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An Interactive Forecasting Technique for Perishable Products

by

John J. Van Sickle and Richard Beilock

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Forecasting is performed by many economists on varied types of commodities for varying periods of time. The period for the forecast may be as short as a day or less, or as long as a century. The type of forecast performed depends on the variable forecasted, its use, and the time frame for the forecast.

The pricing mechanism for most commodities is dependent on market supply and demand. Forecasting and perishable product prices on a short-term basis can yield relatively good results since supply is normally fixed and price adjusts to clear the market. Perishable products have the common characteristic that the quality of the product is normally inversely related to the length of time required for marketing. Because of this relationship between quality and time required for marketing, the accuracy of forecasting perishable products is dependent on the time frame for the forecast.

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Models have been developed which perform well with one-period-ahead forecasts, however, their usefulness is limited. Forecasting annual prices ignores the intraseasonal variation common to perishable products. Forecasting weekly or monthly prices has commonly utilized lagged information in the prior period. Forecasting in this manner decreases the reliability of forecasts for more than one period ahead. Agricultural producers need information more than one period ahead to plan production and need more than just annual forecasts to plan intraseasonal marketing strategies.

Economists attempting to forecast a set of variables often develop structural econometric models, which describe what and how various factors influence the variables to be forecast. While this approach has the advantage of employing additional information and answering why a variable will be of a given magnitude, there are serious drawbacks to its exclusive use.

First, structural models are designed primarily to explain how a system of variables are interrelated, rather than predict future values. Unless all explanatory variables are lagged for at least as many periods back as you wish to forecast ahead. There remains the problem of forecasting the explanatory variables. Limiting explanatory variables to lagged variables may create specification bias in the estimates. Forecasting explanatory variables for use in forecasting variables of interest creates the problem of errors in variables.

One method for improving predictive accuracy is to employ alternative predictors based on different estimation techniques. These alternative predictors can be used as cross-checks to validate the results of one another. When the predictors agree, one can have more confidence in the forecasts. When they diverge, this can be seen as a warning that something unanticipated may be happening. The nature of the techniques employed may offer clues as to the nature and importance of the disturbance. In addition, the predictors may be combined into a composite forecast possessing a confidence interval at least as small as that of any individual forecast.

This is the approach we have chosen to call interactive forecasting. Interactive forecasting allows the individual developing the forecast to take an active part in arriving at a final prediction. The forecaster must choose the individual techniques to employ, estimate them, and then develop forecasts from each of the techniques. These are the steps involved in forecasting with any technique. The interactive forecaster must then combine the forecasts and determine if problems in any of the estimators are implied from the results. This final phase of the interactive forecasting technique requires more of an intuitive process for developing the final forecast.

The following section gives a brief description of the individual estimators employed in our interactive forecasting technique. The method for combining the forecasts is then presented with a description of the intuitive process used for developing a final forecast. Finally, applications of interactive forecasting are presented for two Florida vegetables, watermelons and potatoes. Monthly forecasts for prices received are derived for one season in advance. This involves forecasting four periods ahead for watermelons and six periods ahead for potatoes.

Interactive Forecasting

Cross-validation is the central concept to interactive forecasting. The premise is made that two or more independent estimation techniques which arrive at similar conclusions are better, i.e., they offer more reason for confidence in the forecast than can be derived from any of the estimators alone. When the estimates diverge, there is reason to reassess the accuracy of each of the estimates.

In order to maximize the value of the interactive forecasting technique, each estimator should employ methods which differ from the others to the greatest degree possible while still being unbiased and of reasonable efficiency. In other words, in order to have meaningful cross-validation, the estimators should not be functionally redundant. The estimators chosen for incorporation into our interactive forecasting technique included a structural econometric model designed to minimize the need for modeling the explanatory variables, an ARIMA model, and an exponential smoothing model with an adaptive tracking signal.

Structural econometric model estimation

Structural econometric models offer the advantages of incorporating additional information into the formulation of the forecast and of explaining why variation exists in a variable. While many economists toil endlessly in the specification, estimation, and re-estimation of structural models to explain how various factors may influence the variables, forecasters need only conceive an appropriate model and estimate the reduced form of the structure. Estimating the reduced form can greatly simplify the task of the forecaster since the forecaster need not be as concerned with the magnitudes and signs of the parameters. The forecaster's most important task with this estimation technique is to derive a model which produces good results for forecasting purposes.

Forecasters may also choose to specify larger econometric models for explaining the variation in the model. The degree of detail spent in specifying and estimating the model depends on the investment of time and capital the forecaster chooses.

<u>ARIMA model estimation</u>

ARIMA models are forms of pattern recognition models rather than causal models as typified by regression techniques. Procedures for estimating ARIMA models have been available for some time from numerous sources, with the three-step procedure of Box and Jenkins being the best known. A general univariate representation of the ARIMA process for variable Y_t can be represented as

$$(1)\quad \phi(B)(1-B)^d(Y_t-\mu) = \theta(B)a_t,$$

where $\phi(B)$ is an autoregressive operator of order, p, $\theta(B)$ is a moving average operator of order q, μ is the mean of the series Y_t, B is the lag operator, and a_t is the random error.

The ARIMA forecast which is developed may be viewed as a steady state or baseline forecast. The process for developing forecasts with the ARIMA model involves three steps: 1) identification; 2) estimation; and 3) forecasting.

Exponential smoothing model estimation

Many exponential smoothing models are available for developing forecasts. The Winters Mehod of exponential smoothing was the method chosen as an estimator in our interactive forecasting technique. Exponential smoothing is basically a pattern recognition model, however, it places more emphasis on recent observations than does the ARIMA model. A general representation of the Winters Method of exponential smoothing for variable Y_t can be represented as

(2) $Y_{T+t} = A_T + t.B_T + S_T$

where

(3) $A_T = \gamma_1 (Y_T/S_{T-L}) + (1-\gamma_1)(A_{T-1}+B_{T-1})$

(4) $B_T = \gamma_2 (A_T-A_{T-1}) + (1-\gamma_2)(B_{T-1})$

(5) $S_T = \gamma_3 (Y_T/A_T) + (1-\gamma_3)(A_{T-1}+B_{T-1})$.

In Equations (2) through (5), A_T corresponds to the general level of Y_T forecasted in period T-1, B_T is the trend coefficient for period T forecasted in period T-1, S_T represents the seasonal coefficient for period T forecasted in period T-L, t is the number of periods ahead for the forecast and L is the number of periods in a season. γ_1, γ_2, and γ_3 represent the weights associated with the most recent observations of A_T, B_T, and S_T used for estimating A_T and B_T one period ahead and S_T L periods ahead. In addition, we have incorporated the Trigg and Leach method for adapting the response rate of the forecast by changing the value of γ_1 based on the magnitude of previous forecast errors of the smoothed values (A_T).[1]

The composite forecast

A composite forecast can be estimated once forecasts have been derived from each of the estimators in the first phase of the interactive forecasting technique. The combined forecast will be dependent on the errors of the three individual estimators in the previous season. The combined forecast will be a weighted average of the structural, ARIMA, and exponential smoothing models.

The weight given to the individual estimators for determining the final estimate can be determined from one of many methods. Bates and Granger examined different methods for combining forecasts and suggested the following. The combined forecast can be written as

$$(6) \quad CT = K_1\hat{Y}_{1T} + K_2\hat{Y}_{2T} + K_3\hat{Y}_{3T}$$

where $\hat{Y}_{1T}$, $\hat{Y}_{2T}$, and $\hat{Y}_{3T}$ are the estimates from each of the individual forecasting techniques. The weight associated with each estimator (K_j) is calculated as

$$(7) \quad K_j = \frac{\sum_{\substack{i=1 \\ i \neq j}}^{3} E_i}{2(\sum_{i=1}^{3} E_i)}$$

where E_i is the sum of the squared forecast errors for the i^{th} estimator in the previous season's forecasts. The sum of the weights (K_i) are constrained to equal one.

Cross-validation of the forecasts

The results obtained from each of the estimators and the composite can be viewed to determine if any problems exist in the forecasts. If all forecasts are relatively close, then the composite forecast can be used as our final estimator.

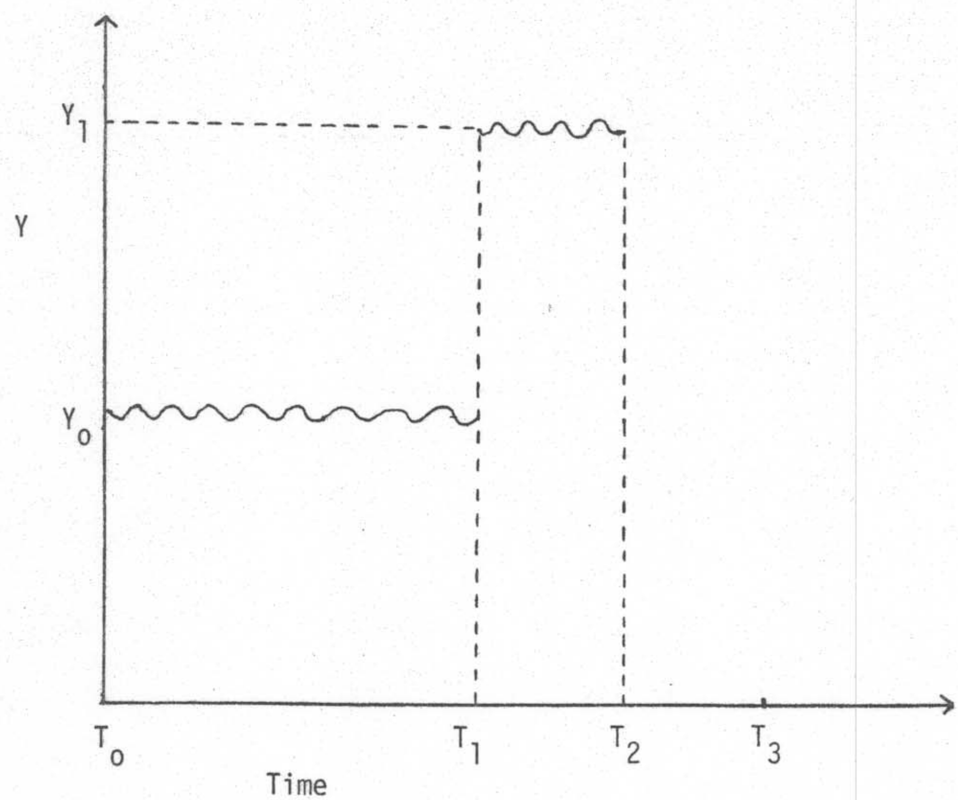
If one or more of the estimators diverge from the others, however, then the models must be reassessed to determine the accuracy of each estimator. Deviations of any of the estimators from any of the others may indicate atypical behavior in the explanatory or predicted variables. An examination should be made of previous season's forecasts and compared with actual results. The results of this examination combined with the forecasters knowledge of how the underlying system operates are employed to derive the final forecast.

The process for cross-validation can best be explained by a hypothetical case. Figure 1 shows a detrended variable which from time T_0 to time T_1 has a constant level Y_0. At time T_1 a structural shift occurs and the variable increases in actual value to Y_1. If the structural and ARIMA models have been estimated correctly, then from time T_0 to T_1 all three estimators (structural, ARIMA, and exponential smoothing) should yield consistent results and the composite forecast should be used as our final forecast for each season in this period. The success of the estimators from time T_1 to T_2 depends on the cause of the shift and the specification of the structural model. If the period from T_1 to T_2 represents one season, then two possibilities exist for the estimates made in advance of the season. If the shift was caused and correctly anticipated by an explanatory variable in the structural model, then the structural model would forecast Y_1 while the ARIMA and exponential smoothing models will continue to forecast Y_0 for the season. If this takes place, then a deviation of the structural estimator from the ARIMA and exponential smoothing estimators will be observed. The forecaster's knowledge and confidence in the structural model ultimately determine if the structural estimator is to be used as the final forecast.

If the shift from Y_0 to Y_1 is not captured by the structural model, then all three estimators will forecast Y_0 and the forecaster will be wrong in his forecast for period T_1 to T_2. The forecast for the season from T_2 to T_3, however, should yield conflicting results for all three forecasts. Here the structural model will continue to forecast Y_0 and the ARIMA and exponential smoothing models will approach Y_1 with the exponential smoothing model giving the forecast closest to Y_1. At this point, the forecaster must reassess the models which have been used for forecasting variable Y. The final forecast derived for the period T_2 to T_3 will depend on the forecaster's knowledge of the variables. If the forecaster determines that a permanent structural shift has occurred which is not captured and cannot be accurately measured with just one season of observations, then the exponential smoothing model will yield forecasts closest to the actual observations. If the forecaster perceives the structural shift to be one caused by a temporary external effect which is not anticipated in the season T_2 to T_3 (e.g., a freeze), then the structural model will yield predictions closest to the actual observation. Here, the forecaster will use the structural foreast as the final forecast since the forecaster believes the variable will once again approach Y_0.

Although the deviations will generally not be of the exact form as in our hypothetical case, the hypothetical case can be used as a procedural guide for developing a final forecast. Cross-validation allows the forecaster to use the knowledge gained from each of the estimated models and to use his own knowledge of the variable in question to develop a final forecast. The final forecast can be that of the structural, ARIMA, exponential smoothing, or some combination of the estimators (e.g., the composite forecast previously defined).

Figure A.1: A Hypothetical Case for Using the Interactive Forecasting Technique



Results

The products, which were forecasted with the interactive forecasting technique previously described, included watermelons and potatoes. These commodities were chosen for two reasons. First, the commodities are major agricultural crops produced in Florida and the outlook provided by the forecasts would prove to be beneficial to the State of Florida agricultural economy. Second, the crops have different amounts of information available for each and, therefore, represent a cross-section for the types of forecasts which might be expected from these techniques. Watermelons have four monthly observations for the years 1964 through 1980, yielding a total of 68 observations. Potatoes have six monthly observations for the years 1956 to 1980 for a total of 150 observations.

Watermelons

Forecasting monthly watermelon prices via the structural econometric model consisted of a recursive forecast. First, a model was estimated for annual watermelon prices which explained 80 percent of the variation in annual prices. The annual price was then used with seasonal adjustments to develop a model for forecasting monthly prices. This model explained 87 percent of the variation in monthly prices for the sample period. The results of the watermelon structural econometric model are listed in Appendix Table A.1.

The ARIMA model estimated for watermelons is also listed in

Appendix Table A.1. The ARIMA model forecasted the natural log of monthly prices for watermelons. The series was regularly differenced and seasonally differenced to attain stationarity. The ARIMA model estimated a moving average process of order 1 and a seasonal moving average process of order 1.

Table 1 shows the forecasts from the individual estimators for the period April 1978 to August 1981 with the observed value for each period. Observing the forecasts from the individual estimators shows a relative consistency across all estimators. The sum of the squared forecast errors for the 1978 through 1981 seasons (defined as E_i in the composite forecast section) are listed in Table 2 for each estimator along with the mean absolute error for each estimator in each season.

The composite estimate has consistently outperformed the other estimators except in 1978 when the ARIMA estimator performed best. A freeze was observed in Florida in 1977 which created a structural shock for that year. It was, however, a temporary shock. The cross-validation phase would have suggested that the structural econometric estimate be used in forecasting 1978. This would have resulted in forecasts which were not as good as the composite forecasts. The 1978 structural econometric forecasts were well under the observed values. The exponential smoothing forecast was high in April and June and low in May and July. The results indicate that the ARIMA model forecasted best, which would indicate that the freeze had a carryover effect into 1978 and that the shock was not entirely temporary. This could be

Table 1. Forecasting Monthly Watermelon Prices for 1981

Period	Obs.	Estimated Structural	Estimated ARIMA	Exponential smoothing	Composite Estimate I
April 1978	6.00	3.73	6.19	10.74	6.17
May 1978	6.00	3.06	5.10	2.80	4.02
June 1978	3.00	1.80	3.00	3.08	2.55
July 1978	2.50	1.40	2.32	2.00	1.96
April 1979	7.20	4.67	5.79	8.93	6.59
May 1979	7.20	4.04	4.54	4.09	4.25
June 1979	4.20	2.85	2.96	4.71	3.54
July 1979	3.40	2.87	2.56	2.75	2.49
April 1980	7.20	5.46	6.38	9.37	7.08
May 1980	7.20	5.19	5.00	4.60	4.93
June 1980	5.50	3.82	3.27	5.35	4.10
July 1980	5.80	3.74	2.83	3.74	3.46
April 1981	8.00	5.50	7.06	12.54	7.87
May 1981	8.00	4.97	5.55	4.27	5.02
June 1981	6.00	4.80	3.63	5.10	4.13
July 1981	5.00	4.50	3.15	4.50	3.98

caused by producers adjusting their production decisions in years following the freeze.

Potatoes

The structural econometric model developed for forecasting monthly potato prices was a three step recursive model. First, acreages planted and yields were estimated for each of the major producing areas in Florida (the south and Hastings producing areas). Second, monthly shipments were estimated using total production from the major producing areas in Florida, seasonal factors, and the size of the previous national fall potato crop. The third step involved estimating monthly real prices from monthly Florida shipments and other information available prior to the season. The monthly real price model explained 66 percent of the variation in real monthly prices. The results for the potato structural model are listed in Appendix Table A.2. The tracking of the monthly model for the sample period showed that the forecasting method was forecasting monthly real prices a season in advance with 47 percent accuracy. Translating the real prices into nominal terms showed that the model was forecasting monthly nominal prices a season in advance with 77 percent accuracy. This compared favorably with the watermelon structural model.

The ARIMA model was also estimated for monthly Florida real potato prices. The series was seasonally differenced to attain stationarity. The ARIMA model estimated an autoregressive process of order 1 and a seasonal moving average process of order 2. The results of the ARIMA

Table 2. The Sum of the Squared Forecast Errors (E) and Mean Absolute Error (MAE) for each Estimator in the 1978 through 1980 Seasons - Watermelons

Year	Structural estimate		ARIMA estimate		Exp. Smooth. estimate		Composite Estimate I	
	E	MAE	E	MAE	E	MAE	E	MAE
1978	16.96	1.92	0.87	0.32	32.95	2.13	4.44	0.785
1979	20.24	2.13	11.30	1.54	13.34	1.50	10.33	1.283
1980	14.84	1.92	19.30	2.06	15.76	1.74	12.60	1.532
1981	19.68	2.01	15.92	1.90	35.58	2.42	13.43	1.500

model are listed in Appendix Table A.2.

Table 3 contains the monthly nominal price forecasts from each of the individual estimators for the period January 1979 to June 1981. The sum of the squared forecasted errors and mean absolute deviations for the price forecasts for each season are listed in Table 4. Because of the poor performance of the exponential smoothing model, a second composite forecast was calculated for each season which excluded the exponential smoothing model. Table 4 shows that the ARIMA model outperformed the other models in 1980 while the structural econometric model performed best in 1979. The composite models generally performed as well as the structural econometric or ARIMA models over the sample period. Except for 1980, the Composite II estimate appeared to be somewhat superior to the Composite I estimate. This was not unexpected, given the poor performance of the smoothing model. The fact that the two composite estimates' performances were nearly equal attests to the ability of the weighting method to assign very low weights to estimators that perform poorly.

Finally, it should be noted that all of the models failed to predict the post-sample-period abnormally high prices in January through April 1981. Had bad weather been assumed, the structural model would have reduced its errors. Moreover, once into the season, the exponential smoothing could react quickly to the exaggerated pattern exhibited.

Table 3. Forecasting Monthly Potato Prices for 1981

Period	Obs.	Estimated Structural	Estimated ARIMA	Exponential smoothing	Composite Estimate I	Composite Estimate II
Jan. 1979	10.89	11.39	13.45	13.37	12.46	12.54
Feb. 1979	6.87	10.22	12.07	18.86	11.65	11.23
Mar. 1979	6.81	7.52	11.59	10.18	9.56	9.74
Apr. 1979	9.79	10.09	11.02	11.39	11.09	11.09
May 1979	5.75	7.27	7.80	17.75	8.20	7.61
June 1979	3.86	3.72	6.10	9.04	5.19	5.05
Jan. 1980	12.87	8.24	11.10	6.13	8.99	8.72
Feb. 1980	12.46	10.28	9.80	15.56	10.90	10.22
Mar. 1980	8.94	9.38	8.10	21.50	8.75	9.19
Apr. 1980	7.39	8.53	7.21	12.38	8.59	8.29
May 1980	4.98	8.90	6.52	9.46	8.06	8.48
June 1980	4.85	7.51	6.88	12.43	7.98	7.43
Jan. 1981	N.A.[a]	10.75	10.56	10.88	10.69	10.63
Feb. 1981	21.18	10.13	8.84	8.29	9.39	9.39
Mar. 1981	25.40	8.91	9.12	8.07	8.98	9.04
Apr. 1981	20.16	6.72	8.06	10.68	7.59	7.53
May 1981	8.87	7.68	7.44	13.38	7.92	7.52
June 1981	7.85	4.08	6.52	9.78	5.56	5.48

[a]N.A. - Not calculated, too few marketings reported.

Note: Sample period ends in June, 1980.

Table 4. The Sum of the Squared Forecast Errors (E) and Mean Absolute Deviations (MAD) for each Estimator in the 1979 through 1980 Seasons - Watermelons

Year	Structural estimate		ARIMA estimate		Exp. smooth. estimate		Composite Estimate I		Composite Estimate II	
	E	MAD	E	MAD	E	MAD	E	MAD	E	MAD
1979	1.09	14.39	3.01	67.17	6.10	334.60	2.36	42.33	2.22	36.88
1980	2.50	50.12	1.50	17.44	6.58	315.22	2.17	38.25	2.27	42.02

Conclusions

In this paper we have presented a technique for employing multiple estimators for forecasting. The technique was employed to derive forecasts for the average monthly prices of watermelons and potatoes received by Florida farmers. The results generally support the underlying premise of the paper that the use of cross-validation and composite forecasts can increase the ability of the forecaster to spot potential troublespots and improve forecasting accuracy.

A structural model, an ARIMA model, and an exponential smoothing model was employed in our analysis as it was felt that these models were sufficiently different to impart a fairly high degree of multidimensionality to the analysis. The Bates and Granger method of deriving composite forecasts was employed since it is straightforward and conceptually appealing as it places emphasis on estimators which have performed well in the recent past. The composite forecasts were shown generally to outperform those of the individual techniques by providing, on average, more reliable forecasts. The superior performance of the composite forecasting technique is, in a heuristic sense, traceable to the nature of perishable products. The production of perishable products is influenced by many factors (e.g., weather) which are difficult to forecast. Any single forecasting technique is limited in its forecasting ability. When a variety of forecasting techniques which have complementary qualities for dealing with such uncertainties can be combined, considerable improvement in forecasting performance can result.

In closing, however, it should be stressed that these individual techniques and the method for combining forecasts are not exhaustive. If, for example, you have access to an industry expert who will share his view of the future with you, it would be wasteful to discard his information. The interactive forecasting viewpoint would be to utilize these estimates as a part of the full set of information to be employed. In addition, other methods for combining forecasts have been developed and used. These methods for combining forecasts should be tested in order to determine the best composite forecast for each commodity.

Appendix

Table A.1. The Watermelon Forecasting Models

Structural Model

Annual prices:

$$AVY = -25.68 - 0.000152 * (LOS) - 1.270 * (FZ)$$

(-5.97) (-2.67) (-2.07)

$$+ 0.1452 * (LUSPOP_{t-1})$$

(6.52)

R^2 = .80 F-ratio = 15.76 Degrees of freedom = 12

Monthly prices:

$$AVM = -0.622 + 0.7012 * (AVY) + 0.096 * (T) + 2.408 * (DA)$$

(-2.28) (5.23) (3.09) (10.98)

$$+ 1.694 * (DM) + 0.267 * (DJ) - 0.723 * (FZ)$$

(7.72) (1.22) (-1.95)

R^2 = .866 F-ratio - 66.22 Degrees of freedom = 61

(Note: t-ratios are in parentheses below estimated coefficient)

where:

LOS = total shipments from areas other than Florida in previous year in units of 1000 cwt.

FZ = dummy variable equal to 1.0 in 1977 representing the freeze,

= 0 otherwise.

LUSPOP = U.S. population in previous year in millions of people,

AVY = annual value received for all watermelons.

AVM = monthly average value received for all watermelons in year in \$/cwt.

T = trend term (year - 1963).

DA = dummy variable equal to 1.0 in April, 0 otherwise.

DM = dummy variable equal to 1.0 in May, 0 otherwise.

DJ = dummy variable equal to 1.0 in June, 0 otherwise.

ARIMA Model:

Differencing: 1 regular, 1 seasonal difference (period length = 4)

Mean of working series: 0.010835 s.d. = .336

Parameter	Estimate	t-ratio
First moving average	0.50975	4.52
First seasonal moving average	0.92283	11.42

Standard error of estimate = 0.2567

Table A.2. The Potato Forecasting Models

Structural Model:

Acreage Planted:

$$WAP = \underset{(.99)}{-2883.} + \underset{(.90)}{5622.} * (EWREV) + \underset{(2.28)}{.02824} * (FALL)$$

$$- \underset{(-2.08)}{174.8} * (T) + \underset{(.138)}{2004.} * (CST) + \underset{(7.38)}{.5392} * (LWAP)$$

$R^2 = .84$ F-ratio = 17.7 Degrees of freedom = 17

$$SAP = \underset{(1.35)}{12526.} + \underset{(.99)}{16920} * (ESREV) - \underset{(-2.01)}{.10813} * (JANST)$$

$$+ 320.0 * (T) + 560.2 * (CST) + .7716 * (LSAP)$$

$R^2 = .73$ F-ratio = 9.29 Degrees of freedom = 17

Yields

$$WYLD = \underset{(4.63)}{.1738} - \underset{(-.40)}{.09155} * (EWYLD) - \underset{(-2.21)}{.000005} * (WAP)$$

$$+ \underset{(1.17)}{0.247} * (EPR) + \underset{(2.30)}{.0023} * (T) - \underset{(-2.54)}{.02217} * (WWTH)$$

$$SYLD = \underset{(5.42)}{.2961} - \underset{(-.199)}{.4260} * (ESYLD) - \underset{(-2.46)}{.000003} * (SAP)$$

$$- \underset{(-.32)}{.00715} * (EPR) + \underset{(2.05)}{.001685} * (T) - \underset{(-4.59)}{.0472} * (SWTH)$$

Production Identity:

WPD = WAP * WYLD

SPD = SAP * SYLD

Monthly Shipments:

$$
\begin{aligned}
P.SHP = \underset{(3.65)}{.00535} &- \underset{(-.68)}{.06209} * (P.WPD * D1) \\
&- \underset{(-.09)}{.00836} * (P.WPD * D2) - \underset{(-1.58)}{.160639} * (P.WPD * D3) \\
&+ \underset{(1.39)}{.091677} * (P.SPD * D3) + \underset{(3.99)}{.235317} * (P.SPD * D4) \\
&+ \underset{(0.24)}{.54496} * (P.SPD * D5) + \underset{(1.16)}{.068494} * (P.SPD * D6) \\
&- \underset{(-2.84)}{.003017} * (P.FALL * D1) - \underset{(-2.91)}{.003095} * (P.FALL * D2) \\
&- \underset{(-1.81)}{.002082} * (P.FALL * D3) - \underset{(-2.41)}{.002776} * (P.FALL * D4) \\
&- \underset{(-2.26)}{.002595} * (P.FALL * D5) - \underset{(-2.58)}{.002968} * (P.FALL * D6)
\end{aligned}
$$

$R^2 = .91$ F-ratio = 101.01 Degrees of freedom = 136

Monthly Prices:

$$
\begin{aligned}
PR = \underset{(-3.07)}{-.8238} &+ \underset{(10.43)}{.6292} * (EPR) + \underset{(1.79)}{.1674} * (D1) \\
&- \underset{(-1.35)}{.1096} * (D2) + \underset{(.98)}{.0698} * (D3) + \underset{(4.17)}{.3321} * (D4) \\
&+ \underset{(3.03)}{.2979} * (D5) - \underset{(-5.73)}{.1982} * (L.P.SHP) - \underset{(-.46)}{.0215} * (L.P.INC) \\
&- .2900 * (L.P.FALL)
\end{aligned}
$$

$R^2 = .66$ F = 27.25 d.f. = 126

(Note: t-ratios are in parentheses below estimated coefficient)

where:

WAP, SAP = acres planted, winter and spring crops

WYLD, SYLD = yields, winter and spring crops

EWREV, ESREV = expected (lagged) regional yields times expected (lagged) Florida average farm price

FALL = total production of previous national fall crop (1,000,000 cwt)

T = trend term

CST = index of costs to farmers of commodites and services deflated by index to prices received for fresh fruits and vegetables

LWAP, LSAP = lagged acreages for winter and spring crops

EWYLD, ESYLD = a weighted average of previous two yields for winter and spring crops

EPR = expected (lagged) Florida average farm price

WWTH, SWTH = weather dummies; 0 if normal, 1 if adverse conditions for winter and spring crops

WPD, SPD = production for winter and spring crops

SHP = monthly shipments (1,000 cwt.)

PR = monthly average price per cwt. deflated by FV

INC = income deflated by C.P.I.

D1,D2,D3,D4,D5,D6 = dummies for the months of January through June

P = per capita

L = natural log

ARIMA Model:

Differencing: 1 seasonal difference (period length = 6)

Mean of working series: -.003 s.d. = .505

Parameter	Estimate	t-ratio
Trend	.00095	.09
Regular auto regressive	.70417	11.46
First seasonal moving average	1.24448	15.62
Second seasonal moving average	-.40664	-5.02

Footnotes

[1]For the adaptive exponential smoothing model γ_1 was initialized as equal to .3, γ_2 was specified as .2 and γ_3 was specified as .2. After the initial period γ_1 was equal to the tracking signal as defined by the Trigg and Leach method.

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