AN ABSTRACT OF THE THESIS OF

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Title: Assessment of Alternative Raw Product Valuation Methodology With Respect To Cooperatives Single Pool Returns

Abstract approved: James C. Cornelius

The market for Oregon's processing vegetables has undergone extensive structural changes in recent years. The role of the cash market between grower and processor has declined in importance, as proprietary processors have relocated outside the Willamette Valley, or been forced out of business entirely. This places increased pressure on producer-owned cooperative processors to synthesize the forces of supply and demand for the raw product.

Synthesizing raw product prices in a vertically integrated structure creates the possibility of inefficient price signals. Prices set too high or too low at the raw product level may lead to misallocated contracted acreage and inappropriate production levels in relation to finished product market conditions. Furthermore, raw product price is used as a basis for calculating payments to growers under the single pool accounting framework used

by many cooperatives. In a single pool, all commodities are included together by the cooperative in a single account; revenues from sale of all the processed products are added together and total processing costs are subtracted to arrive at the pool's net revenue. The fractional shares of net revenues payable to individual growers are then based upon the cooperative's estimate of per unit raw product values. Thus, raw product value estimates that are too low or too high will lead to misallocation of returns to individual members. The objective of the present research is to develop alternative raw product valuation procedures, and to assess the performance of these procedures in allocating member returns in single-pool cooperative. A raw product's value is taken to be the forecasted net return of processing and selling that product.

Four alternative forecasters were developed for two commodities, snap beans and sweet corn: (1) econometric, (2) exponential smoothing, (3) a three-year moving average, and (4) a composite forecaster composed of the three previous procedures. These four methods, along with the valuation method developed by cooperative management, were analyzed over a ten-year forecast horizon.

Descriptive statistics including mean square error and mean absolute percentage error revealed that the three-year moving average and exponential smoothing methods were the most effective in forecasting per ton net

returns. When used to set "economic values" of raw products, these methods also were the most effective in equating expected member pool payments with expected net returns. However, the cooperative's present method of establishing "economic values" for raw products produced the smallest variance in the difference between pool payments and net returns.

Assessment of Alternative Raw Product Valuation Methodology With Respect to Cooperatives Single Pool Returns

by

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A THESIS

presented to

Oregon State University

in partial fulfillment of
the requirements for the
degree of

Master of Science

Completed September 16, 1987

Commencement June 1988

APPROVED:

Associate Professor of Agricultural and Resource Economics in charge of major

Head, Agricultural and Resource Economics

Dean of Graduate School

Date thesis presented September 16, 1987

Typed by Dodi Reesman for Ron R. Meyersick

ACKNOWLEDGMENTS

Special gratitude and appreciation is expressed to Dr. James Cornelius for making this research project possible. Dr. Cornelius must be thanked specifically for many things. Above all, thanks must be expressed for Dr. Cornelius' generosity with time and never-ending patience, also for the ability to keep the essentials of this research project in perspective and finally the unlimited discussions of anadromous creatures and birds of flight to ease times of anxiety during critical stages of this project.

A special thank you to Dr. Steven Buccola for many useful suggestions. Dr. Buccola's willingness to help and sense of direction gave this research essential guidance in many critical areas. Without guidance from Dr. Buccola this paper may never have been completed.

A very special thanks to my parents for their endless support. The always present encouragement they have given me, in large part, has been responsible for an excellent education.

A thank you is also extended to Dodi Reesman for her sense of humor and valuable help in typing this paper as time ran short.

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CHAPTER I

INTRODUCTION

Situation

The market for Oregon's Willamette Valley processing vegetables has undergone extensive structural changes in recent years. The role of the cash market between grower and processor has declined in importance as proprietary processors have relocated outside the Willamette Valley or been forced out of business entirely. Since cash market prices of raw products traditionally have been used as part of the formula for determining members' shares of pool net returns, cooperatives are under increased pressure to find alternative ways of establishing raw market values.

Problem

There are several interrelated market problems arising from the restructuring of the Willamette Valley processed vegetable industry. Financial and operating records obtained from a representative agricultural processing and marketing cooperative provide the basis for illustrating the nature of the raw product pricing dilemma. The con-

fidential nature of this information precludes the disclosure of certain sensitive financial data, and the anonymity of the firm is maintained throughout this thesis. The cooperative uses raw product "price" as a basis for payments to grower-members. As proprietary private processors have relocated outside the Willamette Valley, the number of independent market transactions between grower and the buyer of raw product has been reduced. Thus, signals other than competitive market prices are now relied on to generate estimates of raw product values.

Each year before contracting acreage, cooperative management forecasts raw product values. These values are then relied upon by the cooperative in determining the number of acres to contract out. Grower-members also rely on these estimated values for production decisions.

Raw product values which are simulated within a vertically integrated structure such as a processing cooperative create the possibility of inefficient prices. Many cooperative vegetable processors operate on a pool basis, in which net revenues from all processed products are pooled together. The fractional shares of net revenue payable to individual growers are then based on the per-unit raw product values of each commodity delivered to the cooperative (Buccola and Subaei, 1985). Thus, inefficient raw product values will induce misallocation of payments

back to growers. An economic value[1/] for an individual commodity which is too high or too low will result in a subsidy or tax, respectively, to the grower of that commodity in a single pool, assuming the finished products are sold at competitive equilibrium prices.

This problem is further complicated by the fact that the cooperative relies upon the estimated price for obtaining raw product. Assuming a positive production response to raw product values, estimated prices set either too high or too low will result in inappropriate supply levels relative to the true but unobservable equilibrium in the processed wholesale market. With raw product values set above the equilibrium price, an excess production response from growers will occur. Faced with increasing competition in the finished product market from other regions in the U.S., Willamette Valley growers may find themselves with increased production and excess supplies but a smaller share of the market due to the artificially high raw product price. Similarly, a raw product price set to low might divert acreage from a desired vegetable crop. This may produce lower returns to the pool of revenues, relative to those which could have been

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1/ Economic value refers to the estimated value of a raw product as determined by cooperative management.

obtained if the increased demand in the finished product market was accurately reflected in the raw product price.

Raw product pricing in a vertically integrated structure can create a misallocation of resources at the firm level (Tomek and Robinson, 1982). Potential solutions to this valuation problem include the development of alternative pricing procedures at the raw product level.

Examination of time series data reveals that the raw product values simulated by the cooperative for selected vegetables have varied, on average, from the ex post calculated values based on finished product prices less relevant processing costs. While some variation in estimated versus actual value is expected, a long-term average difference between the two implies per-ton pool returns are distorted.

The cooperative is currently relying upon a relative simple estimation procedure stipulated by its by-laws to generate raw product prices. Other forecasting methods have been developed and could be used to augment the existing procedures.

Objectives

The overall objective of this research is to explore the performance of alternative raw product valuation procedures for a vertically integrated vegetable processing and marketing cooperative. This will be accomplished in

two steps. First, alternative raw product forecasting techniques will be developed and evaluated. Four such alternatives will be utilized to forecast raw product values. Second, these methods, along with the method currently employed by the cooperative, will be used to simulate single pool returns. This will allow comparisons of the different forecasting techniques in terms of the equity of members' associated pool payments.

Procedures

An econometric model, exponential smoothing model, and a three year moving average model will be used to forecast values for raw product. The econometric model will be estimated using ordinary least squares regression incorporating relevant supply and demand variables. These methods then will be used collectively to form a composite fourth forecast for raw product values. Each alternative forecasting technique can be used to calculate simulated single pool returns along with the methodology now employed by the cooperative. These four simulated pool returns, along with the valuation procedure used by the cooperative, will then be compared to the actual net returns to assess the accuracy and suitability of alternative methods.

Limitations

The cooperative upon which this research is based handles nine principal fruit and vegetable products. Currently these products are all accounted for within a single pool framework.[2/] This research utilizes the same pool calculation method for establishing pool returns as does cooperative management. That is, payments to grower-members are calculated from a single pool of revenues. However, this paper only includes two commodities, while the cooperative handles nine separate commodities within a single pool. In this sense, the pool results developed in this paper are simulated and not directly representative of the nine-commodity single pool operated by cooperative management.

Thesis Organization

Chapter II describes relevant market mechanisms upon which this research is based, and the rationale for forecasting raw product values. Previous research in this area is cited and the conceptual framework for the alternative valuation procedures is discussed.

The accounting procedure used by cooperative management is given in Chapter III. Following the development of the time setting for raw product forecasts, the pool-

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2/ Discussed in Chapter II, page 9.

year econometric models are given in detail. The chapter-concludes with a discussion of the methodology used for the calculation of single-pool payments.

In Chapter IV the model specification criterion will be outlined along with goodness-of-fit criteria to be used in evaluation of the alternative forecasting techniques. Results of all models and subsequent pool payments are then presented and evaluated.

Results are summarized and limitations associated with the research are discussed in Chapter V. The chapter concludes with suggestions for further research.

Appendix A contains estimation results for the econometric models. Appendix B gives the results for the pool-year calculations and Appendix C lists the data used to estimate the econometric models.

CHAPTER II

CONCEPTUAL MODEL

> "A cooperative is a private decision-making and risk bearing organization whose equity is held by patrons. Its limits are its physical facilities and its perceived market potentials. The cooperative is a joint vertical expansion, and an integral part of each members operations. Its objectives are to maximize the welfare of the members from their own decision management" (Garoyan, 1983).

In an effort to maximize the welfare of grower-members, it is essential that cooperative management take into account prices in both the raw and finished product markets. This chapter presents a discussion of market pools and grower-member payments based upon single-pool framework. The relevant market mechanisms are given, with particular emphasis on the raw product market. An econometric model will be specified along with a description of other alternatives to the current raw product valuation forecasting method used by cooperative management. A review of literature is included noting previous research where applicable.

Market Pools

Agricultural processing cooperatives such as Willamette Valley vegetable processors, which handle a variety of commodities, must establish a method for al-

location of net revenues to grower-members.

> "Most agricultural processing and marketing cooperatives return net revenues to members on a pooling basis. Pooling involves combing the sales revenue, less processing costs of a class of products and allocating these net revenues among members according to a prearranged formula. The alternative to pooling is to segregate each members delivers until final sale and to compensate the members exclusively on the basis of the sale of such products. This usually is impractical in large, highly mechanized processing and handling systems" (Buccola and Subaei, 1983).

There is a wide range of pool structure possibilities. Subaei (1984) noted that the number of possible pooling rules is equal to the number of all possible combinations of feasible pool breadths and share valuation methods. Extensive research was conducted by Subaei to determine an optimal pool choice among cooperative members. Selection criteria used for pool choice were the risk preference of cooperative members as well as the schemes used to weight individual choices. The group optimal choice usually was to operate separate vegetable pools and to value raw products on a farm price basis.

On one extreme, a pool may be operated for each individual commodity handled. The other extreme would be to group all commodities handled into a single pool.[1/]

1/ In a single pool, all commodities are included together by the cooperative in a single account, and revenues from the sale of all these processed products are added together from which is deducted the total processing costs to arrive at the pools net revenue (Subaei, 1984).

Several other possibilities fall in between these two extremes. Frequently, a single pool is operated due to the commingling of products such as mixed fruits and vegetables. In operating this single pool, the board of directors assigns an established or economic dollar value per-raw-unit in March of each year for each different product it handles. The economic value is a forecasted price upon which growers may base resource allocation decisions for planting specific vegetable crops. The economic value paid for raw products would ordinarily be dependent on prices paid by private processors for the same commodities in the region where the cooperative operates (Subaei, 1984). With the disappearance of private processors in Oregon, this is becoming more difficult.

Member Payment Calculations

"Pooling involves the consideration of three practices: (1) The mingling of products of individual producers into a collective lot; (2) pooling the expenses of operations and allocating them against products handled; and (3) prorating sales among producers contributions to the pool" (Roy, 1976). This last consideration is often seen as the most important among grower-members.

"Cooperatives are obligated to distribute among members any excess of final product sales revenues over

operating costs" (Buccola and Subaei, 1985). Under this obligation it is necessary to find a method of determining the fractional share of net revenue payable to each member-grower. Raw product economic values for all commodities are the basis for calculating this member compensation in a two step procedure.

First, the sales revenue for all products are pooled and all costs of processing, handling, and marketing are deducted to obtain the single pool net revenue $\Sigma A_{ij}Y_{ij}R_j$. The next step in the payment calculation is to express total pool net revenue as a percentage of the pool's raw product valuation. This percentage, R, shows by what percentage a pool net revenue is over or under its total raw product value, and what the payment to any raw product will be relative to its raw value:

$$R = \frac{\sum_i \sum_j A_{ij}Y_{ij}R_j}{\sum_i \sum_j A_{ij}Y_{ij}r_j} \cdot 100. \tag{2.1}$$

where:

A_{ij} = the $i^{\underline{th}}$ grower's acreage of the $j^{\underline{th}}$ product;

Y_{ij} = the $j^{\underline{th}}$ products yield realized by the $i^{\underline{th}}$ grower;

R_j = the per-unit revenue of j minus its per-unit cost;

r_j = the per-unit dollar valuation assigned by the cooperative.

Next, this ratio is multiplied by the raw value of raw prodct delivered by each member to obtain the amount of net revenue payable to that member.

$$(2.2) \quad \text{Member's Payment} = \frac{\sum_i \sum_j A_{ij}Y_{ij}R_j}{\sum_i \sum_j A_{ij}Y_{ij}r_j} \quad A_{ij}Y_{ij}r_j$$

Given current business practices in Oregon, all accounts payable to growers are met with a single-pool of revenues from all commodities combined. Raw product values are the basis for this grower compensation as shown in equation (2.2). Forecasts of this raw product value which do not accurately reflect finished market supply and demand conditions will lead to serious implications regarding grower equity and resource allocation decisions (Knober and Baumer, 1983). If raw product values are artificially high or low some members are taxed and others subsidized. It is not reasonable to assume that forecasted raw product values or "expected net returns" by individual commodity should equate to "actual net returns" every year. One equity criteria many would regard as sensible, however, is that over a reasonable length of run all growers of all commodities should receive approximately what their product's earned at the wholesale level less all costs of processing and selling. If member payments are not approximately equated to wholesale net returns over time, then the cooperative's payments back to

growers are said to be biased. The cooperative under study is currently faced with the problem of bias, to growers of raw products this is a point of major concern. "To resolve this problem but primarily to reassess payment polices in general, the cooperative is considering altering the basis for determining raw product value" (Buccola and Subaei, 1985).

The intent of this research is not to assess alternative pooling rules; this has been accomplished by Subaei. Rather, the objective here is to assess the effects of alternative raw product valuation techniques on pool returns.

Price Determination

Within the Willamette Valley, vertical integration has changed the structure of vegetable marketing and processing. Vertical integration occurs when successive stages of marketing or of production and marketing are linked together. The usual meaning is that of non-price linkage through direct ownership or by contract. That is, successive stages of the marketing chain are tied together in some formal way other than by price (Tomek and Robinson, 1982). Vertical integration may occur for a variety of reasons; the pursuit of lower marketing costs, reduction of price or procurement risks, or as in the case of

vegetable processing cooperatives, the lack of a viable marketing alternative.

Raw Product Market

Vegetable processing cooperatives producer members are in a vertically integrated position where raw products are linked to the final market by means other than price. Methods other than market transactions are required to establish "price" at the farm gate. In a purely competitive market, average market prices will approximate efficient equilibrium prices. However, the Willamette Valley vegetable industry is not perfectly competitive, due to imperfect knowledge, limited number of buyers and fixed resources. Without accurate information about current economic conditions actual transactions at the raw product level may deviate from equilibrium levels in the finished product market. This in turn will have serious implications concerning resource allocation decisions, and equity among grower members from the final pool of net revenues.

At present, cooperative bylaws establish the procedure for "pricing" of vegetables at the raw product level. The current method draws upon market price quotations from Midwestern and Eastern markets along with information sharing among processors, and the judgment of cooperative management. In a given region, each year before contracting acreage, processors determine a tentative raw product

value based on the average of last years prices paid by processors for the raw product. In other words last year's price becomes the naive forecast of this years price. This is essentially a one-period lag forecasting method (Wiese, 1985).

Cooperatives realize that this method of establishing raw product values may result in misallocated contracted acreage, and inappropriate production levels given current market supply-demand conditions in the processed market.

Cooperative vegetable processors are now in a vertically integrated position. Without market signals to set price at raw product levels, strong possibilities exist for these transactions at the farm gate to deviate from the retail equilibrium price. With raw product prices set arbitrarily high or low, grower-members will react accordingly; leaving the cooperative with inappropriate production levels and subsequently in disequilibrium with the finished product market.

As raw product "price" is the basis for payment to cooperative grower-members, a key objective of this research is to access the current method used to establish this value in relation to possible alternative procedures.

Processed Vegetable Market

In contrast to the raw product market is the wholesale market where Willamette Valley processors sell

finished goods in a competitive setting. "The market for food processors is defined by geographical region. Pacific Northwest processors appear to be at a competitive disadvantage relative to the Midwest or Eastern processors due to transportation costs into Eastern population centers. Midwestern processors on the other hand, where there is a large concentration of private processors, may penetrate Eastern and Western markets by virtue of their production capability and location" (Wiese, 1985). Thus, raw product values which are ultimately passed on to the final product must accurately reflect current supply and demand conditions if the processing cooperative is to compete effectively in the processed vegetable market.

Forecasting Raw Product Prices

Several procedures are available to forecast prices of processed vegetables. Two such studies are examined in light of their applicability to the research at hand.

Kuznets (1981) forecasted free on board (fob) prices of five processed tomato products: whole tomatoes, paste, puree, juice, and ketchup. The forecasting equations were conceived as "hybrid reduced forms at the wholesale level derived from demand functions for tomato products at the consumer level". The model was specified as follows.

$$(2.3) \quad P_i = \alpha_{i0} = \beta_{i1}Q_i + \beta_{i2}I + \beta_{i3}P^S + \beta_{i4}B + e$$

P_i = a national average f.o.b. price of a given product, in dollars per case, deflated by the CPI;

Q_i = pack plus carry in inventory in thousands of actual cases;

I = disposable personal income, in billions of dollars, deflated by the CPI;

P^S = the CPI which served as the price of a substitute;

B = a binary variable;

e = an error term.

Several alternative quantity variables were tested at the state and national level. Since substantial quantities of tomato products were produced outside of California during the time period of investigation (1960-1980), national quantity variables were used. The determinants of demand were disposable personal income, the consumer price index (which served as the price of substitutes), and a binary "dummy" variable to permit treatment of rapidly rising prices beginning in 1973. A sample of the estimation results obtained using ordinary least squares is presented in Table 2.1.

Table 2.1. Estimation Results: Selected Tomato Products.[a/]

Product	Const.	Q	I	P^S	B	DW	
C. Tomato	-8.3319	-.0783	1.8836	.0021	.9839	.998	1.69
	(2.977)	(.019)	(.692)	(.004)	(.129)		
T. Paste	-8.7420	-.1054	1.8380	.0727	2.9655	.976	1.15
	(7.462)	(.112)	(1.387)	(.013)	(.670)		
T. Juice	-2.9720	-.1258	1.2158	.0004	1.4180	.984	1.70
	(1.514)	(.040)	(.346)	(.005)	(.207)		

a/ Numbers in parentheses are the standard errors of the coefficients.

Source: Kuznets, 1982.

Criteria such as R^2, coefficient signs consistent with theory, and coefficient significant levels were used in the selection of appropriate models.

The forecasting equations exhibited signs consistent with theory in that the quantity coefficients were negative, income coefficients were positive, and the price of the substitute coefficients positive. All coefficients were significant at the .05 level, and the R^2 of each equation was .95 or higher. One observation in each price series was not used in estimating the coefficients, and subsequently used as a test of predictive power. An equation was considered useful if its forecast of the next period's price fell within the calculated 95 percent prediction interval. Half of the equations fell within their respective prediction interval.

Kuznet's results are encouraging. The explanatory variables all exhibit signs which are consistent with economic theory. All coefficients were significant at the .05 level, and the explanatory power of the equations is quite good.

From these results it appears possible to forecast industry average f.o.b. prices. The Willamette Valley processing cooperative differs from Kuznet's research in that the dependent variable will be a firm specific net returns for a Willamette Valley vegetable processor rather than industry fob prices. The independent variables and their functional form are similar to the ones proposed in this study.

Previous work was conducted by Wiese to forecast raw product values for Willamette Valley vegetable cooperatives. An econometric model and an exponential smoothing process were used to forecast net returns/acre to the cooperative, for both canned and frozen beans and corn.

In Wiese's research the dependent variable was calculated on a pool year basis. Different quantity variables and functional forms were tested in developing the firm-specific supply figures. The approach taken in Wiese's research was to forecast $supply_{t+1}$ using a system of recursive equations estimated by ordinary least squares. The determinants of demand were personal disposable income and the price of a substitute. The substitute for the

canned line was its frozen counterpart, and for the frozen line its fresh counterpart was used. Lagged expenditures on plant and equipment were used as a proxies for disposable personal income. A lagged income variable was also tested and the variable producing the best fit was used. The estimation results are presented in Table 2.2.

Table 2.2. Estimation Results: Canned And Frozen Beans and Corn.[a/]

Product	Const.	Q	I	P^s	R^2	DW
C. Bean	12172	-.1755	-7.7641	-4.9472	.851	1.97
	(2430)	(3.716)	(3.608)			
F. Bean	1566	-.0055	7.3095	----	.634	1.75
	(1106)	(.0063)	(5.766)			
C. Corn	1697	-.1719	4.1155	30.7664	.403	1.84
	(968)	(.0573)	(1.899)	(27.505)		
F. Corn	-1680	-.0051	15.326	-154.22	.780	2.12
	(1353)	(.0030)	(3.353)	(135.56)		

a/ Numbers in parentheses are the standard errors of the coefficients.

Source: Wiese, 1986.

Similar criteria to those cited by Kuznets were used in selection of the appropriate model. Not all the determinants of demand exhibited signs consistent with theory and variables with insignificant coefficients or wrong signs were dropped from the model. Problems with multicollinearity were encountered; but, this was tolerated as the major purpose of the research was forecasting. The ad-

justed R^2s ranged from .403 to .851, suggesting a wide range of explanatory power for the various models. Two observations were used as a test of the model's forecasting power. The results over this time interval were mixed; overall, the econometric model did not forecast well for the test period.

The results of this study are not as encouraging as those of Kuznets. The estimators for canned beans and frozen corn forecasting models, however, perform better than the current method used by the cooperative, for establishing price of raw products. In light of the results for these two commodities, it appears possible to forecast raw product values of select vegetable crops. The econometric model developed in this research will draw upon the methodology used by both Wiese and Kuznets in specification of both the explanatory and dependent variables.

Econometric Model Conceptualization

Willamette Valley vegetable producers are experiencing increased market competition from proprietary processors in the Midwest. Because of the interregional competitive relationship national supply and demand conditions are used to forecast a value of the raw product in Oregon. The dependent variable (raw product value) for this study is derived from the finished product value. It

is assumed that in the long-run competitive conditions exists in the Willamette Valley retail market. Thus, there is no profit accruing to the cooperative over time; therefore, net revenue less all costs of processing, handling, and marketing yields the actual value for raw product. This actual value over time ideally should be the same as the economic value estimated by the cooperative.

Econometric Conceptual Model

In developing the econometric models an autoregressive technique which contains lagged dependent variables and reduced form technique will be utilized. The lost degree of freedom with the autoregressive model will be weighed against the explanatory power of the lagged dependent variable to determine if this type of model is justified. Selection of model structure was derived from economic theory and relationships initially developed by the Agricultural Marketing Service (USDA/Foote, 1959).

As the model is developed in a national context, Supply is defined as the sum of pack in year (t), and carry-in inventory from year (t-1). These pack[2/] or canner supply figures are nationwide totals for each respective vegetable crop. The determinants of demand are assumed to be its own price, personal disposable income, the

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2/ Supply is also referred to as pack, which is the volume of vegetables processed (packed) in a given year.

price of substitute products, population, and a proxy for consumer tastes and preferences (Mansfield, 1985).

Econometric Relationship

The reduced form and autoregressive models have the following structure:[3/]

(2.4) $R_j = \alpha_{io} + \beta_{i1}Q_i + \beta_{i2}I + \beta_{i3}P^s + \beta_{i4}T + e$

(2.5) $R_j = \alpha_{io} + \beta_{i1}Q_i + \beta_{i2}I + \beta_{i3}P^s + \beta_{i5}R_{jt-1}$

R_j = the "actual" net return/ton for cooperative crops in nominal dollars;

Q_i = the level of U.S. production in thousands of pounds;

I = nominal personal disposable income;

P^s = the nominal price of all substitute products;

T = trend variable to account for tastes and preferences;

R_{jt-1} = the actual raw product value/ton lagged one time period;

[3/] A reduced form equation express the endogenous variable R_j solely as a function of exogenous variables (right-hand side variables). A model which includes one or more lagged values of the dependent or endogenous variable is an autoregressive model (Gujarati, 1978).

e = an error term

These functional forms were applied to two processed vegetable crops; snap beans and sweet corn.

Technical Forecasting Method

In time series analysis which utilizes econometric methodology, the assumption is made that the series to be forecasted has been generated by a stochastic process. That is, a process with a structure that can be characterized and explained. In the development of some econometric models, however, there is variability in a time series which cannot be accounted for with observable explanatory variables (i.e. random events such as changes in industry structure or internal management decisions of a firm). There is a broad category of forecasting techniques which attempts to account for this difficulty. This is accomplished not in terms of a cause and effect relationship but rather in terms of the way that randomness is embodied in the process (Pindyck and Rubinfield, 1976).

Common technical forecasting methods are the autoregressive integrated moving average (ARIMA) model and the exponential smoothing technique. These models generate forecasts by estimating past patterns in a time series and projecting them into the future.

> "In time series there are two basic ways of expressing a relationship, autoregressive and moving average. Autoregressive assumes that future values are a linear combination of past values. Moving average models on the other hand assumes that future values are a linear combination of past errors. A combination of the two is called ARIMA" (Makridakis and Wheelwright, 1982).

Thus, ARIMA has an advantage over exponential smoothing in that forecasts are generated through identification and diagnostic checking of certain data properties. The data set upon which this research is based is limited to only 25 observations, annual data (1960-1985). Box and Jenkins (1970) derived a series of ARIMA model building requirements. One such requirement is that a time series data set contain a minimum of 50 observations. With the current research there are only 25 observations and subsequently the use of an exponential smoothing model is dictated.

"Smoothing techniques are a higher form of a naive forecasting model which assume that there is an underlying pattern to be found in historical values of a variable that is being forecast" (McGuigan and Moyer, 1986). These techniques are particularly useful in accounting for random shocks in a series which most likely cannot be captured by an econometric model.

Wiese (1985) developed such a model for Willamette Valley vegetables. In the Wiese model the forecasting

results given in Table 2.3 proved to be more accurate in the long run that the counterpart econometric model for the same time series.

Table 2.3. Smoothing Results Canned and Frozen Beans and Corn.

Crop	Weight	Trend	T-Value
C. Beans	.1	-209.43	-13.20
F. Beans	.9	56.79	4.21
C. Corn	.1	-27.21	-3.05
F. Corn	.5	94.55	6.62

Source: Wiese, 1986.

The exponential smoothing method is based on averaging (smoothing) past values of a time series in a decreasing (exponential) manner. This is achieved by equation (2.6) which, if expanded by substitution of previous forecast values, results in exponentially decreasing weights being given to past observations (Makridakis and Wheelwright, 1978). This is seen in equation (2.7).

(2.6) $Y_{t+1} = wX_t + (1 - w)\hat{Y}_t$

Y_{t+1} = the forecast of next periods observation;

X_t = an observation in the current period;

$\hat{Y}_t$ = the forecast of the current periods value;

w = a weight assigned to the current periods value.

$$(2.7) \quad Y_{t+1} = wX_t + w(1 - w)X_{t-1} + w(1 - w)^2X_{t-2} + w(1 - w)^3X_{t-3} + \ldots.$$

The single exponential smoothing technique is most appropriate for series with a gradually changing mean value. The data series from which the forecasts are to be generated, however, also contained significant trends. To account for this, a double exponential smoothing technique is utilized. This is accomplished by defining both a single and double smoothed average and combining these mathematically to produce an estimate of the level and trend component for forecasting. The trend value may then be multiplied by the level of the estimated dependent variable to obtain the forecast value. In Wiese's research, the assignment of the appropriate weight was limited to one of three options; high, medium, and low (w = .1, .5, .9) the selection of an appropriate weight was then made on the basis of that which minimized the Sum of the Squared Residuals (SSR).

This research uses an exponential smoothing process which is similar to Wiese's, but the assignment of an appropriate weight will not be constrained to three options. The selection of weights will be made with the same criterion of minimizing the SSR; however, any weight between .001 and 1 may be selected. It is hoped that the

omission of selective weight constraints will enhance the forecasting ability of the double exponential smoothing model.

Single Moving Average

A second type of forecasting technique which is not based upon cause and effect relationships is the single moving average. The single moving average consists of calculating the mean of a set of observed values, and then using that average as a forecast for the coming period. This is given in equation (2.8).

$$(2.8) \quad F_{t+1} = \frac{X_t + X_{t-1} + X_{t-2}}{n}$$

F_{t+1} = forecast for the coming period;

X_t = an observed value;

n = number of observations.

The prime objective in using moving averages is to eliminate randomness in a time series. This is achieved in such a way that positive and negative errors usually cancel themselves out. The averaging is done over a constant number of observations. The term "moving average" is used because as each new observation in the series becomes available, the oldest observation is dropped and a new average computed. The result of calculating the

moving average over a set of data points, is a new series of numbers with "little" randomness (Makridakis and Wheelwright, 1979). Often times the use of moving average techniques are employed with data where trends are involved. The dependent data series for which forecasts in this research are being made is a series in which trends exist. For this reason the moving average method of generating forecasts will be utilized along with those previously mentioned.

Composite Forecasting

Three forecasting methods have been outlined with different justification for their use. Any or all of these techniques have the possibility of making large errors for a given time period due to presumed existence of both random and stochastic variables. Composite forecasting is a method of combining alternative forecasting models in an effort to remove the likelihood of large mistakes based on the forecasts of a single model. In general terms, the use of composite forecasting can find its theoretical justification in risk literature.

Bessler and Brandt (1979) developed three alternative forecasting procedures for hog cattle and broiler prices. The alternative methods of forecasting were an econometric model, moving average (ARIMA) process, and expert opinion. Three alternative composite forecasting models were then

developed. These models were essentially combinations of the results generated from the individual methods. The differences among the composite forecasting techniques are in the weighing schemes given to the forecasts of the other models. Three alternative weighting procedures were utilized: (1) minimum variance, (2) adaptive, and (3) simple average. Empirical results from this study are given in Table 2.4.

The empirical results from the three alternative composite forecasts, generated results which were at least as good as any of the individual forecasts. The MSE of the best individual forecasting method was compared with that of the best composite for each of the three commodities. The composite forecast errors of the three commodities averaged 14 percent lower than the errors of the best individual forecasts. In addition, comparing the MSE of the worst individual forecasts with that of the worst individual composite forecast shows that the composite error resulted in an average of 42 percent lower variance for the three commodities.

Bessler and Brandt's results suggest that composite forecasts can be efficient methods of combining predictions into an improved forecast. Composite methodology relies on forecasts from individual models which can be used in a simple average or with alternative weighing schemes. Three alternative forecasting methods have been

Table 2.4. Hog, Cattle and Broiler Forecasts, A Comparison of Alternative Methods.

	MSE		Composite MSE
Hog Prices			
Econometric	20.871	Two Period Adaptive	11.006
ARIMA	10.921	Minimum Variance	10.205
Expert Opinion	23.105	Simple Average	11.669
Cattle Prices			
Econometric	35.412	One Period Adaptive	30.543
ARIMA	34.192	Minimum Variance	31.852
Expert Opinion	37.745	Simple Average	31.884
Broiler Prices			
Econometric	6.329	Nine Period Adaptive	4.738
ARIMA	14.723	Minimum Variance	4.832
Expert Opinion	8.721	Simple Average	5.754

Source: Bessler and Brandt, 1979.

previously outlined for application in this research directed towards processing cooperatives. A composite forecast will also be developed, utilizing alternative weighting schemes.

Summary

At present, the representative processing cooperative operates on a single pool basis. Under this pool design, a method is necessary to allocate net revenues to grower-members. Raw product valuation is the basis for this payment calculation. A discussion of payment calculations and the resulting implications among growers within a single-pool was identified.

A description of the pricing mechanisms for both the raw product and processed goods market has been identified. The use of the current raw product valuation technique utilized by cooperative management, and the resulting implications for misallocated acreage and inappropriate production levels was discussed. The current method for assigning a value to raw products is essentially a one period naive forecast. The hypothesis was made that more efficient alternative forecasting methods for raw product valuation could be developed. Alternative raw product value forecasting methods were developed based on an assessment of the relevant literature and theoretical relationships.

CHAPTER III

MODEL SPECIFICATION

This chapter explains design of alternative raw product valuation procedures. First, the time frame for production and marketing decisions by the cooperative are linked to the subsequent raw product forecast date. The variables to be forecasted on a pool year basis are identified along with a description of their respective explanatory econometric models. A discussion of how single pool payments will be evaluated for alternative economic value forecasters is also given. The chapter concludes with a discussion of the data and the units used.

Accounting Period

A description of the cooperative's accounting period is necessary to understand the organization of data used in the forecasting procedures. Two alternative time frames confront the cooperative in forecasting raw product value. The 12 month fiscal year interval generates data which is used for internal planning. Secondly the 24 month pool year interval, extending from harvest until the processed product is sold to the succeeding pool, from which grower-member payment calculations are estimated. The cooperative's fiscal year runs from April 1 to March 31 of the following year. A single pool accounting period

covers two years so the pool that opened April 1, in year t will close March 31, in year t+2 (Figure 3.1, page 35).

The harvest season for snap beans and sweet corn the two products under consideration in this study extends from early July through the end of August.[1/] Processing begins during the harvest season and sales of processed products begin immediately. Roughly 60 percent of the processed product is still unsold at the end of the first fiscal year and sales continue through the second fiscal year. Any product left in inventory at the end of the pool year is transferred to the succeeding pool (Smith, 1984). Estimated sales value of the transferred products left in inventory at this time is credited to the pool which is closed.

Pool-Year Econometric Model

The Dependent Variable

In this research net returns per ton is treated as the dependent variable. These returns were calculated on a pool year basis using the financial records of the cooperative over the time period 1960 through 1985 (Subaei, 1984). These records list net returns on a fis-

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1/ Snap green beans and sweet corn are analyzed in this study.

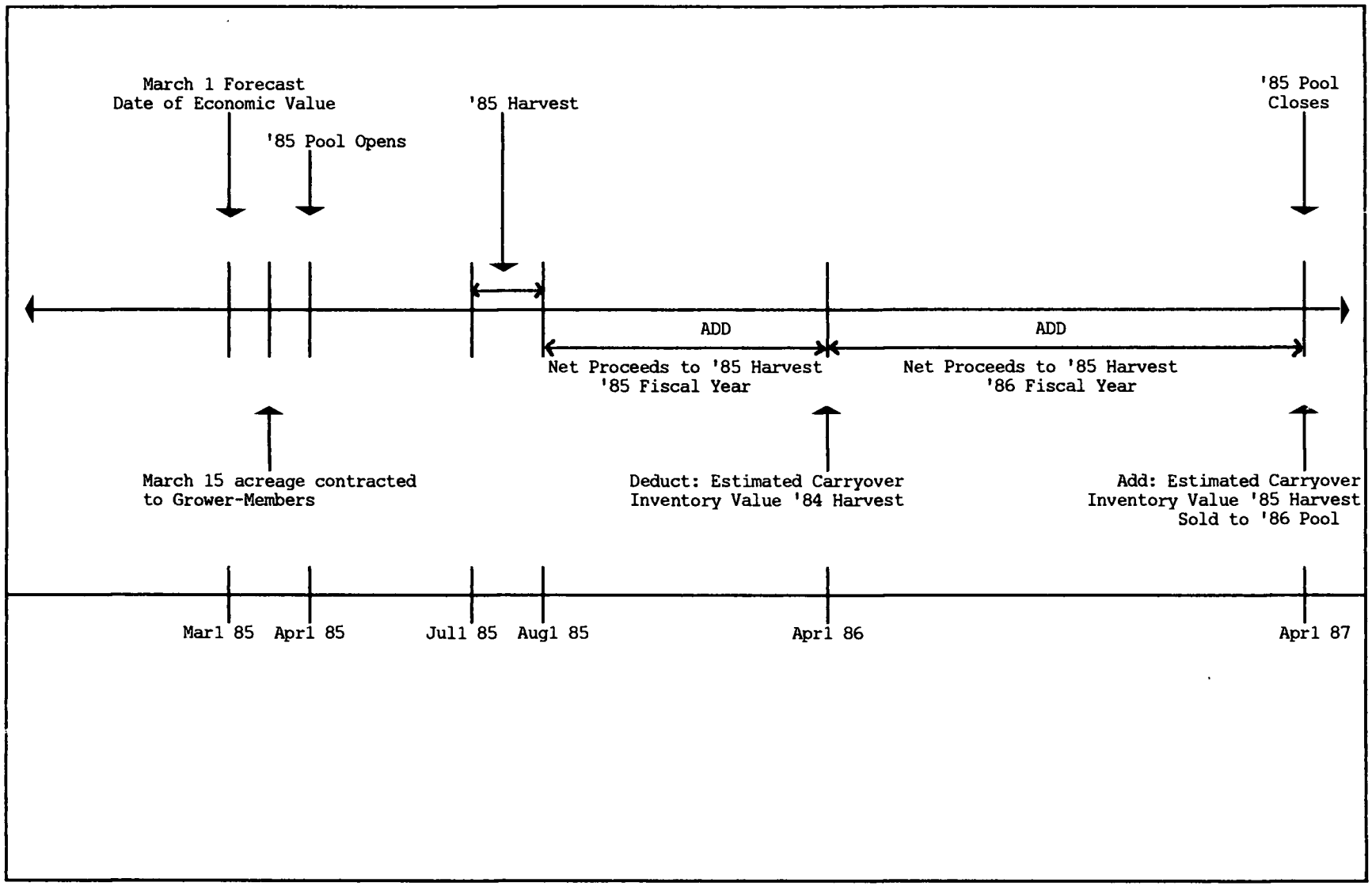

Figure 3.1. Time Line Illustrating Pool Year Net Returns Calculation and Forecast Date.

cal year basis, established economic values[2/] and the estimated carry-over inventory values formed at the close of a pool. For example, for snap beans harvested in July through August of 1985, the net returns realized during the April 1 through March 31 1985 fiscal year, were added to the net returns realized during the 1986 fiscal year to determine net returns payable to the 1985 pool. An adjustment for carry-over inventory is also made. This procedure is illustrated in Figure 3.1, using the 1985 pool as an example. The estimated carry-over inventory value formed at the close of the 1985 pool is added to the 1985 pool net returns, and the estimated carry-over inventory value formed at the end of the 1984 pool (paid out of the 1985 pool) is subtracted out (Weise, 1985).

This calculation yields net returns to products on a pool year basis. Total tons of each respective commodity the cooperative processes were then divided into total net returns of that commodity to yield net returns per ton. The calculation of this value yields returns to cooperatives at the wholesale level, less all costs of processing and selling that product. A raw product's "actual value" is taken to be net returnes per ton at the wholesale

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2/ Established economic values are the basis for raw product payments to grower-members. These values are forecasted in March of each year by cooperative management.

level. These procedures were carried out for both snap beans and sweet corn serving as the dependent variable to forecasted in this study.[3/]

The Explanatory Variables

Supply. The supply of the processed product for the forecast interval comes from two sources; pack in year t and carry-over inventory from year t-1. Summing these yields the total volume of processed vegetables available after harvest in the finished goods market. Willamette Valley vegetable processors have experienced increased competition from other regions for market share in the Northwest. Thus, national pack and carry-over inventory levels were used to estimate product value.

The calculation yielding total pack available was carried out separately for the canned and frozen product lines. These figures were included individually as explanatory variables in the econometric model. The individual figures for the frozen and canned lines were then combined to calculate total pack figures for each commodity.

A Chow test was then used to determine if the two sets of supply coefficients (canned and frozen combined verses canned and frozen individually) used in the

3/ Net Returns = Total Sales - [Processing, Selling and Shipping Costs] + an adjustment for carry-over inventory.

regressions were statistically the same. This was in fact proven to be the case. This same procedure was also carried out for incorporation of either one or the other of the canned or frozen lines for inclusion in the model individually. For snap beans the pack of the canned line is included for the supply figure as the t-statistic proved to have higher degree of significance individually verses the canned and frozen lines combined. A Chow test justified the use of only incorporating the canned pack level in the model for snap beans. The supply figure for sweet corn on the other hand, was best represented as the total pack level for both the frozen and canned processed goods combined.

Demand. The determinants of demand for the finished goods are hypothesized to be personal disposable income and the price of a demand substitute product. Several alternative substitute products were tested in both nominal and real terms. The respective t-statistics and adjusted R^2s were then used in selection of an appropriate model. The best specification utilized the consumer price index (CPI) as the price of all substitute products. As the CPI was included as an explanatory variable, personal disposable income as well as the variable to be forecasted were utilized in nominal verses real terms. This was the case for both snap beans and sweet corn.

During the time period over which the model was estimated the dependent variable exhibited significant trends for both snap beans and sweet corn. This justified the use of a simple trend variable in a linear functional form (1,2,3,...). A lagged dependent variable was also tested separately from the trend variable. The model providing the best fit was selected. The snap bean model uses a lagged dependent variable and the model for sweet corn includes the trend variable.

Model Formulation. The pool year econometric model was estimated using annual data from 1960 through 1975. Pool year net return per ton were regressed against a pack figure, personal disposable income, the CPI, and a trend or lagged dependent variable. The econometric model for snap beans and sweet corn are given in equations (3.1) and (3.2), respectively.

$$(3.1) \quad R_j = \alpha + \beta_1 Qb_{t-1} + \beta_2 I_{t-1} + \beta_3 P^S{}_{t-1} + \beta_4 P_{t-1} + e$$

$$(3.2) \quad R_j = \alpha + \beta_1 Qc_{t-1} + \beta_2 I_{t-1} + \beta_3 P^S{}_{t-1} + \beta_4 T + e$$

where:

R_j = the net return per ton of the raw product to be forecasted;

Qb_{t-1} = pack of canned snap beans in year t-1;

Qc_{t-1} = total pack of both canned and frozen corn in year t-1;

I_{t-1} = U.S. total personal disposable income in year t-1

P_{t-1} = lagged actual raw product value for snap beans;

T = trend variable;

e = an error term.

Forecasted values of raw product per ton by cooperative management are used in establishing raw product price, and in deciding upon the number of acres to contract to growers. Since the forecast date is March 1 (Figure 3.1), all explanatory variables excluding trend must be lagged one period. This is necessary so that explanatory variables may be obtained to generate a forecast of raw product price on or before the forecasting date.

Pool Payments

Four forecasting techniques have been developed in the context of this research in addition to the method currently used by the processing cooperative. These alternative methods of forecasting raw product values can be used to calculate simulated grower-member payments. The calculation of a pool payment for an individual growers is accomplished by multiplying the first term on the right-

hand side of equation (2.2) by the forecasted value of an individual commodity.

$$\text{(3.3)} \qquad \text{Payment} = \frac{(R_j * Q_j) + (R_k * Q_k)}{(r_j * Q_j) + (r_k * Q_k)} * \text{Fcst}$$

where:

R_j = the "actual value" of snap beans raw product, which also serves as the dependent variable for this commodity;

R_k = the "actual value" of sweet corn raw product, which also serves as the dependent variable for this commodity;

Q_j = the yield of snap beans;

Q_k = the yield of sweet corn;

r_j = the forecasted value per ton of snap beans;

r_k = the forecasted value per ton of sweet corn;

Fcst = the forecasted value per ton of either snap beans or sweet corn.

The payment calculation given above simulates what grower-members of individual commodities would receive per ton, based on a single pool of net revenues from the two commodities. This computation will be carried out for all

five economic value forecasters to determine payments on a per ton and per acre basis. The bracketed portion of the payment calculation illustrates by what percentage the pool's net revenue is over or under its total raw product valuation, and what the pool payment of a raw product is relative to its raw value. From this payment scheme residuals are then be calculated over a ten year test period. The residuals are used to analyze the biasedness and variance of the alternative forecasters over time.[4/]

Data Sources

Dependent Variable

Data from the representative processing and marketing cooperative was collected for the time period 1960 through 1985. Data for 1972 was missing necessitating the adoption of a proxy. The proxy value was the previous years value. The forecasting models were developed using data from 1960 through 1975. This provided ten additional years of data, 1976-1985, to serve as a testing period for the alternative forecasters. Net returns, established

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4/ Biasedness is defined as the amount pool payments are over or under the actual value of the raw product. Thus bias is measured in terms of the residuals themselves. Variance is defined as the dispersion of the pool payments around the mean of the raw products actual values (net return per ton) within the ten year test period.

economic values, carry-over inventory estimates and the derived net returns are all expressed in nominal dollars.

Independent Variables

Canned industry inventory and pack data were obtained from The Almanac of the Canning, Freezing and Preserving Industries, (1959-1986). Frozen industry pack data were also obtained from this reference; however, carry-over data were obtained from "Summaries of Regional Cold Storage Holdings," published by the USDA Statistical Reporting Service. Canned industry levels were reported in thousands of actual cases, while frozen levels were reported in thousands of actual pounds.

Representative yield per acre figures were obtained for Oregon's Polk county within the cooperatives membership area, compiled by Extension Economic Information Office, at Oregon State University (1960-1985).

Personal disposable income figures were obtained from "Economic Indicators," (1969-1985), compiled by the Council of Economic Advisors. This variable was expressed in billions of nominal dollars. The price of substitute products, the (CPI), were obtained from "Outlook and Situation," (1960-1985), with 1972 being the base year.

Summary

Econometric forecasting equations for raw product values were developed for two commodities, snap beans and sweet corn. These models were developed utilizing data from 1960 through 1975, leaving 1976 through 1985 to serve as test period for the various models forecasting ability.

The dependent variables for the econometric models as well as the exponential smoothing, moving average and composite techniques were obtained from the cooperative's financial records. The econometric models were developed by regressing the dependent variable against a pack (supply) figure, personal disposable income, the CPI (which served as the price of all substitute products), and a trend or lagged dependent variable. Pool payment calculations were then developed. These calculations will simulate over time how grower-members would be compensated by the cooperative based on five alternative forecasts of economic value.

CHAPTER IV

RESULTS

This chapter starts with a discussion of specification criteria used in selection of alternative forecasting procedures. Comparative statistics which are utilized in the evaluation of different forecasting methods are given. Forecasts of raw product values based the econometric and exponential smoothing models are presented and discussed. This is followed by a discussion of simulated pool year returns as calculated from the five alternative forecasting models. The chapter concludes with an evaluation of forecasting performance over the post-sample period using appropriate statistical measures.

Sample Size and Forecast Interval

Financial data from the representative cooperative for which this study is based was obtained for the period 1960 to 1985. Model estimation was then generated from the period 1960 to 1975, allowing a ten year (1976-1985) post-sample period for evaluation of forecasting procedures and resulting pool year returns. The alternative forecasting models were estimated and subsequently updated each year as further data became available within the test period.

The sample size for the econometric model was held constant with 17 observations beginning in the year 1977. As an additional year's observation became available, the earliest data point was omitted. This was done in an effort to confine the models to periods with relative constant structure. This should allow the explanatory variables to accurately reflected changes in the dependent variable.

Model Specification Criteria

The criteria used to specify the econometric models were the adjusted R^2 values, consistency of the independent variable coefficient signs with economic theory, significant levels of independent variables, and considerations of multicollinearity and serial correlation. The criterion for the exponential smoothing technique was minimization of the SSR. Selection of the appropriate number of periods to include in the moving average and fitting of weights for the composite forecast were also based on the same SSR criterion.

Comparative Statistics of Forecasters

After the model specification was complete, criteria had to be chosen in which comparisons of alternative forecasters could be made. When forecasting over several periods, a series of error values will be generated over

the forecast interval. A summary of these error values provides a measure of how well the forecasting techniques predict the actual values for which the models were developed. There are several ways such a summary of errors could be developed. Two of the most widely used methods are the Mean Square Error (MSE) and the Mean Absolute Percentage Error (MAPE).

Mean Square Error

The MSE[1/] is obtained by squaring the individual errors, then summing these values and dividing by the number of observations. This approach eliminates the canceling effects of positive and negative errors, and also places more weight on larger errors, a result of the squaring process.

Mean Absolute Percentage Error

The MAPE[2/] is determined by calculating the absolute forecast error and expressing this as percentage of the

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1/

$$MSE = \frac{\sum_{i=1}^{n} (Y_i - \hat{Y}_i)^2}{n}$$

where: Y = the actual value;
$\hat{Y}$ = the forecasted value;
$(Y - \hat{Y})$ = the absolute difference between Y and $\hat{Y}$.

2/

$$MAPE = \frac{\sum_{i=1}^{n} \left|(Y_i - \hat{Y}_i)\right|}{n}$$

forecasts. Interpretation of the MAPE is more intuitive than the MSE. A MAPE of eight percent which represents the magnitude of the forecast error, for example, is easier to interpret than a MSE of 12456. Both of these comparative statistics are absolute measures; however, the MAPE gives equal weight to all errors. Based on the ease of interpretation and different weighing schemes both measures will be used.

Parameter Evaluation of Econometric and Exponential Smoothing Models

Econometric Model: Snap Beans

Table 4.1 presents a summary of the estimation results for the snap bean econometric model which was specified in Chapter III (EQ 3.1). Variables for this model are defined on page 39. The results in complete form may be referenced in Appendix A. Pool-year net returns per ton serves as the dependent variable. Numbers in parentheses are standard errors of the coefficients.

Interpretation

The results in Table 4.1 contain multicollinearity between disposable income and the price of substitute

Table 4.1

Table 4.1. Estimation Results: Snap Beans.

	R^2	Coefficient					
		Const.	$Q_{ON}(-1)$	DisInc(-1)	CPI(-1)	Return(-1)	Dummy
1976	.470	1094.198 (263.728)	-.0005 (.0016)	1.6722 (.4459)	-1975.968 (563.949)	- .1403 (.2393)	---
1977	.435	946.882 (222.448)	-.0047 (.0016)	1.432 (.3815)	-1632.196 (456.495)	- .2322 (.2228)	---
1978	.521	963.179 (215.835)	-.0052 (.0014)	1.465 (.3692)	-1643.370 (445.361)	- .2611 (.2133)	---
1979	.627	1007.997 (210.544)	-.0043 (.0012)	1.566 (.3654)	-1798.334 (449.415)	- .3797 (.2108)	---
1980	.488	929.846 (252.805)	-.0027 (.0013)	1.439 (.4472)	-1694.222 (559.117)	- .4876 (.2719)	---
1981	.585	519.654 (154.619)	-.0035 (.0012)	.5926 (.2289)	- 641.784 (382.409)	---	-133.003 (31.042)
1982	.731	476.414 (143.167)	-.0045 (.0012)	.3955 (.2988)	- 386.262 (383.350)	---	-127.625 (25.376)
1983	.672	523.153 (196.213)	-.0031 (.0017)	.5698 (.4224)	- 643.124 (538.123)	---	-151.094 (34.835)
1984	.691	539.566 (203.357)	-.0019 (.0017)	.7122 (.4222)	- 838.334 (531.879)	---	-161.304 (36.553)
1985	.654	347.200 (132.859)	-.0015 (.0022)	.3206 (.2758)	- 355.535 (357.027)	---	-145.420 (38.281)

Standard errors of coefficients denoted in parentheses.

products (CPI). The coefficient of correlation between these variables is .95. The presence of multicollinearity was tolerated, as it is not so important to assess the individual affects of each explanatory variable, but rather that the explanatory variables collectively may explain the behavior of the dependent variable. It is necessary to assume that the pattern of multicollinearity between the two variables in question will remain the same into the future.

As the major purpose of this research is to forecast raw product values, serial correlation is of greater concern than multicollinearity. Under the presence of serial correlation there is a loss of efficiency, in that the standard errors obtained from the least-squares regression will be larger than what could have feasibly been obtained. The regression estimates will still be unbiased; however, ordinary least squares standard error estimates will be biased downward. This leads to the conclusion that the parameter estimates are more precise than they actually are, resulting in larger variances when compared with the predictions based on some other estimators.

The econometric model developed for snap beans was autoregressive (i.e. the dependent variable was lagged and used as an explanatory variable). In this situation the standard measure for serial correlation (Durbin-Watson statistic) cannot be utilized. Instead the Durbin-h

statistic may be used. Over the estimation period a Durbin-h of -0.56 was indicated. This resulted in accepting the null hypothesis at a 90 percent confidence interval of no serial correlation.

The explanatory variables all exhibit signs consistent with economic theory, and are significant at the .01 level excluding lagged returns. Lagged returns were left in the model under the assumption that its explanatory power would improve for subsequent forecasts.

In 1980 the processing cooperative entered a period of rapid expansion, resulting in large losses to certain commodities for a period of two to three years. Based on this a dummy variable was included in forecast models subsequent to 1980 and lagged returns dropped. Justification for this was the assumption that none of the explanatory variables could accurately reflect the profit impacts of changing management practices strictly internal to the cooperative.

The adjusted R^2 values range from .47 to .73 within the ten year test period, suggesting a wide range of explanatory power.

Econometric Model: Sweet Corn

Table 4.2 presents a summary of the estimation results for the sweet corn model specified in Chapter III

Table 4.2. Estimation Results: Sweet Corn.

		Coefficient					
	R^2	Const.	Q(-1)	DisInc(-1)	CPI(-1)	Trend	Dummy
1976	.872	688.235 (115.538)	-.0003 (.000009)	1.6605 (.2498)	-1666.477 (273.640)	- 9.936 (4.562)	----
1977	.782	538.842 (97.594)	-.0002 (.000008)	1.4569 (.2551)	-1356.839 (251.000)	-12.672 (4.876)	----
1978	.761	527.992 (104.487)	-.0002 (.000009)	1.3316 (.2617)	-1285.383 (265.415)	- 8.990 (4.672)	----
1979	.695	453.956 (117.532)	-.0003 (.0601)	.9788 (.2588)	-1014.848 (281.659)	.4966 (3.745)	----
1980	.547	370.598 (133.603)	-.0004 (.0001)	.6913 (.2664)	- 760.512 (309.873)	6.473 (3.542)	----
1981	.475	347.436 (139.159)	-.0004 (.0001)	.6514 (.2758)	- 691.623 (327.502)	5.176 (3.974)	-47.071 (25.119)
1982	.523	333.794 (144.679)	-.0003 (.0001)	.6229 (.2844)	- 658.617 (351.714)	4.894 (4.509)	-48.529 (24.861)
1983	.309	371.481 (175.169)	-.0003 (.0001)	.6524 (.3453)	- 783.731 (420.691)	9.392 (5.193)	-41.866 (31.127)
1984	.300	219.761 (147.515)	-.0001 (.0001)	.3941 (.3045)	- 504.119 (351.9063)	8.688 (4.952)	-23.826 (32.664)
1985	.479	26.768 (62.789)	-.000002 (.000008)	.0322 (.1230)	- 214.991 (193.603)	16.710 (4.695)	15.172 (21.125)

Standard errors of coefficients denoted in parentheses.

(Equation 3.2). Variables for this model are defined on page 38. The results in complete form may be found in Appendix A. Pool-year net returns/ton serves as the dependent variable. Numbers in parentheses are standard errors of the coefficients.

Interpretation

The results in Table 4.2 are similar to those in Table 4.1 in that multicollinearity is also present. The presence of multicollinearity for sweet corn is more severe than the condition exhibited with snap beans. Disposable personal income being correlated with quantity, trend, and the CPI variable. Correlation coefficients are .94, .94, and .95 respectively. In addition the CPI was correlated with the trend variable exhibited by a correlation coefficient of .95. The presence of multicollinearity was again tolerated, as forecasting is the major purpose of these models. Serial correlation apparently was not a factor since the Durbin-Watson statistic of 2.65 allows retention of a null hypothesis that there is no serial correlation.

The explanatory variable coefficients all exhibited signs consistent with economic theory, and were significant to the .01 level. A dummy variable was added to the model in 1981 based on the same reasoning outlined under snap beans. Within the ten year forecasting period

the adjusted R^2 values ranged from a high of .87 to a low of .30. This wide range of values is probably attributed to changes in cooperative management practices, which cannot be accurately reflected by forecasting variables external to the cooperative.

Exponential Smoothing Results

Table 4.3 presents the estimation results of the exponential smoothing model for both snap beans and sweet corn specified in Chapter III (EQ 2.6, page 26). Pool-year net returns per ton is the dependent variable.

Interpretation

Weights were systematically chosen between .001 and .999 and the SSR calculated. The weight which minimized the SSR was chosen for each year as additional data became available. The low values of the weights illustrates the stationarity of the net returns series after the trend has been taken out. The lower the weight, the greater the emphasis placed on the net return value immediately preceding the forecast. This may be seen by the smoothing model specified in (EQ 2.6). The negative trend values for snap beans illustrate declining net returns towards the end of the sample period.

Table 4.3. Estimation Results, Exponential Smoothing.

	Snap Beans			Sweet Corn		
Year	α	RMSE	Trend	α	RMSE	Trend
1976	.034	34.649	3.556	.056	19.774	2.504
1977	.001	32.798	2.441	.001	18.138	1.113
1978	.001	32.688	2.441	.001	18.234	1.113
1979	.001	33.673	1.323	.192	18.994	2.721
1980	.001	33.086	1.322	.162	18.778	1.941
1981	.001	37.419	0.544	.180	18.488	1.879
1982	.001	39.984	0.544	.188	18.402	2.493
1983	.290	47.889	-14.930	.164	19.456	1.299
1984	.260	46.934	-11.773	.164	19.251	0.931
1985	.148	47.709	- 3.404	.168	19.002	0.565

Pool Year Returns

The research objectives for this analysis focuses on five alternative raw product valuation forecasting techniques: (1) economic value which is the forecasted value of raw product by cooperative management and the current basis for grower-member pool payment, (2) econometric, (3) exponential smoothing, (4) three period moving average, and (5) a composite forecast. The development of these models was the first primary objective. The second objective is to simulate a single pool of commodities including snap beans and sweet corn based on the alternative forecasters of raw product value. This was accomplished by calculating pool-year returns per ton and per acre utilizing the methodology given in Chapters II and III. The results of these pool year calculations are given in Appendix B. Select comparative statistics are given in Table 4.4.

Evaluation of Forecasting Techniques

Evaluation Procedure

The ten year post-sample period will provide the basis for evaluation of the different forecasting techniques and their subsequent effects on pool year returns. The sample period from which the models were developed is ignored. The primary concern is future applications for

Table 4.4. Pool-Year Calculation and Comparisons Among Alternative Forecasters.

	Mean Fraction[a]	Mean Residual-2[b]		Standard Deviation of Residual[c]		RMSE[d]	
		Beans	Corn	Beans	Corn	Beans	Corn
Economic Value	.84	66.25	-66.25	111.25		129.48	
Exponential Smoothing	.92	16.19	-16.19	143.12		144.03	
Econometric	.79	20.23	-20.23	129.93		131.49	
Moving Average	.93	- 1.36	1.36	151.85		151.85	
Composite	.88	42.78	-42.78	131.19		137.99	

a/ Basis for raw product payments, given in Chapter II (equation 2.1).

b/ $X_j = G_jQ_j - R_jQ_j$ where: Q_j = yield/acre of jth commodity
X_j = residual
G_j = pool payment/ton to the jth grower
R_j = the actual value less all costs of processing in the finished product market

c/ Standard Deviation = $\sqrt{\sum_j[(G_jQ_j - R_jQ_j) - \sum_j(G_jQ_j - R_jQ_j)/10]^2/10}$

d/ RMSE = $\sqrt{[E(e)]^2 + Var(e)}$ where: $[E(e)]^2$ = residual-2 squared
Var(e) = variance of the above error terms

cooperative management; therefore all attention is focused on ex ante descriptive statistics and ex post evaluation is ignored. Evaluation procedures will include comparative statistics, graphical analysis, and comparison of pool-year returns and their associated biasedness and variances.

Forecasting Comparative Statistics: One or more of the alternative forecasters developed in the context of this research proved superior to the economic values applied by the cooperative, for both commodities. For snap beans, the composite forecaster out performs all others, as indicated by its lower MSE and MAPE. The moving average and exponential smoothing models also performed well over the forecast horizon when compared to the econometric and economic value models (Table 4.5)

The MSE and MAPE show accurate forecasts for the economic value assigned to corn; however, the moving average produces an even better fit to the dependent variable. The composite and exponential smoother also provide encouraging results.

When taking both product lines (snap beans and sweet corn) into account the three year moving average produces better forecasts than any other technique tested. The econometric model produces the poorest fit to the data as measured by the MSE and MAPE.

Table 4.5. Comparative Forecast Statistics

	Beans		Corn	
Forecaster	MSE	MAPE	MSE	MAPE
Economic Value	5973.41	.93	319.67	.27
Exponential Smoothing	3642.92	.70	339.28	.28
Econometric	7191.33	.85	2003.59	.68
Moving Average	3981.60	.64	174.94	.19
Composite	3410.80	.64	364.25	.27

Graphical Analysis. A graph plot of the forecasts provides a visual method for tracking the individual models over time. Major fluctuations (turning points) and general trends are more evident with graphical analysis. Figure 4.1 illustrates the net returns, labeled actual, and the five alternative forecasters for snap beans. Figure 4.2 contains a comparable illustration for sweet corn.

Turning points are not consistently predicted by any individual forecast method for either commodity on a regular basis. The models which perform the best in this regard are the econometric and composite. The moving average and exponential smoothing methods will routinely miss major fluctuations in the data, as dictated by their functional form. These techniques require a downward or upward change in the data before a major shift in the forecast may be realized. Thus, directional change in the forecast will lag at least one period.

In tracking general trends in the data the moving average and exponential smoothing models out perform the formal techniques for both commodities over the entire range of the test period.

Comparison of Pool-year Returns

The rationalization for construction of single commodity pools is based upon variability in returns. Single

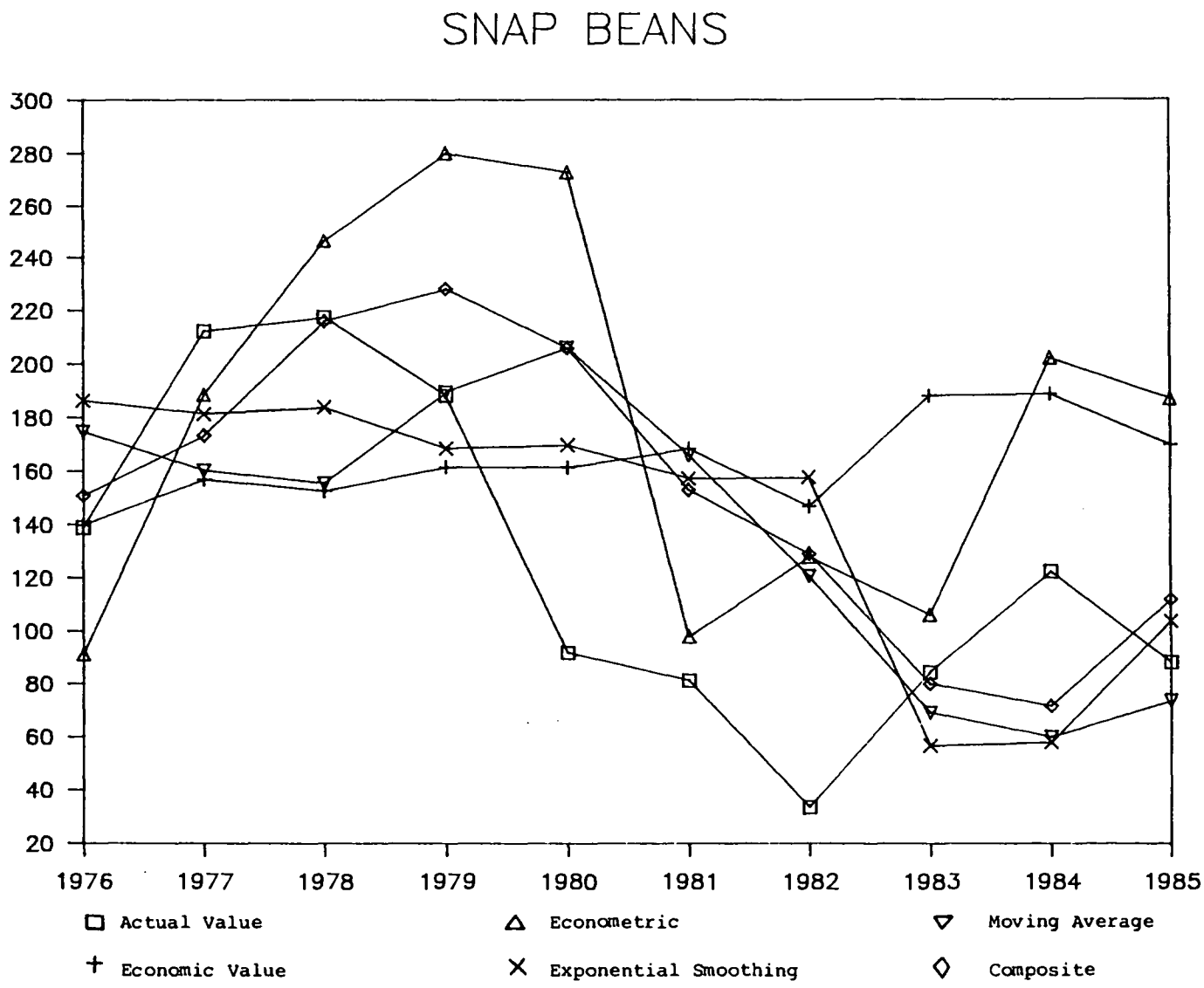

Figure 4.1. Alternative Raw Product Value Forecasts: 1976-1985.

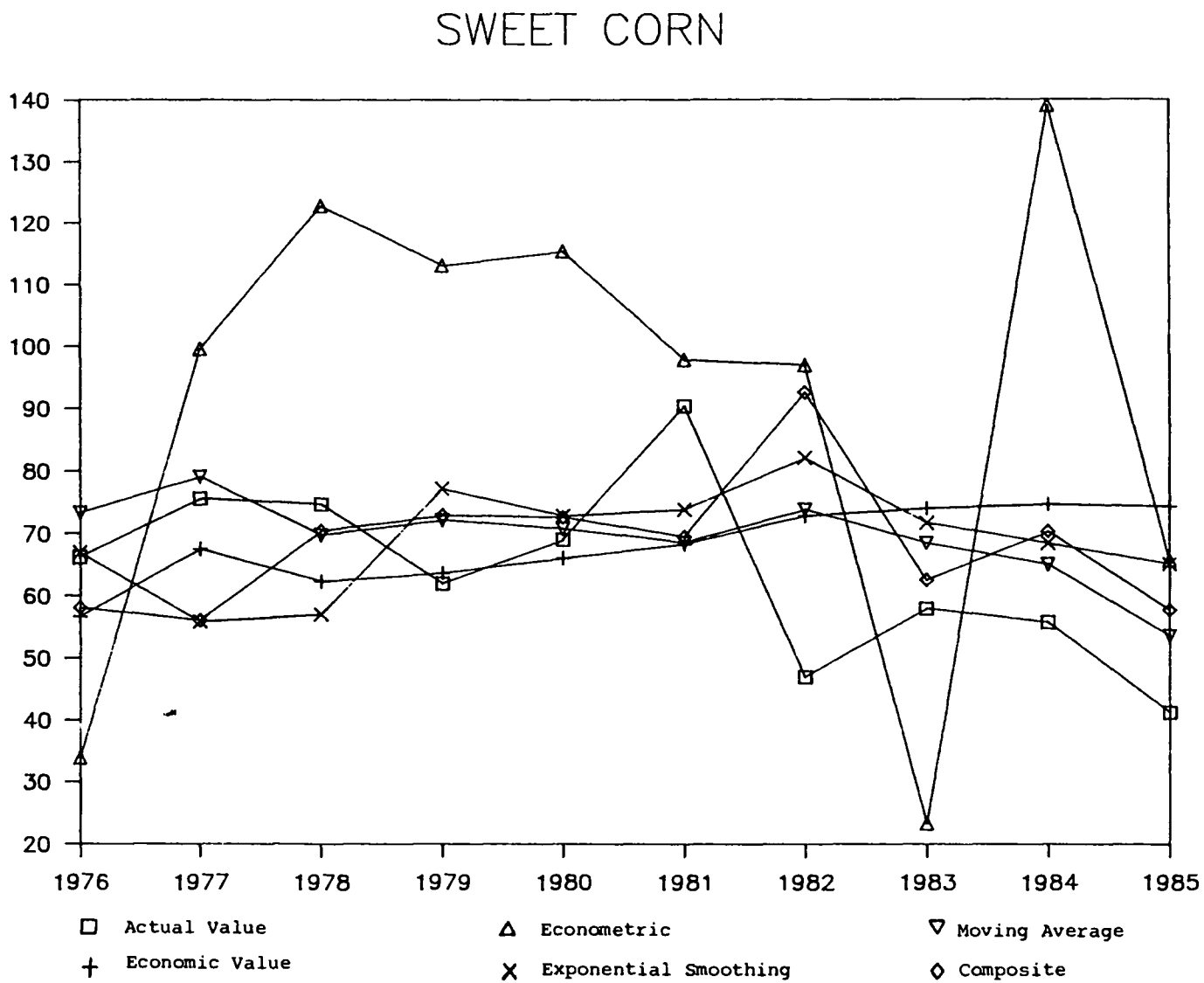

Figure 4.2. Alternative Raw Product Value Forecasts: 1975-1985.

pools should reduce the variability of all commodities within the pool. In any given year a catastrophic loss by one commodity can be compensated by other products in the same pool. Typically the grower of a commodity who is compensated in year t, will be taxed in the years to follow by compensating growers of another commodity. Over time single pool risk management should return to all growers the sum of what their commodity actually received at the wholesale level less costs of processing. In the context of this research the assumption is made that the ten-year forecast horizon should be lengthy enough to accomplish this major objective of single-pools.

Based on the above argument the fractional values given in Table 4.4, which are mean fractional values over the forecast horizon, should converge to a value of one. These values represent the first term on the right-hand side of equation (3.3). The value of this term shows by what proportion a pool's net revenue is over or under its total raw product value. A value of one for this fraction can only be obtained if pool payments are equal to net wholesale receipts. It is unreasonable to assume that a value of one should be obtained every year. It is reasonable, however, to assume that over the ten year test period a mean value close to one should be obtained. Similarly the mean residual figures given in Table 4.4 should converge to a value of zero. These figures were

obtained by subtracting pool payments for each of the alternative forecasters from net returns for a respective commodity for each year within the test period, and calculating their mean over the ten year interval. A mean residual value of zero would be obtained only if pool payments over the ten year interval were equal to net wholesale receipts. These values demonstrate the pool's ability over time to allocate proceeds to the appropriate growers and subsequently the biasedness associated with the various forecasters.

Based on the two criterion listed above the moving average model provides the best raw product value forecasts in terms of pool returns, while the economic value forecaster performs the poorest. Looking at the values for mean residual under the current economic value forecast procedure employed by the cooperative, the corn growers were underpaid (taxed) on average $66.25/acre per year, thus compensating the bean growers by this amount. Under the moving average approach, the bean growers were taxed only $1.36/acre per year in compensating the corn growers. When comparing results across all methods, the poorest forecasting alternative developed in the context of this research and these criterion (i.e. econometric model), produces results 60 percent better in terms of taxation and compensation among growers than the economic value method currently employed by cooperative management.

Thus, in terms of biasedness in raw product prices the alternative forecasters were superior to the cooperatives current forecast procedure.

The level of variance within the forecast interval is also useful in comparing the various forecasters. Variance among the residuals of net revenue and pool payments is utilized as a descriptive statistic. A forecasting technique which results in very little bias in the long run may have extreme variability within a shortened time period. The variance calculations given in Table 4.4 demonstrate that this is indeed the case for the research at hand. The economic value method, which performed the poorest in terms of bias has the lowest variability, among all forecasters within the test interval.

Faced with two alternative forecast criteria (bias and variance) it is difficult to determine which of the forecasters produces the best overall results. An additional criterion therefore was calculated for comparison of the alternative models. If it assumed that the decision makers utility for income is quadratic, then he wishes to minimize the Root Mean Square Error (RMSE).[3/]

[3/] Root Mean Square Error used in this context must be differentiated from the computation given earlier in Chapter IV, page 48. RMSE in Table 4.4 is calculated with the following equation (Kmenta, 1971).

$$RMSE = [E(e)]^2 + Var(e)^2 = \text{Squared Bias} + \text{Variance}$$

This statistical measure provides a criteria which will take into account both the measure of bias and variance.

Computation of this measure may be on a per ton or per acre basis. As farmers make their planting decisions on a per acre basis, the calculation was made utlizing per acre units. When this comparative statistic, which provides a combined measure of bias and variance is taken into account, the economic value forecaster provides the best results in terms of pool year calculations. The method which provides the poorest results is the moving average.

The apparent tradeoff in forecast performance between bias and variance precludes the emergence of a single, superior forecast methodology, of those presented here. Selection of optimal forecast procedure may thus require a conscious recognition of cooperative members' attitudes towards these two criteria.

Summary

Five alternative raw product value forecasting techniques have been analyzed in the context of this research. The first objective of this paper was to determine how well these various forecasting methods predict the actual value of raw products at the wholesale level. Descriptive statistics including MSE and RMSE were used to determine forecasting performance. Utilizing the MSE and RMSE it

was found that the three year moving average and exponential smoothing forecaster provide the best results when taking both snap beans and sweet corn into consideration. Graphical analysis was also used to track all five forecasters over the ten year test period against the actual raw product value. No method in particular tracked the actual raw product value consistently over the ten year period. The econometric and composite forecasters accounted for more turning points than the other methods, while the exponential smoothing and moving average were best able to follow general trends.

The second objective of this research was to determine the effects of the alternative forecasters on single pool payments. The criteria used to evaluate pool payments were biasedness and variance. In terms of bias it was shown that the moving average in particular as well as the exponential smoothing techniques were far superior to all others. When taking variance into account the economic value provided the best results.

CHAPTER V

SUMMARY AND CONCLUSIONS

The objective of this research has been to explore the performance of five alternative raw product valuation procedures for a vertically integrated vegetable processing and marketing cooperative. Four such alternative procedures were developed. These techniques, along with the method currently employed by the cooperative, were then used to calculate single-pool returns. The five procedures were compared utilizing the comparative statistics outlined in Chapter IV.

Assessment of Alternative Forecasting Methods With Respect To Pool-Year Returns

Several criteria were used in assessing the alternative forecasting procedures and their effects on pool-year returns. Comparative statistics (MSE and MAPE) were used to measure how well individual forecasters predicted actual net returns per ton at the wholesale level of raw products. These statistics revealed that the three-year moving average generates the most accurate results when taking both snap beans and sweet corn into consideration.

MSE and MAPE provide insight into how well individual forecasters predict actual net returns per ton. However, MSE and MAPE do not consider biasedness and variance in

reference to pool payments. Thus, additional criteria for biasedness and variance must be taken into account for pool-year returns. Biasedness between pool payments and net returns is assumed to be the most important criteria from the standpoint of grower members. Pool payment bias in the context of this research is defined as the difference between mean net returns per ton and mean pool payments per ton. Stated alternatively, it is the difference between what growers received for their raw products and the net revenues the raw products earned at the wholesale level. The three-year moving average forecaster provided the least biased payment while the econometric model method provided the most biased payments. Payment variance is a measure of the dispersion of the deviation of pool payments around their mean value. The cooperative's present method of setting economic values resulted in the lowest payment variance, over the ten-year test horizon of any of the methods studied.

Forecasting Methods

Econometric Models

The econometric models for both snap beans and sweet corn performed poorly over the ten period forecast interval. These models provided the highest measure of bias of any forecaster. The poor forecasts provided by the

econometric models may have been caused by the absence of firm-specific explanatory variables. Inclusion of a firm-specific variable, for example to account for the rapid expansion of cooperative size in 1980, may have improved forecast performance.

In a later application, the econometric models were fitted to post-1979 data, with subsequent forecasts over the 1983-85 time interval. The adjusted R^2s for the forecasts made over the three-year test horizon were near 0.90. The results provided by this limited data set suggest the importance of the forecast horizon. Providing there are no further near-term structural changes within the Willamette Valley vegetable processing industry, the econometric models may generate better results in the future than those evidenced over the 1975-86 test period.

Naive Forecasters

Results generated by the single-variable forecasting techniques (i.e. three-year moving average and exponential smoothing) suggest that under certain conditions these forecasters perform quite well. The univariate methods are useful in accounting for random shocks in net returns per ton. On the other hand, if these random shocks are turning points of great magnitude, the univariate forecasters tend to perform quite poorly. This shortcoming of the univariate forecasters cannot be avoided due to

the inherent nature of their forecasting process. Thus, these forecasting methods are most appropriate for data with gradually changing means.

Composite Forecaster

The composite forecaster is dependent upon the ability of all forecasters and the weighting scheme used to generate the forecast. Once the weighting scheme is chosen, performance of the composite is dictated by the performance of other methods. The limitation was not in the weight chosen, but in the random performance of the alternative forecasters. Individually, all forecasters performed well at one point in time or another. If an individual technique was providing good results, a large weight would be assigned to that particular forecaster for the next period. Oftentimes a method with large assigned weight would perform poorly in the subsequent period. In that case, the composite forecast for the following time period would also perform poorly.

Applications for Single-Pool Cooperatives

Application of the research findings in this paper are dependent on cooperatives' notions of equity (measure of bias) and dispersion of pool-payments around their mean values (measure of variance). For example, equity may be the foremost concern, with the criterion being that the

long run average pool payments to each member be equal to each member's products average contribution to total pool returns. If this is the criterion sought, then the three-year moving average and double exponential smoothing techniques provide the most desirable results, clearly outperforming the other methods. On the other hand, the cooperative's present method of selecting economic values provides the best results if variance (minimum variation in values over time) is the most important criterion. The economic value method also would provide the best results if variance and bias were were thought of as equal in importance. Thus, applications to processing cooperatives may vary depending on members' perceived importance of various criteria used in evaluation of pool payments.

Some of the alternative forecasting procedures developed in the context of this research did perform quite well, paticularily in terms of biasedness. From the grower-member standpoint it is a reasonable presumption that bias is of greater concern than variance. If bias and variance are not thought of as equal in importance, then cooperative management may wish to incorporate one or more of the methods developed in this research in establishing raw product price. The tendency towards bias and improper price signals in the raw product market are interrelated. The relationship between improper price signals and bias is inherent in the cooperative's calculation

of payments to growers. Raw product forecasts are the basis for payment to growers as shown in equation 2.2. Adoption of one or more of the alternative forecasters would help alleviate problems of disequilibrium between the raw product and finished product markets. Furthermore, decreased bias would help remedy the long run taxation of some growers and the subsidization of others.

Limitations

The cooperative upon which this research is based handles a number of different fruits and vegetables. Revenues from all commodities are grouped into a single-pool. Allocation of these revenues to individual commodities is then derived utilizing equations 2.1 and 2.2. In this paper, a simplified representation of the cooperative was adopted. Calculation of single-pool returns was based upon the methods currently employed by cooperative management. However, only two commodities, snap beans and sweet corn, were included in the modeled pool. Inclusion of more than two commodities would have given a more reasonable representation of the risk-return tradeoff of a single pool and the resulting allocation of revenues to individual commodities.

The two-commodity single pool modeled in the context of this research is justified by the research objectives given in Chapter I. If the research objective had been

solely to measure payment variance, then a two-commodity single pool indeed would have been a serious limitation. The main objective of this research, however, was to assess deviation of members' payments from members' contribution to pool returns. The two commoditites included in this research comprise a major portion of the cooperative's single pool in terms of economic value. Snap beans and sweet corn encompass up to 80 percent of total economic values assigned to all commodities. Thus, in constructing a pool with only two commodities it is evident snap beans and sweet corn were the appropriate choice. Furthermore, the theory which dictates the use of single pools is not dependent on the number of commodities within the pool but the methods used to allocate revenues among growers of different products.

Suggestions for Further Research

The structure of the processed vegetable market in the Northwest Region has undergone extensive change in recent years. Not only has the industry changed, but the firms within the market have changed in both size and operational characteristics. Forecasting models which utilize explanatory variables based on national data cannot completely and accurately reflect changes within these firms. Further research could attempt to incorporate explanatory variables which are firm-specific in nature.

Inclusion of explanatory variables such as fruit or vegetable packed in the Northwest, purchase orders or bookings for final products, or firm-specific stocks might enhance the forecasting ability of an econometric model.

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APPENDICES

APPENDIX A

POOL-YEAR RETURNS AND COMPARATIVE STATISTICS

APPENDIX A

POOL-YEAR RETURNS AND COMPARATIVE STATISTICS

	Multiple Pool (R_j)		Economic Value Forecaster (P_j)			Pool Payment/ Ton (G_j)		Residual (G_j-R_j)		Pool Payment/ AC (G_jQ_j)		Residual (G_jQ_j-R_jQ_j)		
Year	Beans	Corn	Beans	Corn	Fraction	Beans	Corn	Beans	Corn	Beans	Corn	Beans	Corn	Variance (G_jQ_j-R_jQ_j)
EV Forecaster														
1976	138.86	66.27	139.91	56.77	1.07	149.25	60.56	10.39	- 5.71	656.68	484.46	45.70	-45.70	422.64
1977	212.19	75.63	156.78	67.61	1.26	197.08	84.99	-15.11	9.36	867.17	603.44	-66.46	66.46	17614.04
1978	217.60	74.65	152.40	62.32	1.33	202.47	82.80	-15.13	8.15	850.38	645.81	-63.54	63.54	16845.75
1979	188.39	62.03	161.64	63.72	1.08	175.25	69.08	-13.14	7.05	771.08	566.48	-57.84	57.84	15398.72
1980	91.70	69.02	161.49	66.12	.76	122.44	50.13	30.74	-18.89	624.44	416.09	156.77	-156.77	8193.86
1981	81.25	90.45	168.55	68.37	.80	135.51	54.97	54.26	-35.48	691.12	428.76	276.75	-276.75	44307.44
1982	33.63	46.90	146.64	72.83	.42	62.57	30.58	27.94	-16.32	320.15	272.14	145.27	-145.27	6243.44
1983	64.32	57.98	188.14	74.10	.51	95.68	37.69	31.36	-20.29	526.26	320.33	172.50	-172.50	11288.49
1984	122.28	55.70	188.85	74.73	.68	128.63	50.90	6.35	- 4.80	797.50	417.38	39.36	-39.36	723.21
1985	87.92	41.15	169.59	74.27	.53	90.52	39.64	2.60	- 1.51	488.80	368.55	14.03	-14.03	2727.39
Mean Value					.84			12.03	- 7.84	695.36	452.36	66.25	-66.25	111.25
Exponential Smoothing														
1976	138.86	66.27	186.41	66.98	.84	156.87	56.37	18.01	- 9.90	690.22	450.92	79.24	-79.24	3975.31
1977	212.19	75.63	181.45	55.84	1.23	223.33	68.73	11.14	- 6.90	982.64	487.97	49.01	-49.01	1077.10
1978	217.60	74.65	183.95	56.99	1.23	266.13	70.06	8.53	- 4.59	949.74	546.45	35.82	-35.82	385.48
1979	188.30	62.03	168.46	77.24	.97	163.92	75.16	-24.47	13.13	721.26	616.31	-107.66	107.66	16338.16
1980	91.70	69.02	169.83	72.87	.71	120.14	51.55	28.44	-17.47	612.69	427.84	145.02	-145.02	16598.45
1981	81.25	90.45	157.20	73.87	.81	127.76	60.04	46.51	-30.41	651.59	468.29	237.22	-237.22	48854.55
1982	33.63	46.90	157.60	82.14	.38	60.20	31.38	26.57	-15.52	313.04	279.25	138.16	-138.16	14878.41
1983	64.32	57.98	56.69	71.70	.92	52.10	65.89	-12.22	7.91	286.53	560.06	-67.23	67.23	6958.82
1984	122.28	55.70	57.86	68.49	1.32	76.38	90.41	-45.90	34.71	473.53	741.34	-284.60	284.60	90475.75
1985	87.92	41.15	103.55	65.11	.74	76.23	47.93	-11.69	6.78	411.67	445.79	-63.10	63.10	6286.42
Mean Value					.92			4.49	- 2.23	609.29	502.42	15.19	-16.19	143.12
Econometric														
1976	138.86	66.27	91.18	33.91	1.70	154.73	57.54	15.87	- 8.79	680.80	460.35	69.81	-69.81	2458.42
1977	212.19	75.68	188.58	99.63	.96	180.42	95.32	-31.77	19.69	793.85	676.76	-139.79	139.79	25606.96
1978	217.60	74.65	246.46	122.89	.75	184.96	92.23	-32.64	17.58	776.83	719.36	-137.09	137.09	24748.86
1979	188.39	62.03	280.18	113.07	.62	173.50	70.02	-14.89	7.99	763.41	574.15	-65.51	65.51	7351.30
1980	91.70	69.02	272.98	115.44	.44	120.85	51.11	29.15	-17.91	616.35	424.19	148.68	-148.68	16498.25
1981	81.25	90.45	97.85	97.88	.89	86.80	85.82	5.55	- 3.63	442.69	677.19	28.32	-28.32	65.35
1982	33.63	46.90	127.86	96.99	.39	49.56	37.59	15.93	- 9.31	257.70	334.58	82.83	-82.83	3918.38
1983	64.32	57.98	105.91	23.32	1.08	114.84	25.29	50.52	-32.69	631.65	214.94	277.89	-277.89	66386.36
1984	122.28	55.70	202.15	139.10	.51	102.59	70.59	-19.69	14.89	636.05	578.82	-122.08	122.08	20253.84
1985	87.92	41.15	186.94	65.74	.53	98.89	34.78	10.97	- 6.37	534.03	323.43	59.26	-59.26	1523.42
Mean Value					.79			2.90	- 1.85	613.34	498.38	20.23	-20.23	129.93

POOL-YEAR RETURNS AND COMPARATIVE STATISTICS (continued)

Year	Multiple Pool (R_j) Beans	Multiple Pool (R_j) Corn	Economic Value Forecaster (P_j) Beans	Economic Value Forecaster (P_j) Corn	Fraction	Pool Payment/ Ton (G_j) Beans	Pool Payment/ Ton (G_j) Corn	Residual (G_j-R_j) Beans	Residual (G_j-R_j) Corn	Pool Payment/ AC (G_jQ_j) Beans	Pool Payment/ AC (G_jQ_j) Corn	Residual (G_jQ_j-R_jQ_j) Beans	Residual (G_jQ_j-R_jQ_j) Corn	Variance (G_jQ_j-R_jQ_j)
3 Year Average Forecast														
1976	138.86	66.27	174.71	73.30	.84	147.12	61.73	8.26	- 4.54	647.34	493.80	36.36	-36.36	1422.33
1977	212.19	75.63	160.08	79.13	1.16	185.93	91.91	-26.26	16.28	818.08	652.53	-115.56	115.56	13042.12
1978	217.60	74.65	155.25	69.73	1.25	194.23	87.24	-23.37	12.59	815.75	680.44	-98.17	98.17	9372.53
1979	188.39	62.03	189.55	72.18	.94	177.81	67.71	-10.58	5.68	782.35	555.21	-46.56	46.56	2043.47
1980	91.70	69.02	206.06	70.77	.64	130.88	44.95	39.18	-24.07	667.46	373.07	199.79	-199.79	40462.71
1981	81.25	90.45	165.90	68.56	.81	134.55	55.60	53.30	-34.85	686.18	433.70	271.81	-271.81	74520.91
1982	33.63	46.90	120.45	73.84	.46	55.58	34.07	21.95	-12.83	289.03	303.26	114.15	-114.15	13342.78
1983	64.32	67.98	68.86	68.50	.88	60.66	60.35	- 3.66	2.37	333.65	512.94	-20.11	20.11	351.69
1984	122.28	55.70	69.72	65.11	1.34	80.24	87.48	-42.04	31.78	497.50	717.37	-260.63	260.63	67223.43
1985	87.92	41.15	73.41	53.53	.96	70.39	51.33	-17.53	10.18	380.11	477.35	-94.66	94.66	8704.84
Mean Value					.98			- .08	.26	691.75	519.97	- 1.36	1.36	151.85
Composite Forecaster														
1976	138.86	66.27	150.77	58.06	1.01	152.54	58.75	13.68	- 7.52	671.17	469.97	60.19	-60.19	4461.80
1977	212.19	76.73	173.32	56.10	1.27	219.56	71.06	7.37	- 4.57	966.08	504.43	32.44	-32.44	1524.59
1978	217.60	74.65	215.96	70.43	1.03	221.87	72.35	4.27	- 2.30	931.84	564.35	17.92	-17.92	601.72
1979	188.39	62.03	228.08	72.93	.84	190.48	60.91	2.09	- 1.12	838.10	499.46	9.19	- 9.19	249.46
1980	91.70	69.02	205.95	72.59	.63	129.65	45.70	37.95	-23.32	661.24	379.30	193.57	-193.57	40069.48
1981	81.25	90.45	152.99	69.50	.85	129.56	58.86	48.31	-31.59	660.77	459.11	246.40	-246.40	64009.54
1982	33.63	46.90	128.91	92.70	.40	51.06	36.72	17.43	-10.18	265.51	326.78	90.63	-90.63	9455.03
1983	64.32	57.98	79.75	62.52	.87	69.60	54.56	5.28	- 3.42	382.80	463.79	29.04	-29.05	1270.65
1984	122.28	55.70	71.36	70.35	1.19	85.05	83.85	-37.23	28.15	527.32	687.55	-230.81	230.81	50267.98
1985	87.92	41.15	111.77	57.66	.75	84.08	43.38	- 3.84	2.23	454.04	403.43	-20.73	20.73	199.54
Mean Value					.88			9.53	- 5.36	635.89	475.83	42.78	-42.78	131.19

APPENDIX B

ECONOMETRIC MODEL ESTIMATION RESULTS

Table B-1. Econometric Model Estimation Results, Snap Beans.

SMPL 1961 - 1975
15 Observations
LS // Dependent Variable is RETURN

Variable	Coefficient	Std. Error	T-Stat.	2-Tail Sig.
C	1094.1982	263.72834	4.1489594	0.002
QCN(-1)	- 0.0050280	0.0016417	-3.0626048	0.012
DISINC(-1)	1.6721949	0.4459204	3.7499851	0.004
CPI(-1)	-1975.9678	563.94866	-3.5038079	0.006
RETURN(-1)	- 0.1403019	0.2393457	-0.5861895	0.571

R-squared	0.621526	Mean of dependent var	153.1584
Adjusted R-squared	0.470136	S.D. of dependent var	34.72782
S.E. of regression	25.27900	Sum of squared resid.	6390.276
Durbin-Watson stat	2.108918	F-statistic	4.105465
Log likelihood	-66.69270		

SMPL 1961 - 1976
16 Observations
LS // Dependent Variable is RETURN

Variable	Coefficient	Std. Error	T-Stat.	2-Tail Sig.
C	946.88229	222.44850	4.2566360	0.001
QCN(-1)	- 0.0047200	0.0016192	-2.9150092	0.014
DISINC(-1)	1.4320078	0.3815477	3.7531553	0.003
CPI(-1)	-1632.1967	456.49476	-3.5754993	0.004
RETURN(-1)	- 0.2322631	0.2228141	-1.0424074	0.320

R-squared	0.585891	Mean of dependent var	152.2647
Adjusted R-squared	0.435306	S.D. of dependent var	33.74015
S.E. of regression	25.35442	Sum of squared resid.	7071.314
Durbin-Watson stat	2.149104	F-statistic	3.890761
Log likelihood	-71.43272		

SMPL 1961 - 1977
17 Observations
LS // Dependent Variable is RETURN

Variable	Coefficient	Std. Error	T-Stat.	2-Tail Sig.
C	963.17886	215.83529	4.4625643	0.001
QCN(-1)	- 0.0051753	0.0014309	-3.6167916	0.004
DISINC(-1)	1.4655063	0.3692002	3.9694078	0.002
CPI(-1)	-1643.3704	445.36069	-3.6899764	0.003
RETURN(-1)	- 0.2610803	0.2133290	-1.2238385	0.244

R-squared	0.640571	Mean of dependent var	155.7899
Adjusted R-squared	0.520762	S.D. of dependent var	35.75622
S.E. of regression	24.75298	Sum of squared resid.	7352.518
Durbin-Watson stat	2.051570	F-statistic	5.346576
Log likelihood	-75.71343		

SMPL 1962 - 1978
17 Observations
LS // Dependent Variable is RETURN

Variable	Coefficient	Std. Error	T-Stat.	2-Tail Sig.
C	1007.9967	210.54434	4.7875746	0.000
QCN(-1)	- 0.0043016	0.0012167	-3.5355986	0.004
DISINC(-1)	1.5664376	0.3653849	4.2870894	0.001
CPI(-1)	-1798.3338	449.41554	-4.0014944	0.002
RETURN(-1)	- 0.3796985	0.2108306	-1.8009643	0.097

R-squared	0.720645	Mean of dependent var	169.3171
Adjusted R-squared	0.627526	S.D. of dependent var	38.77989
S.E. of regression	23.66761	Sum of squared resid.	6721.868
Durbin-Watson stat	2.192710	F-statistic	7.739012
Log likelihood	-74.95117		

SMPL 1963 - 1979
17 Observations
LS // Dependent Variable is RETURN

Variable	Coefficient	Std. Error	T-Stat.	2-Tail Sig.
C	929.84643	252.80557	3.6781090	0.003
QCN(-1)	- 0.0026877	0.0013324	-2.0172780	0.067
DISINC(-1)	1.4396244	0.4471799	3.2193404	0.007
CPI(-1)	-1694.2219	559.11741	-3.0301719	0.010
RETURN(-1)	- 0.4876264	0.2719342	-1.7931780	0.098

R-squared	0.616300	Mean of dependent var	161.6035
Adjusted R-squared	0.488400	S.D. of dependent var	39.30836
S.E. of regression	28.11577	Sum of squared resid.	9485.961
Durbin-Watson stat	1.250633	F-statistic	4.818615
Log likelihood	-77.87897		

SMPL 1964 - 1980
17 Observations
LS // Dependent Variable is RETURN

Variable	Coefficient	Std. Error	T-Stat.	2-Tail Sig.
C	519.65433	154.61871	3.3608767	0.006
QCN(-1)	- 0.0034974	0.0011618	-3.0101852	0.011
DISINC(-1)	0.5926189	0.2989184	1.9825444	0.071
CPI(-1)	- 641.78417	382.40983	-1.6782628	0.119
DUMMY	- 133.0028864	31.0425912	-4.2845292	0.001

R-squared	0.688792	Mean of dependent var	162.8375
Adjusted R-squared	0.585056	S.D. of dependent var	36.50661
S.E. of regression	23.51616	Sum of squared resid.	6636.118
Durbin-Watson stat	2.379253	F-statistic	6.639848
Log likelihood	-74.84204		

SMPL 1965 - 1981
17 Observations
LS // Dependent Variable is RETURN

Variable	Coefficient	Std. Error	T-Stat.	2-Tail Sig.
C	476.41436	143.16742	3.3276730	0.006
QCN(-1)	- 0.0044926	0.0012207	-3.6803207	0.003
DISINC(-1)	0.3955394	0.2988843	1.3233864	0.210
CPI(-1)	- 386.26170	383.35018	-1.0075949	0.334
DUMMY	- 127.6258064	25.376181	-5.0293538	0.000

R-squared	0.798694	Mean of dependent var	159.3485
Adjusted R-squared	0.731592	S.D. of dependent var	41.28940
S.E. of regression	21.39124	Sum of squared resid.	5491.023
Durbin-Watson stat	2.702645	F-statistic	11.90270
Log likelihood	-73.23204		

SMPL 1966 - 1982
17 Observations
LS // Dependent Variable is RETURN

Variable	Coefficient	Std. Error	T-Stat.	2-Tail Sig.
C	523.15327	196.21308	2.6662507	0.021
QCN(-1)	- 0.0031509	0.0017102	-1.8424122	0.090
DISINC(-1)	0.5698554	0.4224278	1.3490008	0.202
CPI(-1)	- 643.12454	538.12336	-1.1951247	0.255
DUMMY	- 151.0947864	34.834923	-4.3374513	0.001

R-squared	0.754101	Mean of dependent var	151.4455
Adjusted R-squared	0.672134	S.D. of dependent var	51.20229
S.E. of regression	29.31820	Sum of squared resid.	10314.68
Durbin-Watson stat	2.130038	F-statistic	9.200121
Log likelihood	-78.59089		

SMPL 1967 - 1983
17 Observations
LS // Dependent Variable is RETURN

Variable	Coefficient	Std. Error	T-Stat.	2-Tail Sig.
C	539.56644	203.35755	2.6532894	0.021
QCN(-1)	- 0.0019582	0.0017695	-1.1066196	0.290
DISINC(-1)	0.7122129	0.4221913	1.6869436	0.117
CPI(-1)	- 838.33437	531.87927	-1.5761742	0.141
DUMMY	- 161.3040864	36.553223	-4.4128553	0.001

R-squared	0.768069	Mean of dependent var	144.4043
Adjusted R-squared	0.690758	S.D. of dependent var	54.56239
S.E. of regression	30.34187	Sum of squared resid.	11047.55
Durbin-Watson stat	2.066544	F-statistic	9.934874
Log likelihood	-79.17433		

SMPL 1968 - 1984
17 Observations
LS // Dependent Variable is RETURN

Variable	Coefficient	Std. Error	T-Stat.	2-Tail Sig.
C	347.20017	132.85916	2.6132950	0.023
QCN(-1)	- 0.0015241	0.0021772	-0.7000110	0.497
DISINC(-1)	0.3208585	0.2757921	1.1634072	0.267
CPI(-1)	- 355.53502	357.02661	-0.9958222	0.339
DUMMY	- 145.4204964	38.280920	-3.7987720	0.003

R-squared	0.740564	Mean of dependent var	141.6185
Adjusted R-squared	0.654086	S.D. of dependent var	54.40187
S.E. of regression	31.99618	Sum of squared resid.	12285.07
Durbin-Watson stat	1.888696	F-statistic	8.563556
Log likelihood	-80.07683		

Table B-2. Econometric Model Estimation Results, Sweet Corn.

SMPL 1961 - 1975
15 Observations
LS // Dependent Variable is RETURN

Variable	Coefficient	Std. Error	T-Stat.	2-Tail Sig.
C	688.235238	115.53885	5.9567441	0.000
Q(-1)	- 0.0003163	9.020D-05	-3.5062571	0.006
DISINC(-1)	1.6605105	0.2498329	6.6464844	0.000
CPI(-1)	-1666.4777	273.64028	-6.0900306	0.000
TREND	- 9.9366198	4.5624634	-2.1779067	0.054

R-squared	0.876745	Mean of dependent var	44.88374
Adjusted R-squared	0.827442	S.D. of dependent var	21.32567
S.E. of regression	8.858692	Sum of squared resid.	784.7643
Durbin-Watson stat	2.653372	F-statistic	17.78309
Log likelihood	-50.96408		

SMPL 1961 - 1976
16 Observations
LS // Dependent Variable is RETURN

Variable	Coefficient	Std. Error	T-Stat.	2-Tail Sig.
C	538.84249	97.594261	5.5212518	0.000
Q(-1)	- 0.0002327	8.928D-05	-2.6070677	0.024
DISINC(-1)	1.4569881	0.2551303	5.7107612	0.000
CPI(-1)	-1356.8392	251.00062	-5.4057205	0.000
TREND	- 12.672359	4.8760576	-2.5988943	0.025

R-squared	0.839995	Mean of dependent var	46.22055
Adjusted R-squared	0.781811	S.D. of dependent var	21.28516
S.E. of regression	9.942443	Sum of squared resid.	1087.374
Durbin-Watson stat	2.412727	F-statistic	14.43695
Log likelihood	-56.45447		

SMPL 1961 - 1977
17 Observations
LS // Dependent Variable is RETURN

Variable	Coefficient	Std. Error	T-Stat.	2-Tail Sig.
C	527.99245	104.48744	5.0531668	0.000
Q(-1)	- 0.0002549	9.474D-05	-2.6904838	0.020
DISINC(-1)	1.3315931	0.2617454	5.0873590	0.000
CPI(-1)	-1285.3833	265.41648	-4.8428920	0.000
TREND	- 8.9901545	4.6721840	-1.9241867	0.078

R-squared	0.820538	Mean of dependent var	47.95061
Adjusted R-squared	0.760717	S.D. of dependent var	21.80883
S.E. of regression	10.66813	Sum of squared resid.	1365.708
Durbin-Watson stat	2.713961	F-statistic	13.71661
Log likelihood	-61.40478		

SMPL 1962 - 1978
17 Observations
LS // Dependent Variable is RETURN

Variable	Coefficient	Std. Error	T-Stat.	2-Tail Sig.
C	453.95682	117.53220	3.8624037	0.002
Q(-1)	- 0.0003348	0.0001039	-3.2230643	0.007
DISINC(-1)	0.9788812	0.2588764	3.7812687	0.003
CPI(-1)	-1014.8379	281.65961	-3.6030649	0.004
TREND	0.4966104	3.7449206	0.1326091	0.897

R-squared	0.771007	Mean of dependent var	49.55076
Adjusted R-squared	0.694677	S.D. of dependent var	22.74721
S.E. of regression	12.56921	Sum of squared resid.	1895.822
Durbin-Watson stat	2.328114	F-statistic	10.10087
Log likelihood	-64.19261		

SMPL 1963 - 1979
17 Observations
LS // Dependent Variable is RETURN

Variable	Coefficient	Std. Error	T-Stat.	2-Tail Sig.
C	370.59766	133.60330	2.7738660	0.017
Q(-1)	- 0.0003733	0.0001223	-3.0518574	0.010
DISINC(-1)	0.6913490	0.2664424	2.5947412	0.023
CPI(-1)	- 760.51204	309.83742	-2.4545520	0.030
TREND	6.4739358	3.5423050	1.8276054	0.093

R-squared	0.660381	Mean of dependent var	51.61852
Adjusted R-squared	0.547174	S.D. of dependent var	22.14719
S.E. of regression	14.90336	Sum of squared resid.	2665.321
Durbin-Watson stat	2.036488	F-statistic	5.833420
Log likelihood	-67.08832		

SMPL 1964 - 1980
17 Observations
LS // Dependent Variable is RETURN

Variable	Coefficient	Std. Error	T-Stat.	2-Tail Sig.
C	347.43167	139.15917	2.4966495	0.030
Q(-1)	- 0.0003676	0.0001247	-2.9493898	0.013
DISINC(-1)	0.6514089	0.2758937	2.3610866	0.038
CPI(-1)	- 691.62337	327.50211	-2.1118135	0.058
TREND	5.1762180	3.9746337	1.3023132	0.219
DUMMY	- 47.0713154	25.1191852	-1.8739189	0.088

R-squared	0.639310	Mean of dependent var	54.50352
Adjusted R-squared	0.475360	S.D. of dependent var	20.92899
S.E. of regression	15.15929	Sum of squared resid.	2527.846
Durbin-Watson stat	2.198470	F-statistic	3.899419
Log likelihood	-66.63819		

SMPL 1965 - 1981
17 Observations
LS // Dependent Variable is RETURN

Variable	Coefficient	Std. Error	T-Stat.	2-Tail Sig.
C	333.79444	144.67948	2.3071304	0.042
Q(-1)	- 0.0003537	0.0001192	-2.9666371	0.013
DISINC(-1)	0.6229181	0.2843697	2.1905219	0.051
CPI(-1)	- 658.61696	351.71421	-1.8725913	0.088
TREND	4.8939519	4.5093083	1.0852999	0.301
DUMMY	- 48.5293414	24.860815	-1.9520414	0.077

R-squared	0.672407	Mean of dependent var	57.72564
Adjusted R-squared	0.523502	S.D. of dependent var	22.03761
S.E. of regression	15.21231	Sum of squared resid.	2545.560
Durbin-Watson stat	2.205856	F-statistic	4.515658
Log likelihood	-66.69754		

SMPL 1966 - 1982
17 Observations
LS // Dependent Variable is RETURN

Variable	Coefficient	Std. Error	T-Stat.	2-Tail Sig.
C	371.48076	175.16961	2.1206919	0.058
Q(-1)	- 0.0003408	0.0001548	-2.2020159	0.050
DISINC(-1)	0.6524369	0.3453829	1.8890249	0.086
CPI(-1)	- 783.73086	420.69060	-1.8629626	0.089
TREND	9.3921836	5.1930602	1.8086029	0.098
DUMMY	- 41.8657264	31.126898	-1.3450016	0.206

R-squared	0.524758	Mean of dependent var	57.41976
Adjusted R-squared	0.308740	S.D. of dependent var	22.15629
S.E. of regression	18.42120	Sum of squared resid.	3732.747
Durbin-Watson stat	1.759101	F-statistic	2.429225
Log likelihood	-69.95129		

SMPL 1967 - 1983
17 Observations
LS // Dependent Variable is RETURN

Variable	Coefficient	Std. Error	T-Stat.	2-Tail Sig.
C	219.76125	147.51497	1.4897555	0.164
Q(-1)	- 0.0001766	0.0001375	-1.2846993	0.225
DISINC(-1)	0.3940806	0.3045263	1.2940777	0.222
CPI(-1)	- 504.11947	351.96354	-1.4323059	0.180
TREND	8.6884523	4.9521091	1.7544953	0.107
DUMMY	- 23.8262894	32.664114	-0.7294332	0.481

R-squared	0.518931	Mean of dependent var	57.41717
Adjusted R-squared	0.300263	S.D. of dependent var	22.15622
S.E. of regression	18.53374	Sum of squared resid.	3778.493
Durbin-Watson stat	2.010086	F-statistic	2.233150
Log likelihood	-70.05483		

SMPL 1968 - 1984
17 Observations
LS // Dependent Variable is RETURN

Variable	Coefficient	Std. Error	T-Stat.	2-Tail Sig.
C	26.768369	62.789981	0.4263159	0.678
Q(-1)	- 1.771D-05	8.676D-05	-0.2041616	0.842
DISINC(-1)	0.0322636	0.1230455	0.2622088	0.798
CPI(-1)	- 214.99991	193.60281	-1.1105206	0.290
TREND	16.710232	4.6953905	3.5588589	0.004
DUMMY	15.1722414	21.124669	0.7182238	0.488

R-squared	0.641666	Mean of dependent var	57.35467
Adjusted R-squared	0.478787	S.D. of dependent var	22.15968
S.E. of regression	15.99820	Sum of squared resid.	2815.366
Durbin-Watson stat	2.214135	F-statistic	3.939524
Log likelihood	-67.55385		

APPENDIX C

DATA FOR ECONOMETRIC MODEL ESTIMATION

Table C.1. Snap Beans: Estimation for Econometric Model.

Observation	QCN	DISINC	CPI	Dummy
1960	33074	349.9	0.687	0
1961	38611	364.4	0.693	0
1962	38426	385.3	0.706	0
1963	37804	404.6	0.717	0
1964	43006	438.1	0.728	0
1965	41839	473.2	0.744	0
1966	44721	511.9	0.768	0
1967	52965	546.5	0.791	0
1968	57671	590.0	0.825	0
1969	55647	630.4	0.868	0
1970	54179	685.9	0.915	0
1971	54483	742.8	0.960	0
1972	49074	801.3	1.000	0
1973	53594	901.7	1.058	0
1974	61058	984.6	1.151	0
1975	62548	1084.4	1.258	0
1976	56086	1185.8	1.323	0
1977	54998	1314.0	1.401	0
1978	57985	1474.0	1.504	0
1979	64110	1650.2	1.634	0
1980	65103	1828.9	1.784	1
1981	60892	2047.6	1.962	1
1982	54776	2176.5	2.074	1
1983	50339	2425.4	2.153	1
1984	50740	2670.2	2.234	1
1985	55168	2801.1	2.305	1

Table C.2. Sweet Corn: Estimation for Econometric Model.

Observation	Q	DISINC	CPI	Trend	Dummy
1960	200198	349.9	0.687	1	0
1961	245847	364.4	0.693	2	0
1962	259829	385.3	0.706	3	0
1963	280571	404.6	0.717	4	0
1964	282076	438.1	0.728	5	0
1965	342525	473.2	0.744	6	0
1966	414834	511.9	0.768	7	0
1967	442612	546.5	0.791	8	0
1968	522470	590.0	0.825	9	0
1969	492320	630.4	0.868	10	0
1970	465665	685.9	0.915	11	0
1971	504215	742.8	0.960	12	0
1972	526605	801.3	1.000	13	0
1973	554261	901.7	1.058	14	0
1974	545918	984.6	1.151	15	0
1975	588554	1084.4	1.258	16	0
1976	617435	1185.8	1.323	17	0
1977	718636	1314.0	1.401	18	0
1978	798696	1474.0	1.504	19	0
1979	774878	1650.2	1.634	20	0
1980	744890	1828.9	1.784	21	1
1981	803294	2047.6	1.962	22	1
1982	957390	2176.5	2.074	23	1
1983	818160	2425.4	2.153	24	1
1984	931686	2670.2	2.234	25	1
1985	975677	2801.1	2.305	26	1

For a complete description of data sources and units, see the section Data Sources in Chapter III of this thesis, page 43 .

The net returns/ton are confidential and are not reported in this Appendix.