients

Theil-Goldberger Mixed Estimation

Although Shiller's original work was presented in a Bayesian format, Taylor demonstrated the mixed estimation procedure developed by Theil and Goldberger (1961) is a straightforward method of incorporating smoothness priors into the estimation process. The mixed estimation procedure is developed by incorporating stochastic linear restrictions to modify the regression model so that:

$$\begin{bmatrix} Y \\ \lambda \end{bmatrix} = \begin{bmatrix} X \\ R \end{bmatrix} \delta + \begin{bmatrix} u \\ v \end{bmatrix}, \tag{3.12}$$

where

Y and u = (n x 1) vectors,

λ and v = ((r-q)+(f-q) x 1) vectors,

X = a known (n x (r+1)+(f+1)) matrix,

R = a known ((r-q)+(f-q) x (r+1)+(f+1)) matrix, and

δ = a ((r+1)+(f+1) x 1) vector of regression parameters.

Further, it is assumed E[u], E[v] = 0, cov[u] = $\sigma^2 I$, cov[v] = ψ, and u and v are independent. Also, it is required that λ has a non-zero variance. The first set of n equations is the linear representation of sample information, while the second set of (r-q)+(f-q) equations refers to the prior information that supplements the sample. The vector v represents the deviations of the outcomes of λ from the vector $R\delta$ (Mittelhammer and Conway, 1988). Using Generalized Least Squares, the Theil-Goldberger (TG)

estimator is defined as

$$\hat{\delta}_{TG} = (\sigma^{-2}X'X + R'\psi^{-1}R)^{-1}(\sigma^{-2}X'Y + R'\psi^{-1}\lambda) \; . \qquad (3.13)$$

However, the TG mixed estimator has come under criticism (e.g., Swamy and Mehta, 1969, 1983; and Mittelhammer and Conway). The source of the disapproval involves the prior introspective estimator λ (Mittelhammer and Conway). According to TG, λ is formulated subjectively in that it is an a priori point estimate. Both the point estimate and sampling variance are provided by researchers. The subjectivity of λ is based on best guesses of the corresponding elements of $R\delta$ (Thiel, 1971). However, Swamy and Mehta contend a researcher's best guess will be a fixed constant, therefore λ must have a zero variance (degenerate stochastic).

The Shiller procedure requires λ to be set equal to zero, hence TG mixed estimation is no longer appropriate since it requires λ to be non-degenerate stochastic. An alternative procedure must therefore be employed.

Prior Integrated Mixed Estimation

The Prior Integrated Mixed Estimator (PIME) developed by Mittelhammer and Conway overcomes the weakness of the TG mixed estimator. This procedure expresses the prior information on $R\delta$ in terms of a subjective probability distribution on potential $R\delta$ values with mean vector Ω and covariance matrix ψ. The subjective distribution assigned to λ then represents the perceived relative degrees of belief that the various estimates of the model are correct. This explicit assumption, in addition to the basic assumptions underlying (3.12), form the foundation of the PIME procedure. The PIME

estimator is expressed as

$$\hat{\delta}_{PIME} = (\sigma^{-2}X'X + R'\psi^{-1}R)^{-1}(\sigma^{-2}X'Y + R'\psi^{-1}\Omega) \; . \tag{3.14}$$

Note that the PIME and TG estimators are the same except that λ is replaced by Ω. The PIME estimator has two advantages relative to TG: (1) it has a smaller mean square error matrix, and (2) it is consistent with Theil's notion of incorporating "best guesses" and Swamy and Mehta's belief that a researcher's best guess should be a constant (Venkateswaran, et al.). Further, the subjective probability distribution defined in the PIME procedure subsumes the TG mixed estimator as a special case and permits the use of zero in place of λ, which is necessary for the Shiller procedure (Venkateswaran, et al.). Therefore, the Shiller estimator is defined as

$$\hat{\delta}_S = (\sigma^{-2}X'X + R'\psi^{-1}R)^{-1}(\sigma^{-2}X'Y) \; . \tag{3.15}$$

If the stochastic restrictions can be assumed to be independent with a common variance ϕ^2, then $\psi = \phi^2 I$. Equation (3.15) can then be written as

$$\hat{\delta}_S = (X'X + kR'R)^{-1}X'Y \; . \tag{3.16}$$

From (3.16), k is a parameter given by σ^2/ϕ^2, where σ and ϕ are assumed known. The parameter indicates how confident researchers are with respect to sample versus prior information (Venkateswaran, et al.). In addition to the advantages of using smoothness priors, the Shiller procedure is flexible in that it subsumes the OLS and Almon estimators as special cases. For example, as k approaches 0, OLS estimates are

obtained. As k approaches infinity, Almon estimates for a q^{th} degree polynomial are acquired (Shiller).

The Shiller procedure requires an estimate for k when σ and ϕ are unknown. Shiller suggested a rule of thumb which involves taking σ^2 as the estimate of residual variance from OLS and setting $\phi^2 = 64S^2/p^2$, where S is the sum of the lag coefficients obtained from OLS and p is the lag length. The problem with this approach is that using a constant value of ϕ^2 implies k is not invariant to changes in units of measurement of the variables (Maddala). Lindley and Smith (1972) suggest a procedure which iteratively estimates k. It involves starting with the OLS estimates of the δ_i and taking their variance as an estimate of ϕ^2. This is expressed as

$$\hat{\phi}^2 = \left(\frac{1}{(r+1)+(f+1)} \right) \sum_{i=1}^{(r+1)+(f+1)} \left(\hat{\delta}_i - \bar{\delta} \right)^2 , \qquad (3.17)$$

where $\bar{\delta}$ is the mean of the $\hat{\delta}_i$. The new (Shiller) estimates of the δ_i are computed using $\hat{k} = \hat{\sigma}^2/\hat{\phi}^2$, where $\hat{\sigma}^2$ is the OLS residual variance. Next, $\hat{\phi}^2$ is revised using the new $\hat{\delta}_i$, and the process is repeated until a satisfactory level of convergence is attained (typically when the sum of the absolute values of the changes in the coefficients is less than .001).

The variance-covariance matrix for the Shiller estimates can be obtained by evaluating the expression

$$E\left\{ [\hat{\delta}_S - E(\hat{\delta}_S)][\hat{\delta}_S - E(\hat{\delta}_S)]' \right\} . \qquad (3.18)$$

Equation (3.16) can be written as

$$\hat{\delta}_S = (X'X + kR'R)^{-1}X'(X\delta + e) ,$$

since $Y = X\delta + e$. Factoring this expression yields

$$\hat{\delta}_S = ZX'X\delta + ZX'e , \tag{3.19}$$

where $Z = (X'X + kR'R)^{-1}$. The expected value of equation (3.19) is

$$E(\hat{\delta}_S) = ZX'X\delta , \tag{3.20}$$

since $E(e) = 0$ and $ZX'X$ are nonstochastic. The difference between equation (3.19) and (3.20) is

$$\hat{\delta}_S - E(\hat{\delta}_S) = ZX'e . \tag{3.21}$$

Applying equation (3.18) results in evaluating the expression

$$VAR\text{-}COV(\hat{\delta}_S) = E\{(ZX'e)(e'XZ')\}$$

$$= ZX'E\{(ee')\}XZ'$$

$$= \sigma^2 ZX'XZ' ,$$

since $E\{(ee')\} = \sigma^2$. Applying Z and using its symmetry results in the variance-covariance matrix of the Shiller estimates:

$$VAR\text{-}COV(\hat{\delta}_S) = \sigma^2(X'X + kR'R)^{-1}X'X(X'X + kR'R)^{-1} \; . \qquad (3.22)$$

Data

Tomatoes were selected for an empirical application. They were chosen based on data availability, abundance of seasonal fluctuations throughout the growing periods, and steady seasonal demand at the final consumption level. The data are comprised of weekly observations at the shipping point and retail levels.

Shipping Point

These prices and shipments were acquired from a Florida tomato committee and reflect the average weekly FOB price received by member producers for a twenty-five pound box of mature green and vine-ripe tomatoes. The shipping season was from mid-October through mid-June every year. Tomatoes from this region comprise the primary supply for the United States during these months (Fahey, 1976 and How, 1991), therefore their prices are an accurate reflection of those paid by retailers. The data extended from 1988 through 1996.

Retail

Weekly retail prices and item movement were obtained from five Knoxville area retail grocery stores that are part of a national chain. Price and item movement were tracked for three long-running fresh tomato series that differed by size and packaging. The first and second series, which were both tray packs, extended from May 1988 through September 1996, and March 1992 through September 1996, respectively. The

last series, priced on a per pound basis, covered the period June 1988 through December 1993.

The chain typically used uniform pricing in the area, but there were weeks during which different prices were reported by store. Therefore, for each series, the weekly retail price was multiplied by its respective item movement during that week for each store. These values were then summed across the five stores and divided by the week's total item movement over all reporting stores for the respective series to yield the average weekly retail price. Computing prices in this manner ensures that more weight is given to those stores selling relatively more of the produce. These data are an accurate reflection of retail prices in the Knoxville area since they are taken directly from retail scanner tapes, and this particular chain controls the largest market share in Knoxville. Each series is composed of different volumes and sizes, thus prices reflect the average weekly retail price per unit.

Combining Shipping Point and Retail Prices

Each retail price series was matched to the shipping point data by date. Therefore, data sets for the models comprised yearly mid-October to mid-June intervals. Retail prices are per pound, per package, or count, and the shipping point prices are per carton. Although these are not the same measures, each retail-shipping point price series differs by a constant. Consequently, there is no need to make any adjustment in the series in order to estimate the price transmissions.

The shipping point data vary considerably both within and across years with respect to rising and falling shipments and prices. Similarly, although relatively more

stable, the retail prices exhibit rising and falling variations throughout their spans. Seasonal variability in the data implies variability in the *j* vector, which adds additional inferences to the modeling results. Furthermore, variability in the price series gives reliability to the assessment of the asymmetry hypotheses developed using the proposed techniques in this chapter (Kinnucan and Forker). In the next chapter, some descriptive statistics will be presented to support these assertions.

A final point concerns the use of the Shiller procedure with seasonally varying data. Some advantages have been mentioned previously in this chapter. An additional advantage concerns the effects of weather. There are currently no methods available to account for the effects of weather in an econometric model precisely. However, requiring a model's seasonal parameters to vary smoothly can be regarded as a way of approximating the average effects of weather on the parameters (Gersovitz and MacKinnon, 1978). Combining this notion with the flexible *j* scheme developed earlier should greatly enhance the model inferences relative to previous approaches.

CHAPTER IV

RESULTS

Introduction

This chapter is composed of three sections. Initially, the data are examined in order to provide a perspective of the pricing relationships between the shipping point and retail levels. Consequently, the first two sections contain the results of the graphical and descriptive analyses, respectively. The final section reports the statistical results of the model methodology developed in chapter 3.

Results of the Graphical Analysis

Figure 4.1 details the relationship between shipping point prices and shipments of tomatoes over the period 1988-1996. The Florida tomato growing cycle has harvest/shipping periods that begin in October of each year and end in June. However, the exact week of the start and end varies somewhat, due to changes in the weather. Comparisons of shipment patterns across harvest periods point to the absence of a uniform shipment cycle. Shipments reached the highest peak in the October 1989 to June 1990 and October 1991 to June 1992 growing seasons, respectively. The October 1988 to June 1989 and October 1994 to June 1995 periods were also intervals of relatively high shipments.

The varying seasonal patterns of shipments that occurred during each growing season give support to the flexible j scheme developed earlier. A general pattern

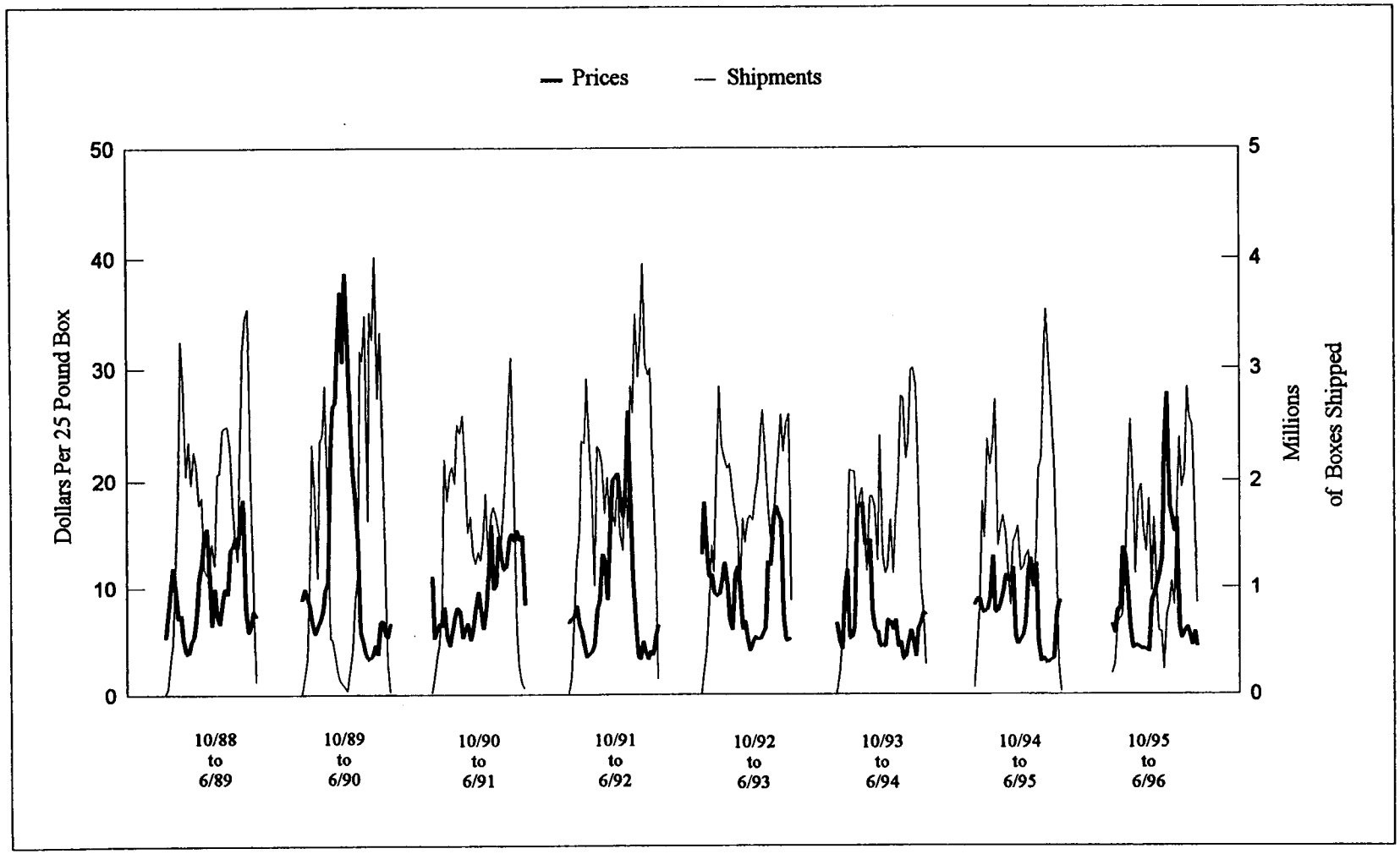


Figure 4.1. Tomato Shipping Point Prices and Shipments

cannot be detected from the data, therefore a flexible way of accounting for seasonal effects is appropriate. This procedure should minimize the bias in inferences that might occur when a fixed seasonal pattern is applied to data that vary seasonally from period to period.

Shipping point prices fluctuated around a $10 range both within and across seasons. The October 1989 to June 1990 and October 1995 to June 1996 periods can be attributed to the severe decline in shipments experienced during those intervals. A sharp increase in prices also occurred in the October 1991 to June 1992 growing period.

Figure 4.2 presents the retail prices of tomatoes used in this study. The changes in the first and third series roughly mirrored each other, with the former always exhibiting a higher price. Both peaked sharply during the period February 17, 1990 to March 3, 1990, likely in response to the low level of tomato shipments during that period (figure 4.1). From June 1, 1991 to July 6, 1991, both series maintained a steady period of high prices. The first series reached its highest overall price on March 28, 1992. Based on the price movements over time, the third series appears to be relatively more variable.

For the second retail series, prices predominantly remained within the $1.50 to $2.50 range. From December 25, 1993 to January 15, 1994, second series prices were consistently high relative to the other observations. The highest price occurred on

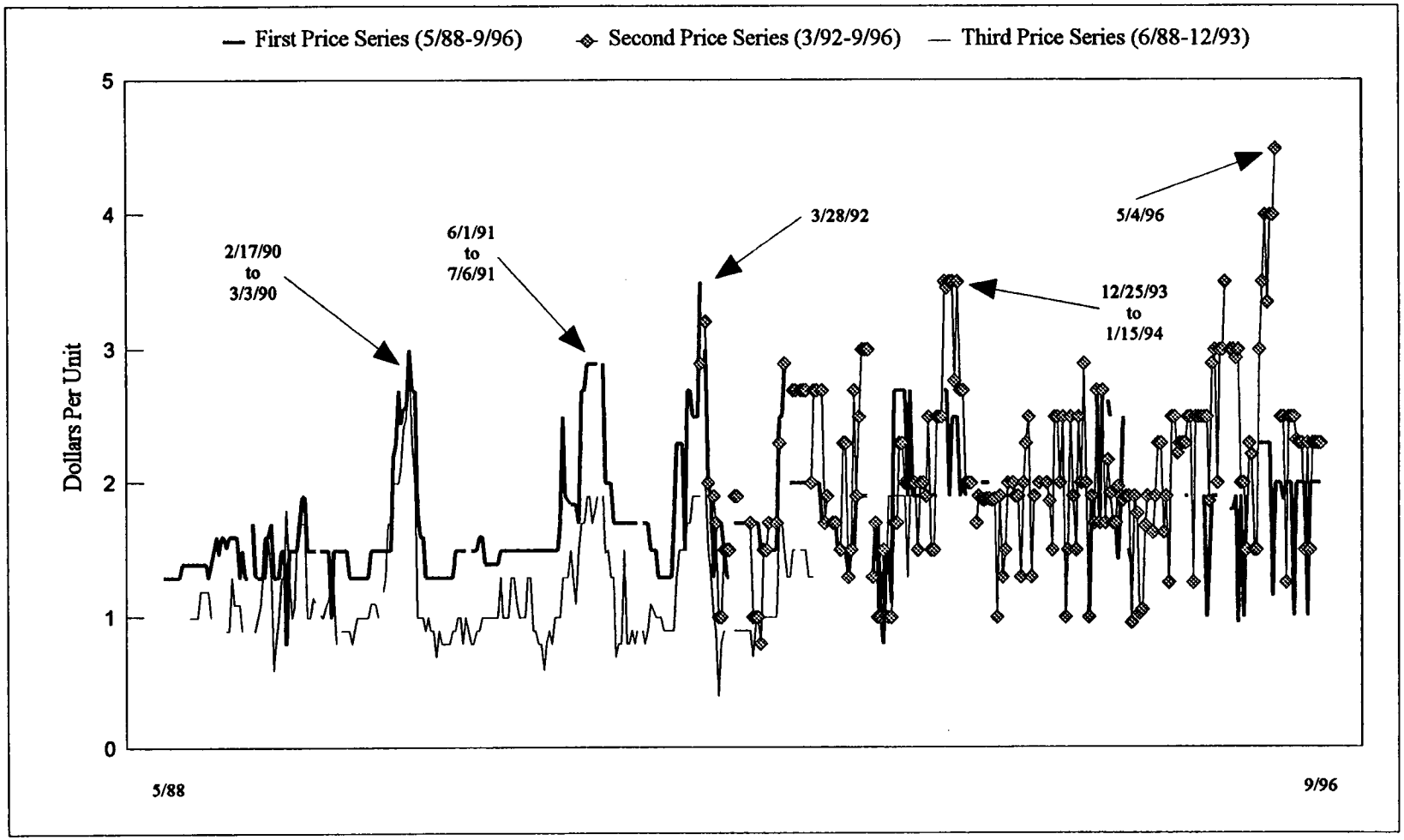


Figure 4.2. Retail Tomato Prices

May 4, 1996, which was likely due to an abrupt decline in shipping point supply (figure 4.1). Because the first series had several missing observations throughout its latter weeks, a comparison relative to the second series could not be made.

Results of the Descriptive Analysis

Table 4.1 contains the means, ranges, coefficients of variation, and price correlations for the shipping point and retail levels. Shipping point prices ranged from \$3 to \$39. The coefficient of variation was much higher for shipping point prices (.62) relative to the retail prices. Previous studies have suggested this is an indication that downstream prices may not respond completely to upstream price changes (e.g., Pick, et al.). The third series had the lowest mean and highest coefficient of variation among the retail prices. The second series had the highest mean, while the first series possessed the lowest coefficient of variation.

Table 4.1. Descriptive Statistics and Correlations

	First Retail Series (tray)	Second Retail Series (tray)	Third Retail Series (pound)	Shipping Point (box)
Mean (dollars)	1.74	2.10	1.22	9.48
Range (dollars)	0.79 - 3.49	0.79 - 4.49	0.39 - 2.99	2.99 - 38.67
Coeff. of Var.	.26	.32	.34	.62
		Correlations		
First Retail Series	1.00			
Second Retail Series	.41	1.00		
Third Retail Series	.73	.46	1.00	
Shipping Point	.47	.31	.67	1.00

The correlations indicate the first and third retail series are closely related in terms of their price changes (.73), which is consistent with figure 4.1. This suggests the chain is applying similar pricing strategies for both types of fresh tomatoes. The shipping point prices were most correlated with the third retail series. They were least correlated with the second.

Table 4.2 presents the correlations between each retail price series and lags of the shipping point prices. The third retail series had the strongest correlations with the lagged shipping point prices. The patterns of correlations among the first and second retail series with lagged shipping point prices were more closely related, with the first series having a relatively stronger relation over the first three time periods, and the second series over the last three. This suggests the chain may be waiting longer to evaluate upstream price changes for the second series.

The fact that the correlations between the third retail series and lagged shipping point prices were stronger compared to the other retail prices can be explained by the merchandising strategies of the chain. The third series was displayed in bulk, whereas the first and second series were packaged in trays. Since less marketing is involved

Table 4.2. Price Correlations Between Retail and Lagged Shipping Point Prices

Retail Series$_t$	Shipping Point Price$_t$	Shipping Point Price$_{t-1}$	Shipping Point Price$_{t-2}$	Shipping Point Price$_{t-3}$	Shipping Point Price$_{t-4}$	Shipping Point Price$_{t-5}$	Shipping Point Price$_{t-6}$
First	.47	.55	.60	.53	.47	.37	.31
Second	.31	.48	.61	.58	.56	.46	.34
Third	.67	.73	.77	.69	.59	.46	.36

with the third series, its price changes are more likely to resemble those occurring at the shipping point level.

The correlations also reveal a distinct pattern that is prevalent for all three retail series. In each case, they consistently increase up to period *t-2*, and then begin to decline. This supports the notion that lags in price response exist between the retail and shipping point levels, as discussed in chapter 3. Furthermore, this pattern indicates a source of a priori information in that the lagged shipping point prices should follow a polynomial, specifically of the second degree, in order to increase the efficiency of the estimates. It should also be noted that differences in the correlation coefficients vary from period to period both up to and beyond their peak, thus the Shiller procedure is more appropriate for incorporating this a priori information rather than restricting the lagged coefficients to lie exactly on a polynomial.

Results of the Statistical Analysis

Estimating equation (3.5) for each retail price series first involves finding the "best" OLS model and then using its results to begin the Shiller procedure (chapter 3). Crucial in this step is identification of the appropriate lag length for the rising and falling lagged shipping point prices (i.e. r and f). This was accomplished by arbitrarily setting $r, f = 8$ and eliminating the last lag periods if they were insignificant, then re-estimating equation (3.5). This process was continued until the last lag period was statistically different from zero at the five percent level.

Initial results from this procedure indicated significant first-order autocorrelation in all three equations. The Durbin-Watson statistic for each model was

far below the lower bound critical value for a no-intercept regression equation (Table Source: Farebrother, 1980). Thus, although the parameter estimates are unbiased and consistent, they are not efficient. Consequently, Generalized Least Squares (GLS) was utilized to identify the "best" model to begin the Shiller procedure.

Estimates based on the Prais-Winsten procedure (Judge, et al. (b)) were used to identify the appropriate lag lengths for r and f. In addition to identifying r and f, other model selection criteria included minimizing the mean square error and noting whether parameter signs were consistent with the Houck procedure. After the appropriate GLS model was identified for each equation, the parameter estimates and error variances were used to initiate the Shiller procedure.

The transformed data were used to provide Shiller estimates of equation (3.5) for all three retail price series. In addition to the parameter estimates, tests for symmetry and speed of price adjustment were also conducted.

Model I

The model used to determine response of the first retail series to rising and falling shipping point prices was expressed as

$$RP_{i,t} = \sum_{m=0}^{5} \delta_{1,i,m}(j*SPR_{i,t-m}) + \sum_{m=0}^{5} \delta_{2,i,m}(j*SPF_{i,t-m}) + e_{i,t} ,$$

where

RP = retail price changes from period 0 to period t,

SPR = sum of all week-to-week increases in the FOB shipping point price from period *0* to period *t*,

SPF = sum of all week-to-week decreases in the FOB shipping point price from period *0* to period *t*,

j = a vector of seasonal variables, and

e is a random error term. P_0 (the base period retail price) is determined for the start of each harvest season by using the date of the initial price used to construct *SPR* and *SPF*.

A lag length of five was determined to be appropriate for both the rising (*r*) and falling (*f*) shipping point prices. As noted elsewhere (e.g., Powers), model results from the Houck procedure can be sensitive to initial starting values of the data, therefore a four-week moving average of the retail price was used in place of $P_{i,0}$ at the start of each harvest cycle. This may be interpreted as the retailer is pricing relative to recent history as reflected in the past four week period, instead of re-formulating a new price at each time period just based on current and lagged shipping point prices. Given the stability of retail prices relative to shipping point (table 4.1, coefficient of variation), this appears to be a reasonable assumption.

Table 4.3 presents the Shiller estimates of Model I. Table 4.3 contains the coefficient estimates, standard errors, R^2, F-tests, and Durbin-Watson results. Except for SPF_t, the parameter estimates for the first and last lag periods of the rising and falling shipping point prices were insignificant. Conversely, all other coefficients were

Table 4.3. Model I Results [a]

Independent Variables	
SPR_t	0.00266 (0.00177)
SPR_{t-1}	0.00654** (0.00113)
SPR_{t-2}	0.00808** (0.00122)
SPR_{t-3}	0.00788** (0.00126)
SPR_{t-4}	0.00604** (0.00116)
SPR_{t-5}	0.00265 (0.00181)
SPF_t	0.00315* (0.00170)
SPF_{t-1}	0.00687** (0.00107)
SPF_{t-2}	0.00855** (0.00124)
SPF_{t-3}	0.00791** (0.00124)
SPF_{t-4}	0.00553** (0.00117)
SPF_{t-5}	0.00175 (0.00176)
R^2	0.25
Equation F	5.586**
Symmetry F[b]	0.00022
Speed F[c]	0.00639
Durbin-Watson	1.594

[a] Standard errors are in parentheses. A single asterisk indicates significance at the .10 level, double asterisks, the .01 level.

[b] Distributed as F(1,204) under the null hypothesis.

[c] Distributed as F(6,204) under the null hypothesis.

significant. This implies the chain conducts most of its significant price adjustment within periods *t-1* to *t-4*.

The equation's F-value leads to the inference of a significant relationship. The R^2 indicates twenty-five percent of variation in period-to-period retail price changes are explained by the independent variables. Although low, this is not surprising since other factors such as competitive environment enter into the chain's pricing decisions (Eastwood, et al.). The Durbin-Watson value of 1.594 lies in the inconclusive region at the .01 level of significance for a no-intercept regression model.

There are three concerns with respect to the symmetry of price transmissions. First, is the length of the adjustment time of retail prices the same for both rising and falling shipping point prices? Second, is the sum of the price transmissions from rising prices equal to the sum of the price transmissions from falling shipping point prices? Third, on a period-to-period basis are the coefficients of the rising prices the same as those for falling prices?

The five week lag for both rising and falling shipping point prices leads to the conclusion that the chain used the same amount of time to adjust retail prices to rising and falling shipping point prices. F-tests were also performed to examine the other two concerns as reflected in equation (3.3) for the sum and equation (3.4) for the intra period adjustment. These restrictions were incorporated by altering the R matrix (equation 3.16) to include one extra row for testing symmetry or p extra rows for the intra period (speed) adjustment, where p is the number of pairwise restrictions (equation 3.4). For model I, $p=6$.

The computed F-value for symmetry was 0.00022 versus the critical value of 3.84 leads to acceptance of the null hypothesis. The inference is the aggregate impacts of changes in rising and falling shipping point prices have comparable total effects on retail price changes. That is, the overall impact of a positive shipping point price change is not significantly different from a negative shipping point price change. With respect to the pairwise comparisons within the same lag period, the computed F-value was 0.00639 versus a critical value of 2.10. This leads to the inference that there is no difference in the chain's retail pricing behavior with respect to rising versus falling shipping point prices.

The results from the tests of symmetry and speed of price adjustment can be discussed further by constructing a pairwise table of the parameter estimates (table 4.4). From periods *t* to *t-3*, the coefficients of the falling shipping point prices were

Table 4.4. Pairwise Comparisons of the Parameter Estimates - Model I

Time Period	***SPR***		***SPF***
t	0.00266	<	0.00315
t-1	0.00654	<	0.00687
t-2	0.00808	<	0.00855
t-3	0.00788	<	0.00791
t-4	0.00604	>	0.00553
t-5	0.00265	>	0.00175
Avg. Diff.	0.00046		
Sum	0.03385	>	0.03376

greater than those of the rising prices, although the difference narrowed with each passing period. In periods *t-4* and *t-5*, the coefficients of the rising prices were substantially greater, therefore causing their sum total to be slightly larger than that of the falling prices. The inequality for the sums is not large enough to reject the symmetry assumption that the aggregate price transmission for rising prices is the same as the one for falling prices. The fact that the average difference between the parameters at each time period is only 0.00046 supports the null hypothesis that the chain responds similarly to intra period rising and falling prices.

The effects that seasonal variation in shipping point prices have on retail prices can be investigated by constructing elasticities adjusted for information contained in the *j* vector. Using equation (3.6), the period-to-period percentage change in *RP* with respect to a one percent change in *SPR* is expressed as

$$\varepsilon_{SPR_{i,t-m},\, RP_{i,t}} = \left(\hat{\delta}_{1,i,m} * j\right) * \left(\frac{SPR_{i,t-m}}{RP_{i,t}}\right) . \qquad (4.1)$$

Notice that this elasticity depends, in part, on the level of shipments (*j*) and on the ratio of rising shipping point to retail price changes. The usefulness of this elasticity can be extended by altering the elements of the normalizing fraction $SPR_{i,t-m}/RP_{i,t}$. For example, average values over the entire shipping point and retail series, averages of values at the beginning and end of each shipping season, and averages of values over the typical "peaks" and "valleys" of the shipping season can all be utilized. These different ratios give additional insight into how the volume of shipments affects the

relationship between shipping point and retail prices. The same approach can also be applied to decreases in shipping point prices. Using equation (3.7), the elasticity of *RP* with respect to *SPF* is shown to be

$$\varepsilon_{SPF_{i,t-m},\, RP_{i,t}} = \left(\hat{\delta}_{2,i,m} * j\right) * \left(\frac{SPF_{i,t-m}}{RP_{i,t}}\right) . \qquad (4.2)$$

Table 4.5 contains the elasticities evaluated at mean values of *SPR*, *SPF*, and *RP* for different values of *j*. Only the elasticities corresponding to significant parameter estimates are reported. The *j* vector, as discussed in chapter 3, is composed of a set of integers based on the level of shipments in each period. For the shipping point data used in this study, the elements of *j* ranged from 1 to 4.

Consistent with the parameter estimates, the elasticities were highest for both *SPR* and *SPF* between periods *t-1* and *t-4*, implying the chain is most sensitive to shipping point price changes during these periods. For each elasticity estimate, as shipments increase (*j* becomes larger), the chain becomes more sensitive to upstream price changes. An interpretation is that as more of the product enters the marketing system, the chain becomes more aware of moving the produce through in order to avoid perishability. For both rising and falling prices, the elasticities were highest in period *t-2*, indicating the chain's most responsive period.

The elasticities of the falling prices were larger than the rising ones through period *t-2*, where the trend began to reverse. However, as noted by the results of the F-tests constructed earlier, these trends are not significant. This supports previous

Table 4.5. Seasonal Elasticities of Retail Price With Respect To Shipping Point Prices (Mean Values) - Model I

	j			
Elasticity	1	2	3	4
$\varepsilon_{SPR_{t-1}, RP}$	3.053	6.106	9.159	12.212
$\varepsilon_{SPR_{t-2}, RP}$	3.587	7.174	10.761	14.348
$\varepsilon_{SPR_{t-3}, RP}$	3.294	6.589	9.883	13.178
$\varepsilon_{SPR_{t-4}, RP}$	2.338	4.675	7.103	9.351
$\varepsilon_{SPF_t, RP}$	1.491	2.983	4.474	5.965
$\varepsilon_{SPF_{t-1}, RP}$	3.104	6.207	9.311	12.415
$\varepsilon_{SPF_{t-2}, RP}$	3.636	7.271	10.907	14.543
$\varepsilon_{SPF_{t-3}, RP}$	3.145	6.291	9.436	12.582
$\varepsilon_{SPF_{t-4}, RP}$	2.032	4.063	6.095	8.127

findings (e.g., Powers) in that firms may be slow to adjust prices either up or down if they consider upstream price changes to be transitory rather than permanent. Another reason for the lack of a significant retail pricing trend may be to avoid frequent price changes that can create consumer confusion (Powers).

Tables 4.6 and 4.7 present the elasticities associated with the beginning and end of the shipping season. They were obtained by altering the normalizing fractions $SPR_{i,t-m}/RP_{i,t}$ and $SPF_{i,t-m}/RP_{i,t}$. For the beginning of the shipping season, SPR_{t-m}, SPF_{t-m}, and RP_t were defined as their averages over the first two weeks of each growing season for which observations were available on all independent variables. Similarly, their averages over the last two weeks of each growing season were used to calculate the season ending elasticities.

Similar to the elasticities evaluated at mean levels, both the season-beginning and season-ending elasticities grew larger as the level of shipments in the system increased. However, there was a difference between the three types of measures in terms of the peak response to shipping point price changes.

For the season-beginning elasticities, peak response at the retail level occurred in period *t-1* for both the rising and falling prices. An interpretation could be that at the beginning of the shipping season, there are still a few alternative supplies of fresh tomatoes. Therefore, the chain will be quick to capitalize on any upstream price trends, since they may be an indication of future tendencies in the Florida market.

Conversely, the peak response for the season-ending elasticities occurred in period *t-3* for both the rising and falling prices. This could be interpreted as the chain

Table 4.6. Seasonal Elasticities of Retail Price With Respect To Shipping Point Prices (Average Season-Beginning Values) - Model I

	j			
Elasticity	1	2	3	4
$\varepsilon_{SPR_{t-1},\ RP}$	2.976	5.951	8.927	11.902
$\varepsilon_{SPR_{t-2},\ RP}$	2.429	4.857	7.286	9.715
$\varepsilon_{SPR_{t-3},\ RP}$	1.545	3.090	4.635	6.180
$\varepsilon_{SPR_{t-4},\ RP}$	0.805	1.609	2.414	3.219
$\varepsilon_{SPF_{t},\ RP}$	2.498	4.995	7.493	9.990
$\varepsilon_{SPF_{t-1},\ RP}$	3.766	7.532	11.298	15.063
$\varepsilon_{SPF_{t-2},\ RP}$	2.780	5.560	8.341	11.121
$\varepsilon_{SPF_{t-3},\ RP}$	1.329	2.658	3.988	5.317
$\varepsilon_{SPF_{t-4},\ RP}$	0.658	1.317	1.975	2.634

Table 4.7. Seasonal Elasticities of Retail Price With Respect To Shipping Point Prices (Average Season-Ending Values) - Model I

	j			
Elasticity	1	2	3	4
$\varepsilon_{SPR_{t-1},\ RP}$	4.796	9.592	14.388	19.184
$\varepsilon_{SPR_{t-2},\ RP}$	6.681	13.362	20.044	26.725
$\varepsilon_{SPR_{t-3},\ RP}$	7.411	14.823	22.234	29.645
$\varepsilon_{SPR_{t-4},\ RP}$	6.073	12.145	18.218	24.291
$\varepsilon_{SPF_{t},\ RP}$	2.317	4.635	6.952	9.269
$\varepsilon_{SPF_{t-1},\ RP}$	5.426	10.853	16.279	21.705
$\varepsilon_{SPF_{t-2},\ RP}$	7.315	14.630	21.945	29.260
$\varepsilon_{SPF_{t-3},\ RP}$	7.467	14.933	22.400	29.867
$\varepsilon_{SPF_{t-4},\ RP}$	5.420	10.840	16.260	21.680

is waiting longer to evaluate these price changes since it will soon begin to receive supplies from other source(s). Therefore, they are beginning to base their prices on the alternative source(s), not Florida.

Tables 4.8 and 4.9 contain elasticities describing retail price responses at the typical "peaks" and "valleys" of the shipping season. The typical "peaks" used were those that occurred in the October 1989 to June 1990 and October 1991 to June 1992 shipping seasons, respectively (figure 4.1). The typical "valleys" used were those that occurred in the October 1989 to June 1990 and October 1995 to June 1996 seasons, respectively. The values of the dependent and independent variables that occurred at each "peak" and "valley" were averaged and those results used in the normalizing ratios $SPR_{i,t-m}/RP_{i,t}$ and $SPF_{i,t-m}/RP_{i,t}$.

Comparing tables 4.8 and 4.9 reveals a substantial difference in magnitude of the parameters. The elasticities evaluated at "peak" levels were much larger than those at the "valleys". This indicates the chain is much more sensitive to upstream price changes in times of relatively large supply. On the other hand, when there is a shortage of supply, the chain is much less sensitive to upstream price changes. Once again, it appears that the perishable nature of the commodity is the deciding factor in how the chain responds to shipping point price changes.

The highest elasticity response in table 4.8 occurred in period *t-2* for both the rising and falling prices. The highest elasticity response in table 4.9 occurred in period *t-1* for the rising prices, and *t-2* for the falling prices, respectively. An explanation for the discrepancy of highest responses between the rising and falling prices in table 4.9

Table 4.8. Seasonal Elasticities of Retail Price With Respect To Shipping Point Prices (Average Prices at "Peak" Shipments)[a] - Model I

	j			
Elasticity	1	2	3	4
$\varepsilon_{SPR_{t-1},\ RP}$	72.010	144.020	216.029	288.038
$\varepsilon_{SPR_{t-2},\ RP}$	104.882	209.763	314.645	419.527
$\varepsilon_{SPR_{t-3},\ RP}$	70.531	141.062	211.593	282.123
$\varepsilon_{SPR_{t-4},\ RP}$	66.166	132.331	198.500	264.662
$\varepsilon_{SPF_{t},\ RP}$	51.677	103.354	155.031	206.708
$\varepsilon_{SPF_{t-1},\ RP}$	84.400	168.759	253.139	337.519
$\varepsilon_{SPF_{t-2},\ RP}$	124.090	248.180	372.270	496.360
$\varepsilon_{SPF_{t-3},\ RP}$	74.758	149.516	224.275	299.033
$\varepsilon_{SPF_{t-4},\ RP}$	61.251	122.502	183.753	245.004

[a] See figure 4.1 for "peak" shipments.

Table 4.9. Seasonal Elasticities of Retail Price With Respect To Shipping Point Prices (Average Prices at "Valley" Shipments)[a] - Model I

	j			
Elasticity	1	2	3	4
$\varepsilon_{SPR_{t-1}, RP}$	0.218	0.437	0.655	0.874
$\varepsilon_{SPR_{t-2}, RP}$	0.178	0.355	0.533	0.711
$\varepsilon_{SPR_{t-3}, RP}$	0.216	0.431	0.647	0.863
$\varepsilon_{SPR_{t-4}, RP}$	0.192	0.385	0.577	0.769
$\varepsilon_{SPF_t, RP}$	0.050	0.010	0.149	0.200
$\varepsilon_{SPF_{t-1}, RP}$	0.086	0.172	0.259	0.345
$\varepsilon_{SPF_{t-2}, RP}$	0.107	0.214	0.322	0.429
$\varepsilon_{SPF_{t-3}, RP}$	0.070	0.139	0.209	0.279
$\varepsilon_{SPF_{t-4}, RP}$	0.084	0.168	0.252	0.336

[a] See figure 4.1 for "valley" shipments.

may be explained by the fact that in periods of low shipments, shipping point prices are trending upward so the chain may be waiting an extra week to evaluate fully a price decline. It could also be argued that since shipping point prices are trending upward, the chain is expecting prices to continue to increase, therefore their response to rising prices requires less reaction time compared to a price decrease. The latter case implies that in times of low shipments, the chain will pass on a price increase faster compared to periods of high shipments.

Interpretation of equation (3.8) involves the sum row in table 4.4. That is, for a fixed rising and falling shipping point price change (e.g., the average), the calculation of equation (3.8) focuses on the sum of the parameter estimates (table 4.4) to trace the marginal impact of j on retail price changes over the transmission process. The inference is that the elasticities for a given shipping point price increase/decrease are not significantly different in terms of j.

Model II

The model used to determine response of the second retail series to rising and falling shipping point prices was expressed as

$$RP_{i,t} = \sum_{m=0}^{4} \delta_{1,i,m}(j*SPR_{i,t-m}) + \sum_{m=0}^{4} \delta_{2,i,m}(j*SPF_{i,t-m}) + e_{i,t} ,$$

where RP now refers to series two retail prices, and all other variable definitions are as before. A lag length of four was determined to be appropriate for both the rising (r) and falling (f) shipping point prices. A three-week moving average of the retail price

was used. As in the first model, GLS results were used to start the Shiller procedure.

Table 4.10 presents the Shiller estimates of Model II. It contains the coefficient estimates, standard errors, R^2, F-tests, and Durbin-Watson results. For time periods *t* and *t-1*, neither the rising nor falling coefficients were significant. On the other hand, the rising and falling coefficients from periods *t-2* to *t-4* were significant, indicating the chain carries out its significant price adjustments during these periods. This is not surprising since the correlation results from table 4.2 revealed that the chain is waiting longer in the transmission process to evaluate upstream price changes for this particular series.

The R^2 indicates thirty-three percent of variation in period-to-period retail price changes is explained by the independent variables. Once again, this is low but not unexpected since other factors are influencing the chain's pricing decisions. Nevertheless, the F-test for overall equation fit is significant at the .01 level. The value of 1.353 for the Durbin-Watson statistic lies in the inconclusive region at the .01 level for a no-intercept regression model.

The four week lag for both rising and falling shipping point prices leads to the conclusion that the chain used the same amount of time to adjust retail prices to rising and falling shipping point prices. The F-value for symmetry was 0.00254 versus the critical value of 3.92 leads to acceptance of the null hypothesis. This implies the aggregate impact of a positive shipping point price change is not significantly different from a negative shipping point price change. The null hypothesis of the pairwise comparisons was also accepted, due to the computed F-value of 0.00241 versus the

Table 4.10. Model II Results [a]

Independent Variables	
SPR_t	-0.00403 (0.00385)
SPR_{t-1}	0.00193 (0.00273)
SPR_{t-2}	0.01093** (0.00298)
SPR_{t-3}	0.01789** (0.00285)
SPR_{t-4}	0.01753** (0.00402)
SPF_t	-0.00405 (0.00354)
SPF_{t-1}	0.00145 (0.00242)
SPF_{t-2}	0.00918** (0.00271)
SPF_{t-3}	0.01486** (0.00255)
SPF_{t-4}	0.01865** (0.00360)
R^2	0.33
Equation F	5.420**
Symmetry F[b]	0.00254
Speed F[c]	0.00241
Durbin-Watson	1.353

[a] Standard errors are in parentheses. A double asterisk indicates significance at the .01 level.

[b] Distributed as F(1,108) under the null hypothesis.

[c] Distributed as F(5,108) under the null hypothesis.

critical value 2.29. The inference here is that there is no difference in the chain's pricing behavior with respect to rising versus falling shipping point prices.

Table 4.11 provides pairwise comparisons of the parameter estimates. From periods *t* to *t-3*, the coefficients of the rising shipping point prices were greater than the falling ones. Period *t-4* was the only interval in which the opposite was true. Although it appears that in aggregate the rising prices are being passed on through the retail level more so than the falling (sum row), there is not enough difference to be statistically significant. Also, since the average difference between the rising and falling parameters at each time period is only 0.00128, the null hypothesis that the speed of price adjustment is the same is also verified.

The elasticities evaluated at mean levels of *SPR*, *SPF*, and *RP* for different values of *j* are presented in table 4.12. Only the elasticities corresponding to significant parameter estimates are reported. The fact that increasing values of *j* imply

Table 4.11. Pairwise Comparisons of the Parameter Estimates - Model II

Time Period	*SPR*		*SPF*
t	-0.00403	>	-0.00405
t-1	0.00193	>	0.00145
t-2	0.01093	>	0.00918
t-3	0.01789	>	0.01486
t-4	0.01753	<	0.01865
Avg. Diff.	0.00128		
Sum	0.04425	>	0.04009

Table 4.12. Seasonal Elasticities of Retail Price With Respect To Shipping Point Prices (Mean Values) - Model II

	j			
Elasticity	1	2	3	4
$\varepsilon_{SPR_{t-2},\ RP}$	1.131	2.262	3.394	4.525
$\varepsilon_{SPR_{t-3},\ RP}$	1.738	3.476	5.214	6.951
$\varepsilon_{SPR_{t-4},\ RP}$	1.553	3.105	4.658	6.210
$\varepsilon_{SPF_{t-2},\ RP}$	0.993	1.986	2.978	3.971
$\varepsilon_{SPF_{t-3},\ RP}$	1.502	3.005	4.507	6.009
$\varepsilon_{SPF_{t-4},\ RP}$	1.721	3.443	5.164	6.885

the elasticities grow larger reveals that as more tomatoes enter the marketing system, the chain reacts by becoming more sensitive to upstream price changes. Since fresh tomatoes are perishable, the chain is likely concerned about the limited shelf-life, and therefore, is more sensitive toward adjusting their prices in order to accommodate the increased supply.

Period *t-3* was the interval of highest sensitivity for the rising prices. The most elastic period for the falling prices was *t-4*. These differing results are likely due to the chain being more concerned over temporary decreases in shipping point prices relative to increases. By waiting longer to evaluate upstream price decreases, the chain may be trying to avoid frequent retail price decreases, which may be more difficult to raise subsequently.

Tables 4.13 and 4.14 contain the elasticities corresponding to the beginning and end of the shipping seasons, respectively. For the season-beginning elasticities, peak response at the retail level occurred in period *t-2* for the rising prices and period *t-3* for the falling ones. When evaluated at mean levels, the associated highest responses were periods *t-3* and *t-4*, respectively. These differing results may be attributed to the chain's behavior at the beginning of the shipping season. Since there may still be a few other lingering sources of fresh tomatoes at the beginning of the Florida shipping season, the chain may choose to evaluate potential trends in the Florida market more rapidly since it will soon be the primary supply. The peak responses of the season-ending elasticities for both lagged rising and falling prices were identical to the findings evaluated at mean levels, implying that compared to the beginning of the shipping

Table 4.13. Seasonal Elasticities of Retail Price With Respect To Shipping Point Prices (Average Season-Beginning Values) - Model II

	j			
Elasticity	1	2	3	4
$\varepsilon_{SPR_{t-2},\ RP}$	0.150	0.300	0.450	0.601
$\varepsilon_{SPR_{t-3},\ RP}$	0.135	0.270	0.405	0.539
$\varepsilon_{SPR_{t-4},\ RP}$	0.090	0.180	0.270	0.360
$\varepsilon_{SPF_{t-2},\ RP}$	0.095	0.189	0.284	0.379
$\varepsilon_{SPF_{t-3},\ RP}$	0.136	0.271	0.407	0.542
$\varepsilon_{SPF_{t-4},\ RP}$	0.128	0.256	0.383	0.511

Table 4.14. Seasonal Elasticities of Retail Price With Respect To Shipping Point Prices (Average Season-Ending Values) - Model II

	j			
Elasticity	1	2	3	4
$\varepsilon_{SPR_{t-2},\ RP}$	24.181	48.363	72.544	96.725
$\varepsilon_{SPR_{t-3},\ RP}$	44.754	89.509	134.263	179.017
$\varepsilon_{SPR_{t-4},\ RP}$	42.314	84.627	126.941	169.254
$\varepsilon_{SPF_{t-2},\ RP}$	21.776	43.552	65.327	87.103
$\varepsilon_{SPF_{t-3},\ RP}$	38.898	77.795	116.693	155.590
$\varepsilon_{SPF_{t-4},\ RP}$	47.839	95.677	143.516	191.355

season, the chain prefers to wait longer to evaluate upstream price changes. This could be an indication the chain is beginning to analyze other sources of fresh tomatoes thus waiting longer to evaluate prices from the last few weeks of the Florida market shipments.

Table 4.15 presents the elasticities describing retail price response at a typical "peak" level of shipments. The observation used was that which occurred in the October 1994 to June 1995 shipping season. Because the retail price change corresponding to this period was negative, only the elasticities for the lagged falling prices are reported.

The highest response for the falling prices occurred in period *t-3*. This result is one period less than the highest response for the falling price elasticities evaluated at mean levels. This indicates that in a period of high shipments, the chain will pass on a

Table 4.15. Seasonal Elasticities of Retail Price With Respect To Shipping Point Prices (Prices at "Peak" Shipments)[a] - Model II

	j			
Elasticity	1	2	3	4
$\varepsilon_{SPF_{t-2}, RP}$	1.902	3.803	5.705	7.607
$\varepsilon_{SPF_{t-3}, RP}$	2.832	5.665	8.497	11.330
$\varepsilon_{SPF_{t-4}, RP}$	1.247	2.495	3.742	4.989

[a] See figure 4.1 for "peak" shipments.

price decrease faster likely in order to avoid retail level spoilage.

Table 4.16 presents the seasonal elasticities evaluated at a typical "valley" in the shipping season. The observation used for this analysis occurred in the October 1995 to June 1996 shipping season (figure 4.1). As in table 4.15, the retail price change at this point was negative, therefore only the elasticities of the lagged falling prices are reported. The highest retail level response occurred in period *t-4*, which is identical to the highest response evaluated at mean levels. This suggests that compared to a "peak" level of shipments, the chain's highest response to a decrease in upstream prices will be later in the transmission process.

The elasticities in table 4.15 are much larger than those in table 4.16. This implies that when shipments are large, the chain is much more sensitive to upstream price declines relative to periods of low shipments. The difference in peak response

Table 4.16. Seasonal Elasticities of Retail Price With Respect To Shipping Point Prices (Prices at "Valley" Shipments)[a] - Model II

	j			
Elasticity	1	2	3	4
$\varepsilon_{SPF_{t-2},\,RP}$	0.184	0.368	0.551	0.735
$\varepsilon_{SPF_{t-3},\,RP}$	0.297	0.595	0.892	1.190
$\varepsilon_{SPF_{t-4},\,RP}$	0.747	1.493	2.240	2.987

[a] See figure 4.1 for "valley" shipments.

between tables 4.15 and 4.16 may be attributed to the fact that in periods of low levels of shipments, shipping point prices are trending upward, therefore the chain may be waiting longer to evaluate a price decline.

Interpretation of equation (3.8) involves the sum row in table 4.11. That is, for a fixed rising and falling shipping point price change (e.g., the average), the calculation of equation (3.8) focuses on the sum of the parameter estimates (table 4.11) to trace the marginal impact of j on retail price changes over the transmission process. The inference is that the elasticities for a given shipping point price increase/decrease are not significantly different in terms of j.

Model III

The model used to determine response of the third retail series to rising and falling shipping point prices was expressed as

$$RP_{i,t} = \sum_{m=0}^{5} \delta_{1,i,m}(j*SPR_{i,t-m}) + \sum_{m=0}^{5} \delta_{2,i,m}(j*SPF_{i,t-m}) + e_{i,t} ,$$

where *RP* now refers to series three retail prices, and all other variable definitions are as before. A lag length of five was determined to be appropriate for both the rising (*r*) and falling (*f*) shipping point prices. A four-week moving average of the retail price was used. As in the other models, GLS results were used to initiate the Shiller procedure.

Table 4.17 presents the Shiller estimates of Model III. It contains the coefficient estimates, standard errors, R^2, F-tests, and Durbin-Watson results. The

Table 4.17. Model III Results [a]

Independent Variables	
SPR_t	0.00211 (0.00125)*
SPR_{t-1}	0.00551 (0.00081)**
SPR_{t-2}	0.00734 (0.00083)**
SPR_{t-3}	0.00748 (0.00082)**
SPR_{t-4}	0.00669 (0.00077)**
SPR_{t-5}	0.00573 (0.00124)**
SPF_t	0.00226 (0.00125)*
SPF_{t-1}	0.00514 (0.00082)**
SPF_{t-2}	0.00682 (0.00083)**
SPF_{t-3}	0.00739 (0.00082)**
SPF_{t-4}	0.00683 (0.00078)**
SPF_{t-5}	0.00520 (0.00120)**
R^2	0.55
Equation F	11.905**
Symmetry F[b]	0.04365
Speed F[c]	0.00793
Durbin-Watson	1.289

[a] Standard errors are in parentheses. A single asterisk indicates significance at the .10 level, double asterisks, the .01 level.

[b] Distributed as F(1,119) under the null hypothesis.

[c] Distributed as F(6,119) under the null hypothesis.

rising and falling coefficients were significant across all time periods, indicating for this particular series, significant price adjustments occur each week of the transmission process. This is not surprising since the correlation coefficients from table 4.2 were the highest with respect to this series.

The R^2 indicates fifty-five percent of variation in period-to-period retail price changes is explained by the independent variables. Similar to the other models, this low result is not surprising since other factors are influencing the chain's retail pricing decisions. However, the F-test for equation fit is significant at the .01 level. The value of 1.289 for the Durbin-Watson statistic is very near the lower bound critical value for a no-intercept regression at the .01 level.

The five week lag for both rising and falling shipping point prices leads to the conclusion that the chain used the same amount of time to adjust retail prices to rising and falling shipping point prices. The F-value for symmetry was 0.04365 versus the critical value of 3.92 which leads to acceptance of the null hypothesis. This indicates the total impact of a positive shipping point price change is not significantly different from a negative shipping point price change. For the pairwise comparisons within the same lag period, the F-value of 0.00793 versus a critical value of 2.18 leads to the inference that there is no difference in the chain's retail pricing behavior with respect to rising versus falling shipping point prices.

Table 4.18 contains pairwise comparisons of the parameter estimates. In periods *t* and *t-4*, the falling price coefficients were greater than the rising. In all other periods, the rising price coefficients were greater. The sum total of the rising price

Table 4.18. Pairwise Comparisons of the Parameter Estimates - Model III

Time Period	*SPR*		*SPF*
t	0.00211	<	0.00226
t-1	0.00551	>	0.00514
t-2	0.00734	>	0.00682
t-3	0.00748	>	0.00739
t-4	0.00669	<	0.00683
t-5	0.00573	>	0.00520
Avg. Diff.	0.00028		
Sum	0.03486	>	0.03364

coefficients was greater than the falling, which appears to imply that in the long run, rising shipping point prices are being passed through more so than falling shipping point prices. However, there is not enough difference to be statistically significant. Also, since the average difference between the rising and falling parameters at each time period is only 0.00028, the null hypothesis that the chain responds similarly to intra period rising and falling prices is supported.

The elasticities evaluated at mean levels of *SPR*, *SPF*, and *RP* for different values of *j* are presented in table 4.19. Since all the parameter estimates are significant, an elasticity for each period of the rising and falling prices is reported. As the value of *j* grows larger, the elasticities increase in magnitude. This implies that as more tomatoes enter the marketing system, the chain reacts by becoming more sensitive to upstream price changes. The chain is likely concerned about the limited shelf-life,

Table 4.19. Seasonal Elasticities of Retail Price With Respect To Shipping Point Prices (Mean Values) - Model III

	j			
Elasticity	1	2	3	4
$\varepsilon_{SPR_t, RP}$	0.340	0.681	1.021	1.361
$\varepsilon_{SPR_{t-1}, RP}$	0.867	1.733	2.600	3.467
$\varepsilon_{SPR_{t-2}, RP}$	1.112	2.224	3.337	4.449
$\varepsilon_{SPR_{t-3}, RP}$	1.077	2.154	3.231	4.309
$\varepsilon_{SPR_{t-4}, RP}$	0.898	1.797	2.695	3.593
$\varepsilon_{SPR_{t-5}, RP}$	0.702	1.403	2.105	2.806
$\varepsilon_{SPF_t, RP}$	0.343	0.686	1.029	1.372
$\varepsilon_{SPF_{t-1}, RP}$	0.758	1.515	2.273	3.031
$\varepsilon_{SPF_{t-2}, RP}$	0.966	1.931	2.897	3.862
$\varepsilon_{SPF_{t-3}, RP}$	0.985	1.971	2.956	3.942
$\varepsilon_{SPF_{t-4}, RP}$	0.842	1.684	2.526	3.368
$\varepsilon_{SPF_{t-5}, RP}$	0.579	1.158	1.738	2.317

and therefore, accommodates the increased supply of tomatoes by more aggressively adjusting their prices to quickly move the produce through the system.

Periods *t-2* and *t-3* were the intervals of highest sensitivity for both the rising and falling prices, but there are only minor differences between the periods. This suggests the chain is not practicing a clear pricing strategy with respect to evaluation of temporary increases or decreases in shipping point prices. The chain is likely stabilizing their prices in order to avoid frequent changes which can confuse consumers.

Tables 4.20 and 4.21 present the elasticities corresponding to the beginning and end of the shipping seasons, respectively. For the season-beginning elasticities, peak response at the retail level occurred in periods *t-1* and *t-2* for both the rising and falling prices. From table 4.19, the associated highest responses were periods *t-2* and *t-3*, respectively. Apparently, the chain is choosing to evaluate the Florida market more rapidly at the beginning of the shipping season, presumably in order to capitalize on any potential trends that may be developing since it will soon be the primary supply. The peak responses of the season-ending elasticities occurred in periods *t-3* and *t-4* for both the rising and falling prices. Compared to the beginning of the shipping season, the chain prefers to wait longer to evaluate upstream price changes at the end of the season. Since shipments from the Florida market will soon end, the chain is likely beginning to assemble price information from other sources, therefore the priority placed on reaction to the last few weeks of the Florida market is diminished and thus occurs later in the transmission process.

Table 4.20. Seasonal Elasticities of Retail Price With Respect To Shipping Point Prices (Average Season-Beginning Values) - Model III

	j			
Elasticity	1	2	3	4
$\varepsilon_{SPR_t, RP}$	0.279	0.558	0.837	1.116
$\varepsilon_{SPR_{t-1}, RP}$	0.591	1.183	1.774	2.365
$\varepsilon_{SPR_{t-2}, RP}$	0.531	1.062	1.593	2.123
$\varepsilon_{SPR_{t-3}, RP}$	0.351	0.703	1.054	1.406
$\varepsilon_{SPR_{t-4}, RP}$	0.228	0.456	0.684	0.912
$\varepsilon_{SPR_{t-5}, RP}$	0.122	0.243	0.365	0.486
$\varepsilon_{SPF_t, RP}$	0.446	0.893	1.339	1.785
$\varepsilon_{SPF_{t-1}, RP}$	0.760	1.520	2.280	3.039
$\varepsilon_{SPF_{t-2}, RP}$	0.628	1.256	1.884	2.512
$\varepsilon_{SPF_{t-3}, RP}$	0.335	0.670	1.006	1.341
$\varepsilon_{SPF_{t-4}, RP}$	0.218	0.435	0.653	0.870
$\varepsilon_{SPF_{t-5}, RP}$	0.115	0.229	0.344	0.459

Table 4.21. Seasonal Elasticities of Retail Price With Respect To Shipping Point Prices (Average Season-Ending Values) - Model III

	j			
Elasticity	1	2	3	4
$\varepsilon_{SPR_t, RP}$	0.545	1.089	1.634	2.179
$\varepsilon_{SPR_{t-1}, RP}$	1.654	3.309	4.963	6.617
$\varepsilon_{SPR_{t-2}, RP}$	2.719	5.438	8.157	10.876
$\varepsilon_{SPR_{t-3}, RP}$	3.666	7.333	11.000	14.665
$\varepsilon_{SPR_{t-4}, RP}$	3.666	7.332	11.000	14.664
$\varepsilon_{SPR_{t-5}, RP}$	3.078	6.156	9.235	12.313
$\varepsilon_{SPF_t, RP}$	0.605	1.210	1.816	2.421
$\varepsilon_{SPF_{t-1}, RP}$	1.586	3.171	4.757	6.342
$\varepsilon_{SPF_{t-2}, RP}$	2.589	5.178	7.768	10.357
$\varepsilon_{SPF_{t-3}, RP}$	3.639	7.278	10.917	14.556
$\varepsilon_{SPF_{t-4}, RP}$	3.623	7.246	10.869	14.492
$\varepsilon_{SPF_{t-5}, RP}$	2.693	5.385	8.078	10.770

Table 4.22 contains the elasticities describing retail price responses at a typical "peak" level of shipments. The observations used were those that occurred in the October 1989 to June 1990 and October 1991 to June 1992 shipping seasons, respectively (figure 4.1). The highest elasticity response for both the rising and falling prices clearly occurred in period *t-2*, as opposed to tables 4.19 - 4.21 where no individual period could be singled out as the highest response. This suggests that in periods of great supply, the chain will wait no longer than period *t-2* of the transmission process to make its most profound retail price adjustment.

Table 4.23 contains the seasonal elasticities evaluated at a typical "valley" in the shipping season. The observation used for this analysis occurred in the October 1989 to June 1990 shipping season (figure 4.1). The highest retail level response for the rising prices was shared by periods *t-2* and *t-3*. A more distinct result was found for the falling prices, where period *t-2* was clearly the peak retail response.

The elasticities in table 4.22 are much larger than those in table 4.23. This suggests that when shipments are very large, the chain is more sensitive to upstream price changes relative to periods of very low shipments. The limited shelf-life of tomatoes likely causes the chain to be more sensitive to upstream price changes in times of great supply, therefore, moving the produce quickly through the system becomes a top priority.

Interpretation of equation (3.8) involves the sum row in table 4.18. That is, for a fixed rising and falling shipping point price change (e.g., the average), the calculation of equation (3.8) focuses on the sum of the parameter estimates (table 4.18)

Table 4.22. Seasonal Elasticities of Retail Price With Respect To Shipping Point Prices (Average Prices at "Peak" Shipments)[a] - Model III

	j			
Elasticity	1	2	3	4
$\varepsilon_{SPR_t, RP}$	3.564	7.127	10.691	14.254
$\varepsilon_{SPR_{t-1}, RP}$	6.745	13.490	20.235	26.980
$\varepsilon_{SPR_{t-2}, RP}$	10.592	21.184	31.776	42.368
$\varepsilon_{SPR_{t-3}, RP}$	7.436	14.872	22.308	29.744
$\varepsilon_{SPR_{t-4}, RP}$	8.151	16.301	24.452	32.603
$\varepsilon_{SPR_{t-5}, RP}$	6.983	13.965	20.948	27.931
$\varepsilon_{SPF_t, RP}$	4.124	8.247	12.371	16.494
$\varepsilon_{SPF_{t-1}, RP}$	7.023	14.046	21.069	28.092
$\varepsilon_{SPF_{t-2}, RP}$	11.033	22.066	33.099	44.133
$\varepsilon_{SPF_{t-3}, RP}$	7.759	15.518	23.277	31.036
$\varepsilon_{SPF_{t-4}, RP}$	8.409	16.818	25.228	33.637
$\varepsilon_{SPF_{t-5}, RP}$	5.760	11.520	17.281	23.041

[a] See figure 4.1 for "peak" shipments.

Table 4.23. Seasonal Elasticities of Retail Price With Respect To Shipping Point Prices (Prices at "Valley" Shipments)[a] - Model III

	j			
Elasticity	1	2	3	4
$\varepsilon_{SPR_t, RP}$	0.067	0.135	0.202	0.270
$\varepsilon_{SPR_{t-1}, RP}$	0.177	0.353	0.530	0.707
$\varepsilon_{SPR_{t-2}, RP}$	0.188	0.376	0.564	0.752
$\varepsilon_{SPR_{t-3}, RP}$	0.191	0.383	0.574	0.766
$\varepsilon_{SPR_{t-4}, RP}$	0.146	0.292	0.439	0.585
$\varepsilon_{SPR_{t-5}, RP}$	0.102	0.204	0.305	0.407
$\varepsilon_{SPF_t, RP}$	0.029	0.058	0.087	0.116
$\varepsilon_{SPF_{t-1}, RP}$	0.043	0.086	0.129	0.172
$\varepsilon_{SPF_{t-2}, RP}$	0.057	0.115	0.172	0.229
$\varepsilon_{SPF_{t-3}, RP}$	0.024	0.049	0.073	0.097
$\varepsilon_{SPF_{t-4}, RP}$	0.022	0.045	0.067	0.090
$\varepsilon_{SPF_{t-5}, RP}$	0.017	0.034	0.051	0.068

[a] See figure 4.1 for "valley" shipments.

to trace the marginal impact of j on retail price changes over the transmission process. The inference is that the elasticities for a given shipping point price increase/decrease are not significantly different in terms of j.

CHAPTER V

SUMMARY AND CONCLUSIONS

Summary

The main purpose of this study was to develop and test an extension of an empirical description of price relationships between different levels in the market distribution channel. Specifically, this study focused on the vertical price linkages between the shipping point and retail levels in the fresh produce industry. The goal was to develop a more flexible empirical model of shipping point to retail price transmission which could be used to test for price symmetry. Symmetry has several components, so the goal was separated into several objectives, or to:

(1) assess whether the length of the adjustment time of retail prices is the same for both rising and falling shipping point prices,

(2) assess whether the sum of the price transmissions from rising shipping point prices is equal to the sum of the price transmissions from falling prices,

(3) assess whether on a period-to-period basis the coefficients of the rising prices are the same as those for falling prices,

(4) assess price responsiveness at the retail level with respect to rising and falling shipping point prices at different points in the shipping cycle, and

(5) assess how price responsiveness at the retail level with respect to rising and falling shipping point prices reacts to seasonal fluctuations in the shipping cycle.

Houck's procedure for disaggregating price changes into positive and negative components was extended to include seasonality and flexible distributed lags for transmitting price increases and decreases. A distributed lag model, augmented to examine symmetry of price response and to include Shiller lags and seasonality, was introduced into the Houck procedure to fulfill the objectives of this study for three long-running fresh tomato series. An iterative GLS procedure was developed to test the model. Restricted and unrestricted forms of the model were constructed. Model assumptions are compatible with fresh produce, so tomatoes were selected as the commodity to test the model. Retail level scan data provided three alternative price series. Shipping point prices were for mature green and vine-ripe tomatoes. Estimated coefficients, F-tests, and elasticities of price responses were used to provide inferences for each of the three models.

GLS results led to inferences about the first objective prior to implementation of the Shiller procedure. For the first and third models, the lag length for the rising and falling shipping point prices was five, respectively. The lag length for both the rising and falling prices in the second model was four. The length of the adjustment time appears to be the same with respect to rising versus falling shipping point prices and is four or five weeks.

The second objective was assessed by using an F-test which compared the sum of squared errors with and without the restriction that the sums of the rising and falling price coefficients were the same. Although the sum of the rising price coefficients was greater than the falling in each model, there was not enough difference to be statistically significant. Therefore, the null hypothesis of this test was accepted in each model, inferring the aggregate (long run) impact of a positive shipping point price change is not significantly different from a negative shipping point price change.

An F-test using the restricted and unrestricted sum of squared errors was also used to draw inferences about the third objective. The restriction here was that the rising and falling price coefficients in each period were the same. The null hypothesis of this test was accepted in all three models, suggesting there is no difference in the chain's retail pricing behavior with respect to rising and falling prices within the same time period.

Elasticities of period-to-period retail price changes with respect to significant shipping point price changes were used to assess the fourth objective. The issue here is whether retail price transmissions changed with respect to various points in the yearly Florida shipping cycle. Four types of average prices were used to generate elasticities. These were (1) averages over the entire shipping point and retail series, averages across the years at the (2) beginning and (3) end of each shipping season, and (4) typical "peak" and "valley" prices in the shipping seasons.

The elasticities evaluated at mean values for the entire time period for which data were available indicated the chain's highest responses to rising and falling shipping point prices were between periods *t-2* and *t-4*. For the first retail series, the highest

response to rising and falling prices occurred in period *t-2*. The highest response for the second retail series was period *t-3* for the rising prices and *t-4* for the falling, respectively. With respect to this retail tomato, the chain may be more concerned over temporary shipping point price decreases compared to increases, since its highest response to falling prices is one period later than the rising. For the third retail series, the chain was almost equally responsive in periods *t-2* and *t-3* for both the rising and falling prices, showing the lack of a clear period-specific pricing strategy.

Elasticity results concerning the beginning and end of the shipping season were similar in that they showed a distinct difference in the chain's peak response to rising and falling shipping point price changes. In each model, results showed the chain's highest response to upstream price changes at the beginning of the Florida shipping season occurred faster in the transmission process compared to the end of the season. This suggests that at the beginning of the season, the chain is likely evaluating potential trends in the Florida market faster since it will soon be the primary supply. On the other hand, at the end of the season, the chain is likely beginning to assemble price information from other sources thus the last few weeks of the Florida market shipments are given less emphasis.

The results of the three models were also in agreement concerning retail price responses with respect to "peaks" and "valleys" of shipments across the seasons. Elasticities evaluated at "peak" levels of shipments were much larger in magnitude compared to those evaluated at typical "valleys". This indicates when shipments are very large, the chain is much more sensitive to upstream price changes relative to periods of

very low shipments. Table 5.1 summarizes the highest elasticity responses at the retail level over different points in the Florida shipping cycle.

The fifth objective was assessed by evaluating the elasticities of period-to-period retail price changes with respect to rising and falling shipping point prices over different values of the *j* vector. Results from each model suggest that as the level of shipments increases, both the rising and falling price elasticities increase. An interpretation is that as more tomatoes enter the marketing system, the chain reacts by becoming more sensitive to upstream price changes. Since fresh tomatoes are perishable, the chain is concerned about the limited shelf life and is, therefore, more sensitive toward adjusting their prices to accommodate the increased supply.

Conclusions

Implications of the Empirical Results

The lag lengths for the rising and falling prices in each model suggested the chain used the same amount of total adjustment time to respond to rising and falling upstream

Table 5.1. Highest Retail Level Elasticity Response At Different Points in the Florida Shipping Cycle

	Highest Elasticity Response (Time Period)									
	Mean Levels		**Beginning**		**End**		**"Peaks"**		**"Valleys"**	
	SPR_{t-n}	SPF_{t-n}	SPR_{t-n}	SPF_{t-n}	SPR_{t-n}	SPF_{t-n}	SPR_{t-n}	SPF_{t-n}	SPR_{t-n}	SPF_{t-n}
Model										
I	*t-2*	*t-2*	*t-1*	*t-1*	*t-3*	*t-3*	*t-2*	*t-2*	*t-1*	*t-2*
II	*t-3*	*t-4*	*t-2*	*t-3*	*t-3*	*t-4*	NA	*t-3*	NA	*t-4*
III	*t-2* and *t-3*	*t-2* and *t-3*	*t-1* and *t-2*	*t-2* and *t-3*	*t-3* and *t-4*	*t-3* and *t-4*	*t-2*	*t-2*	*t-2* and *t-3*	*t-2*

tomato prices. This implies the chain had a specific pricing strategy which was to make its total price adjustments within an allotted amount of time, likely due to the perishable nature of fresh tomatoes. A similar result was found in Mohamed, et al. However, Powers found that retail markets may have different lag periods for rising compared to falling upstream lettuce prices.

The fact that the long run effects of upstream price increases on retail price changes were similar to decreases implies the chain is not using its market power abusively. Heien and Pick, et al. also found that in the long run, retail prices responded symmetrically to rising and falling upstream price changes. These inferences were contrasted by the findings of Ward, Hansmire and Willet, Powers, and Mohamed, et al. Reasons for the disagreement are likely due to the different data aggregation methods and methodologies employed by the researchers. Both Ward and Hansmire and Willet used monthly data, which may inhibit understanding of the true price linkage relationship (chapter 2). Although Powers and Mohamed, et al. used weekly data, the retail prices used were constructed as averages across several different retail chains, thus resulting in a loss of detail. Also, neither Hansmire and Willet, Powers, nor Mohamed, et al. used a polynomial distributed lag structure, the result being they may have neglected an important piece of a priori information.

The result that the retailer responds similarly to intra period rising and falling upstream prices indicates they are hesitant toward frequently adjusting their prices in response to the highly seasonal nature of Florida tomato production. An explanation is that frequent retail price changes might confuse consumers (Powers) thereby potentially

disrupting the flow of produce from the retailer, which may lead to spoilage. This lends support to a retail pricing strategy based on recent history, which was applied in this study. Mohamed, et al. also found intra period retail response to rising and falling upstream price changes to be identical for most of the fresh produce investigated in their study.

The results of the elasticities evaluated at various points in the Florida shipping cycle indicate market information from upstream sources readily influences retail level price responsiveness. For example, changes in the chain's peak response to rising and falling shipping point prices occur as it switches to and from reliance on the Florida market for its fresh tomatoes. Also, drastic changes in supply at the shipping point level are reflected at the retail level, as noted by the differences in elasticities at the "peaks" and "valleys" of the shipping seasons.

All the inferences from the results of this study point toward efficiency in price linkages for the shipping point to retail distribution channel for fresh tomatoes. Efficient price linkages infer the price information in the distribution channel is being fully used to affect change by reallocating resources between what is produced at the shipping point level and what is consumed at the retail level.

The price linkage efficiency found in this study is likely due to the biological nature of fresh tomatoes and how retailers in the distribution channel have adjusted to accommodate those demands. The fact that tomatoes have a limited shelf-life ensures retailers will make timely changes in their pricing strategies to ensure the minimization of loss. Also, to gain more control over the biological demands, most retailers can purchase

fresh produce directly from shipping point sources. This practice can facilitate efficient price adjustment by eliminating intermediate channel participants who may provide barriers to smooth transition of information through the distribution channel.

Ward's contention that retailers may be reluctant to pass on price increases for perishable commodities is not supported here. Results from this study show that retailers are just as likely to pass on price increases as they are decreases. This may be explained by the fact that tomatoes are typically considered staples, therefore their demand is relatively more inelastic compared to other fresh vegetables (How). Consequently, retailers may not be reluctant to pass on small price increases since item movement is likely to remain relatively stable.

The results of this study also support the contention of Holloway that competitive conditions dominate the retail food industry. However, as Binkley and Connor (1996) warn, supermarket retail pricing strategies can vary over different types of goods.

Implications of the Methodology and Procedures

The extension of the traditional methodology developed in this study offers several advantages over previous studies. First, except for Griffith and Piggott, no other study has examined seasonality within this framework. This is unfortunate, since many agricultural products are seasonal in production. Also, consumers are often aware of the quality of products entering the supermarket and thus have varying consumption habits throughout the year (Hermann, et al.). Consequently, the inferences from studies of price linkages that did not consider seasonal variation in the independent variables may be incorrect.

Although they considered seasonality, Griffith and Piggott used the traditional dummy variable approach (discussed in chapter 2), which can consume degrees-of-freedom. An alternative approach was pioneered by Lambregts and Capps and Hermann, et al. Although they provided a potential remedy for the degrees-of-freedom problem when examining seasonal effects on one independent variable, their approach did not consider the incorporation of lagged values of the independent variables. Had they considered this option, their approach would have also resulted in substantial losses of degrees-of-freedom.

The methods for measuring seasonal effects developed in this study are an improvement over the other studies since seasonal inferences from lagged values of the independent variables can be attained without severe losses in degrees-of-freedom. There is no need to increase the number of independent variables to assess seasonality. Also, the elements of the j vector are not required to follow a specific pattern, thus enabling the seasonal effects to randomly vary. Further, this approach could be easily extended to accommodate other exogenous influences such as government programs and international trade.

Second, no other study has considered applying Shiller lags within the traditional methodology. Previous studies, which applied the Almon method to fit distributed lags, were faced with the troublesome decision of choosing the degree of the polynomial. With the Shiller procedure, this decision is replaced by a set of parameter restrictions that are stochastic (called smoothness priors). The implication is that the parameter means, instead of the parameters, are forced to lie on a given polynomial. The parameters themselves are

allowed to vary smoothly around the polynomial. Hence, the problematic decision of choosing the polynomial degree is relaxed, and its statistical consequences mitigated (chapter 2). Other advantages of smoothness priors are that they are thought to be better representations of prior information compared to the Almon method and that they imply the lagged seasonal effects in an econometric model will vary smoothly over time. The latter point may result in an increase in the efficiency of the estimated parameters in the presence of plentiful data or steady retail demand throughout the observation period.

Third, the use of weekly observations in this study, and especially store-level scanner data, are improvements over previous studies. Other researchers have used weekly data (e.g., Pick, et al., Powers, and Mohamed, et al.), however the retail data used were averaged over a metropolitan area(s), which may have resulted in masking the true price signals taking place within the distribution channel. Except for these studies, most other applications have used monthly data which match neither the time intervals used by channel participants nor consumer's planning horizons.

The additions introduced in this study to extend the current methodology of assessing market efficiency via price linkages were oriented toward providing an empirical model that is more reflective of the true environment in which market information is processed. Such a model is well suited for the changing conditions facing the fresh produce retail sector today and is easily adaptable to other products and regions. The movement toward a global economy (e.g., GATT and NAFTA) and the changing domestic environment (e.g., proliferation of warehouse stores, food services, and restaurant industries) are forcing retail supermarkets to become more competitive in terms

of their retail pricing behaviors and sources of products. Empirical methods for assessing a chain's competitive edge are, therefore, paramount and of potentially great use for both public policy and private interests.

Limitations

Initially, it would seem that forcing the parameters of the rising and falling price coefficients to both follow a similar predetermined pattern may bias the aggregate symmetry and intra period coefficient tests toward acceptance of the null hypotheses. This may be a convincing argument if the price coefficients were forced to lie strictly on a polynomial. However, with smoothness priors, the parameters are allowed to vary freely, as long as their means lie on the polynomial. Consequently, this additional wrinkle should give the parameters more flexibility thus mitigating any potential bias.

Two, other limitations are this study included only one metropolitan area and one commodity. However, this methodology could be easily applied to any area or commodity. Further, regional differences are likely to occur thus aggregating regions may mask the true price linkage relationships.

Finally, all three empirical models exhibited R-squares comparable to previous studies, which were quite low. This suggests there are other factors involved in the chain's retail pricing decisions. The problem that remains is how, if possible, to quantify and specify these factors so that they can be merged into this new methodology to help improve understanding of distribution channel price linkages.

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