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Jim Cornelius, Ron Myersick, and Steve Buccola

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FORECASTING NET RETURNS OF PROCESSED VEGETABLES

Jim Cornelius, Ron Meyersick and Steve Buccola*

The Oregon fruit and vegetable processing industry has undergone significant structural changes in recent years. Role of the raw product cash market between grower and processor has declined in importance as proprietary processors have relocated outside the region or ceased business operations entirely. Grower-owned agricultural processing and marketing cooperatives have persisted through this industry transition and have emerged as the primary fruit and vegetable processors in the region.

Increasing thinness of the proprietary raw product cash market has posed a dilemma for the cooperatives that have remained. Most of these cooperatives operate on a pool basis in which net returns from all or most products are combined in a common payment fund. In order to calculate the share of pool returns payable to a particular raw product, one must impute the patronage value of this raw product which has been delivered by members. Total payment to the product then is the total pool return times the ratio of the product's patronage value to total pool patronage.

Heretofore, the cooperative under investigation has for patronage purposes valued each raw product according to an estimate of its market price. The estimation procedure is dictated by cooperative bylaws requiring that raw product value be representative of comparable prices in proprietary cash markets. As proprietary processors have relocated outside the region, independent market transactions between raw product grower and buyer have become fewer. In the absence of a local cash market, the cooperative relies upon a relatively simple estimation procedure allowed by its bylaws to generate estimates of raw product value. The procedure is to follow a one-year lag: estimated unit raw product value for the coming year equals last year's cash "price." Last year's price is, in this case, a subjective determination based partly on prices in other states.

Intuitively, a lagged or naive estimation procedure creates the possibility that unit values may be inefficient. This can lead to serious misallocation problems in a cooperative. That is, inefficient raw product values will induce a misallocation of payments back to growers. If the raw product value the cooperative estimates for a commodity is too high (low), member-growers of the commodity will be subsidized (taxed) provided that finished products are sold at competitive equilibrium prices.

Such a pricing problem is further complicated by the fact that the cooperative may rely upon per-unit patronage valuations to induce grower members to offer products through acreage contracts. Assuming a positive

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* The authors are associate professor, former research assistant, and professor, respectively, Department of Agricultural and Resource Economics, Oregon State University. This research was partially financed by the Agricultural Cooperative Service, U.S. Department of Agriculture.

unobservable equilibrium. Practically, this could lead to excess or inadequate inventories, hampering the cooperative's competitive position in the finished product market.

The objective of the present investigation is to explore performance of alternative raw product valuation procedures for a fruit and vegetable processing and marketing cooperative. We argue that a raw product's patronage value is an implicit forecast of the product's net return from processing. Four alternative raw product forecasting techniques are developed and evaluated. These estimates, along with the method currently employed by the cooperative, are used to simulate pool returns. The simulation allows for the comparison of different forecasting techniques in terms of both the mean and variance of members' associated pool payments.

Forecasting Models

In a perfectly efficient market, a raw product's price is a perfect forecast of the product's net return from processing. This explains the common notion that a raw product's value is best represented by its market price. However, when market prices are unavailable or unreliable, unit value is best found by appealing to the net return forecast itself. That is, raw product values are estimated by developing good forecasts of final product price less processing cost. The approach requires that costs be prorated to each commodity group in the pool.

Work by Kuznets provides encouragement for the potential to forecast net returns for processed fruit and vegetable products. Kuznets developed "hybrid" reduced form equations at the wholesale level derived from demand functions for five processed tomato products at the consumer level during the 1960-1980 period. His basic model specified national fob price as a function of available supply, disposable personal income, the price of a substitute (CPI served as the proxy), and a binary dummy variable to account for a change in overall price levels that began in 1973. His forecasting equations provided excellent explanatory power consistent with theoretical expectations. Forecast performance was somewhat lower when tested outside the data set.

In order to address firm-specific conditions and to develop a pool payment formula, the dependent variable is specified in the present study as processor net return, that is, the firm's fob finished product price less reported processing cost. Independent variables and functional form are similar to the ones used by Kuznets.

Econometric Models

Efforts to forecast net returns focused on two representative commodities, snap beans and sweet corn. Both of these can be processed in either canned or frozen form. Our initial attempt to develop econometric net return forecasting models involved first forecasting available supply of each finished product in the coming year, using a system of recursive equations estimated by ordinary least squares. Final product prices and net returns then were regressed against the supply forecasts and against demand variables

such as income and prices of substitutes. Recursive model specification is explained in Wiese. Resulting forecasting equations exhibited some signs inconsistent with theory; significance of many variables was relatively low. Adjusted R^2's ranged from .40 to .85, suggesting a wide interval of explanatory power. Initially estimated with 1965-1980 data, the forecasting equations were used to predict raw product values for two years outside the data set. Overall forecast performance was poor.

The recursive form had been utilized in an effort to improve net return predictability by having available forecasts of future supply levels. The model's poor performance and its cumbersome nature limited management applications even though its forecast performance was superior to the naive method the cooperative presently uses.

In order to simplify and improve things, we next specified reduced form models along the lines of Kuznets. Net return per ton was hypothesized to be a function of the nationwide pack of the relevant product form in the previous year, nominal personal disposable income in the previous year, and the lagged price of a substitute product. A one-year net return lag in the snap bean model and a linear trend term in the sweet corn model improved forecast performance. Final models were:

(1) $R_{jt} = \alpha_1 + \beta_1 Qb_{t-1} + \beta_2 I_{t-1} + \beta_3 P^S{}_{t-1} + \beta_4 R_{j,t-1} + e_1$ snap beans

(2) $R_{jt} = \alpha_2 + \beta_1 Qc_{t-1} + \beta_2 I_{t-1} + \beta_3 P^S{}_{t-1} + \beta_4 T + e_2$ sweet corn

where:

R_{jt} = net processing return per ton in t;
Qb_{t-1} = industry pack of canned snap beans in t-1;
Qc_{t-1} = industry pack of canned plus frozen corn in t-1;
I_{t-1} = U.S. total personal disposable income in t-1;
$P^S{}_{t-1}$ = index of the price of substitutes in t-1;
$R_{j,t-1}$ = lagged snap bean net return;
T = trend variable; and
e_1, e_2 = error terms.

Supply of processed product 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 compete with other regions in the U.S. for national market share. Thus, we used national rather than regional packs and carry-over inventory levels.

Carry-over inventories proved nonsignificant and were excluded as explanatory variables in both models. Frozen pack was distinguished from canned pack and a Chow test was used to determine whether supply coefficients differed between the two product types. For snap beans, the canned pack alone provided the most useful supply proxy; for example, its t statistic was considerably higher than that for frozen-plus-canned pack. Sweet corn supply was best represented as total pack for frozen and canned lines (Meyersick).

Estimates provided by fitting equations (1) and (2) had mediocre explanatory power when compared with Kuznets' results. For snap beans, R^2's ranged from 0.44 to 0.73 and for sweet corn they ranged from 0.30 to 0.87. Coefficient signs were consistent with expectations, although t-values varied dramatically as the equations were refitted over the ten-year test period.

Technical Forecasting Methods

In contrast to the explanatory logic embodied in the regression models, two "smoothing" technical forecasting methods were applied to the net return forecasting problem. Smoothing techniques represent a more advanced form of the naive forecasting approach utilized currently by the cooperative. Both assume there is an underlying pattern in the historical values of the variable being forecast. These techniques are useful in accounting for certain predictable variations in the series which can't be captured through regression. The two smoothing techniques applied were: (a) a simple three-year moving average (equation 3), and (b) an exponential smoothing model (equation 4):

$$(3)\quad \hat{R}_{j,t+1} = (R_{jt} + R_{j,t-1} + R_{j,t-2})/3$$

$$(4)\quad \hat{R}_{j,t+1} = R_{jt} + (1-w)\hat{R}_{jt}$$

where:

$\hat{R}_{j,t+1}$ = forecast of next period's net return;
$\hat{R}_{jt}$ = a previous forecast of current net return;
$R_{jt}, \ldots R_{j,t-2}$ = observed values; and
w = a weight assigned to the current net return.

An exponentially smoothed average provides a means of incorporating information about errors with which past prices have predicted subsequent ones [Makridakis and Wheelwright].

Composite Forecasting

The three forecasting methods outlined above (econometric, exponential smoothing, and moving average) differ in conceptual rationale and forecasting strength. Any of them may induce large forecast errors in a given period. Composite forecasting is a method of combining alternative forecasting models in an effort to limit the likelihood of large mistakes from a single model's forecast or in an effort to reduce overall forecast variance. Bessler and Brandt suggest several alternative weighting schemes for developing composite forecasts. We found the best scheme was to weight each model in proportion to the absolute error of its forecast in the previous period.

Composite forecast models often provide superior forecasts and they have useful risk management properties. For example, they permit one simultaneously to consider traditional and unfamiliar forecast techniques or econometric and technical ones. This may enhance their popularity with lay forecasters in cooperative management.

Data

Data were collected from the cooperative for the period 1960-1985. Initial forecast models were developed using only 1960-1975 data; this allowed ten additional years to serve as a test period. Forecasts were updated yearly as additional data became available during the test period. Sample size for the econometric model was held constant at 17 observations; as an additional year's observation became available, the earliest data point was omitted. A binary dummy variable was added to both econometric models to account for substantial changes in the cooperative's finance and cost structure after 1980. Complete results are reported in Meyersick.

Processed vegetable inventory and pack data were obtained from The Almanac of the Canning, Freezing, and Preserving Industries. Per-acre yields used were those quoted by the Extension Service serving the region. The Consumer Price Index (1972=100) served as the most effective proxy for prices of substitute products.

Evaluation Criteria

We compared alternative forecasters in two ways. The first consideration was net return forecast accuracy as measured by mean forecast error, root mean squared error (RMSE), and mean absolute percentage error (MAPE). The second consideration was the impact of a forecast on pool returns. As indicated above, cooperative payments G_jQ_j to members are based on the formula:

$$(5) \quad G_jQ_j = \left[\frac{\Sigma_i \Sigma_j A_{ij}Y_{ij}R_j}{\Sigma_i \Sigma_j A_{ij}Y_{ij}r_j}\right] A_{ij}Y_{ij}r_j$$

where:

A_{ij} = $i^{\underline{th}}$ member's acreage of the $j^{\underline{th}}$ product;
Y_{ij} = $i^{\underline{th}}$ member's per-acre yield of the $j^{\underline{th}}$ product;
R_j = per-unit final product revenue of the $j^{\underline{th}}$ product minus its per-unit processing cost; and
r_j = per-unit value assigned by the cooperative to the $j^{\underline{th}}$ raw product.

Each pool is closed two years after harvest because processed vegetables from a given harvest typically are marketed over a two-year interval. The bracketed term in (5) is the ratio of total pool returns to the total valuation of all raw products delivered to the pool. Second term is the cooperative's valuation of the $j^{\underline{th}}$ raw product delivered, which depends on the per-unit patronage value r_j assigned to it. The latter unit values essentially are forecasts of subsequent final product net returns. Thus, quality of a forecast (r_j) of net return (R_j) may be measured in terms of the forecast's effect on member payment (5).

Cooperative members recognize that pooling tends to diversify returns and that in any given year one may not receive the actual profit from one's own products. However, one naturally hopes to receive a product's net

returns in the long run. If net return forecasts r_j comprising per-unit patronage values are proportionate to unbiased forecasts of subsequent net returns R_j, this hope will be fulfilled under certain conditions (Buccola, Cornelius, and Meyersick). If forecasts of pool commodities' net returns are biased in different proportions, one commodity's net return likely will subsidize another.

In summary, two alternative types of measures of forecast performance are available to the cooperative: (1) conventional measures of goodness-of-fit between forecasted and actual net returns, and (2) measures of the extent to which a member's average payments approximate the average processing net returns of the products he has contributed.

Results

Annual net return forecasts generated by the various models are illustrated in figures 1 and 2.

Forecast Performance: Goodness-of-Fit

Comparative forecast statistics listed in table 1 indicate that one or more of the forecast models employed always proved superior to the naive (lagged raw product market price) forecast. With snap beans, the composite forecast provided the lowest forecast variability measured by RMSE or MAPE. Moving average and exponential smoothing models also performed relatively well. The econometric model was marginally worse than naive forecasts. With sweet corn, on the other hand, the naive forecast provided a much better fit than did the econometric model. Smoothing and composite forecasters performed somewhat similarly to the naive forecast and the moving average model provided the lowest RMSE and MAPE of all.

Table 1. Comparative Forecast Statistics

	Snap Beans			Sweet Corn		
Forecaster	Mean Error	RMSE	MAPE	Mean Error	RMSE	MAPE
Naive (Lagged Market Price)	-39.59	77.29	.93	-4.12	17.88	.27
Exponential Smoothing	-18.49	60.36	.70	-5.15	18.42	.28
Econometric	-56.20	84.80	.85	-26.82	44.76	.68
Moving Average	-14.59	63.10	.64	-5.49	13.23	.19
Composite	-28.07	58.40	.64	-4.31	19.09	.27

Figures 1 and 2 provide visual explanation for the difference in forecast performance between these two raw products. Actual snap bean net returns exhibit somewhat cyclical behavior. Sweet corn returns appear to have a stable mean from 1976 to 1981 and another (lower) stable mean after 1981. Naive and moving average approaches perform poorly in situations where

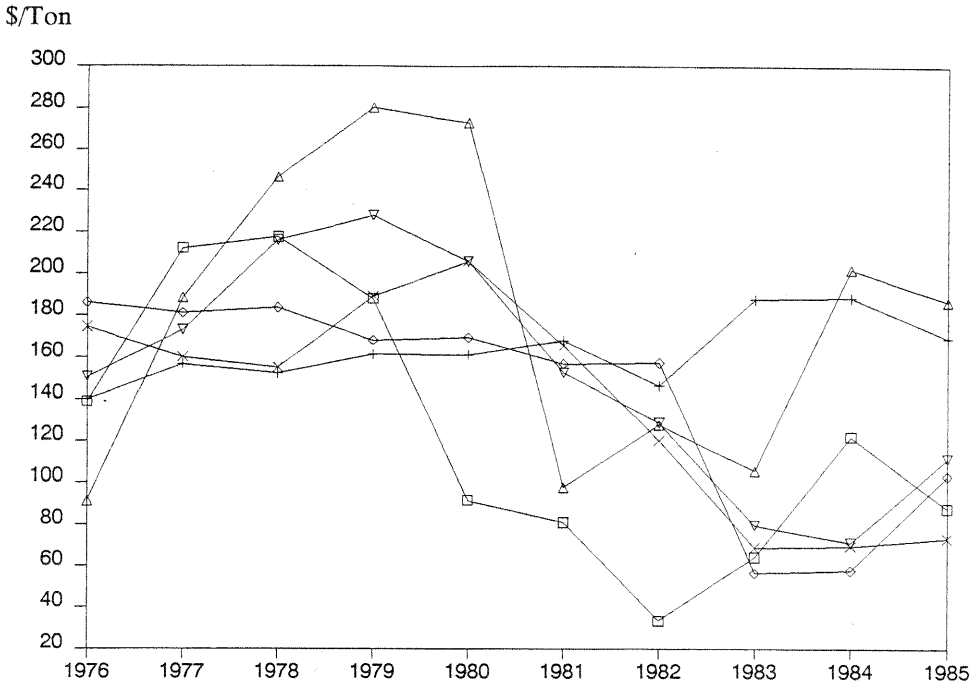

Figure 1. Snap Bean Net Return Forecasts: 1976-1985

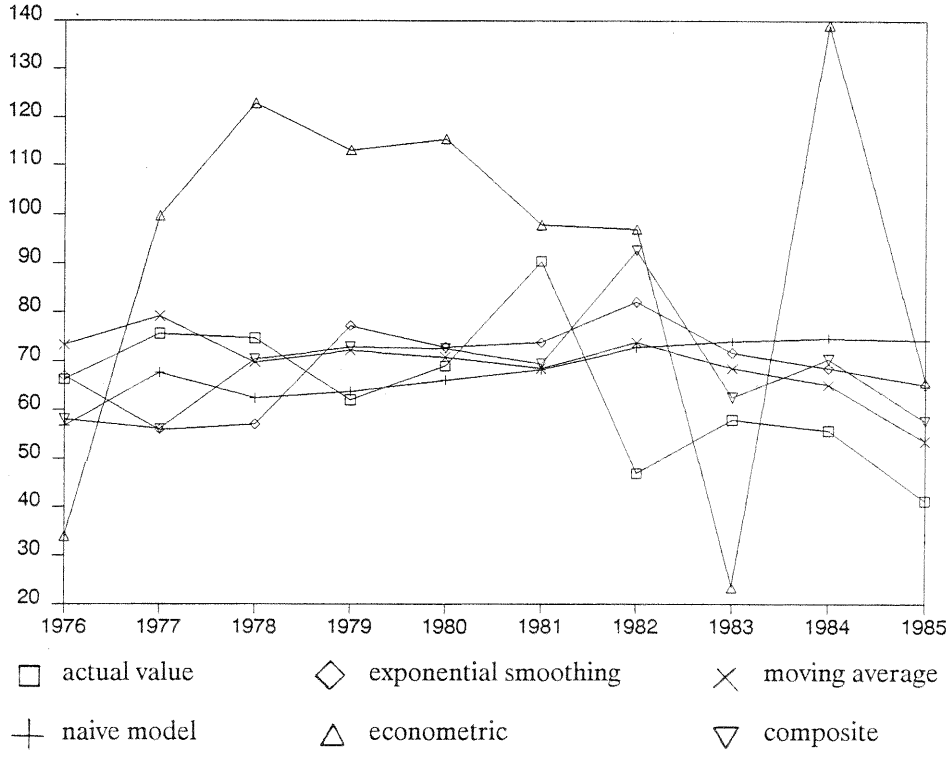

Figure 2. Sweet Corn Net Return Forecasts: 1976-1985

there are strong trends, especially if trends often change abruptly as they have with beans. Hence, these approaches would be expected to serve us better in the sweet corn market than in the snap bean market. This expectation is fulfilled.

The exponential smoother adjusts for previous forecast errors, so should accommodate trends more effectively than does a moving average. Yet the waviness of bean returns continually throws exponential smoothing forecasts off beam. Exponential smoothing actually performs worse in the bean market than in the corn market. As one would hope, the econometric model had lower MAPE in corn forecasts than in bean forecasts. Corn returns had more turning points than did bean returns and regression should do relatively well in the presence of turning points.

Taking both product lines into account, the exponential smoothing and three-year moving average models produced better forecasts than did any other technique tested. The econometric model produced the poorest forecasts, likely due to weak specifications of firm-specific explanatory variables. Although the reduced forms might have been expected to perform relatively well for industry-wide returns, they could not anticipate firm-specific changes that significantly influenced returns in this particular cooperative. When, for example, the cooperative began a rapid expansion in 1980, finance costs rose and member earnings fell. Our dummy variables did not well represent such effects.

A composite model's forecast power depends on the performance of each individual forecast mechanism and on the weighting scheme used to aggregate the mechanisms. In the present application, the composite scheme actually did a good job of shaking off the frequently wild inaccuracy of its constituent econometric forecasts. However, the composite approach did not outperform all of its constituents in corn forecasts. Much of the problem was that an individual mechanism such as the naive model frequently would follow a highly accurate forecast with a highly inaccurate one. Since weights were based on previous forecast errors, composite forecasts often were seriously wrong.

Forecast Performance: Pool Returns

Net return forecasts determine raw product values and hence members' pool payments. Table 2 shows the ten-year impact of each forecast procedure on a single pool consisting of snap beans and sweet corn. Column (1) of the table gives the mean annual per-acre subsidy paid to bean growers as a result of using the indicated forecasting model to value raw corn and beans. Column (2) gives the variance of per-acre subsidies. Since the simulated pool consists of just two commodities, a subsidy on bean acreage is an equivalent tax on corn acreage.

A forecast procedure ideally should result in zero mean subsidy or tax. Subsidy variances will be nonzero whenever there is forecast error. As forecast error variances increase, so do the riskiness of pool payments; that is, it becomes more likely that a payment will deviate by more than a given distance from the mean subsidy shown. For risk averse cooperative members, this is an unhappy development.

Table 2. Cooperative Payment Subsidies Induced by Alternative Forecasters

	Per-Acre Subsidy to Bean Growers*	
	Expectation	Standard Deviation
Naive Forecast	66.25	111
Exponential Smoothing	16.19	143
Econometric	20.23	130
Moving Average	-1.36	152
Composite	42.78	131

* Per-acre subsidy is calculated as $G_jQ_j - R_jQ_j$ where:

Q_j = yield/acre of j^{th} commodity
G_j = pool payment/ton to the j^{th} product
R_j = finished product value less all costs of processing

In terms of the mean subsidy criterion, the three-year moving average model provided the best forecast performance and the naive forecaster presently used by the cooperative provided the poorest performance. Naive forecasting induced a mean tax on corn growers of $66.25 per acre per year during the ten years tested, thus subsidizing bean growers by an equal amount. In contrast, the moving average model taxed bean growers only $1.36 per acre per year.

Despite its greater research cost, the econometric model generated a greater mean subsidy than did the moving average or smoothing model. This resulted from the fact that, on average, regression equations over-forecasted bean net returns more than they did corn net returns. Raw beans became more overvalued than was raw corn, biasing the allocation of pool net returns in favor of beans. Composite forecasts (combining smoothing, econometric, and moving average forecasters) provided higher mean subsidies than did any of the constituent models.

There is a clear trade-off between each model's subsidy (or tax) mean and its subsidy variance. Choosing a model that produces lower average subsidies requires that one accept greater subsidy or tax variability. Since most cooperative members probably are risk averse, the greater subsidy variability likely increases member dissatisfaction. Thus, it is impossible to select a net return forecast procedure that unequivocally produces superior raw product valuations and pool payments. Choosing an optimal forecast model may require recognizing cooperative members' subjective trade-offs between mean subsidy and subsidy risk.

Practical Implications

In order to allocate net returns, pooling-type marketing cooperatives must assign values to the raw products which members have contributed. Such

valuations may be viewed as forecasts of the raw products' net returns in processing. The cooperative we have investigated presently bases raw product valuations on judgments of raw product market values that existed in the previous year. Such a procedure does not necessarily make the best use of available forecast information. In fact, use of this method has tended to overforecast both snap bean and sweet corn returns; furthermore, the overforecasts for beans have been proportionately greater than the overforecasts for corn. Simulated results demonstrate that snap bean producers have been subsidized by sweet corn producers.

The present paper has shown that alternative net return forecast procedures have advantages over the use of lagged market prices in determining raw product values. Econometric or technical net return forecasts may have smaller bias or smaller variance than that provided by the naive model. They may also result in lower mean pool subsidies or lower annual subsidy variability. However, standard measures of forecast performance such as mean error (bias) and mean square error do not necessarily reflect a forecast model's influence on pool subsidies. Mean subsidies depend on relative forecast biases across commodities, while subsidy variance depends on producer yields as well as on per-unit return forecast variance. Hence, one ought to consider the subsidy implications of a forecast rule as well as the more traditional measures of predictive ability.

It is interesting that the relatively simple smoothing models tended to outperform econometric and composite forecast approaches. If this experience were to be replicated for other commodities, it would provide consolation to managers who regard regression as too costly or complex for practical use. Most smoothing models are only modestly more complicated than are naive forecasters. Yet as we have demonstrated, they may provide better forecast returns and make substantial improvements in the inter-member allocation of a cooperative's income.

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