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Forecasting Ex-Vessel Prices for Hard Blue Crabs in the Chesapeake Bay Region: Individual and Composite Methods

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Given the relative importance of the Chesapeake Bay hard blue crab fishery to the U.S. blue crab fishery, this paper analyzes ex-vessel prices for hard blue crabs landed in this region. The purpose is to evaluate alternative methods of forecasting ex-vessel prices for hard blue crabs in the Bay; both individual methods (trend extrapolation, econometric, and time-series) and composite methods. Examining the mean squared errors for the individual methods, the time-series model performs the best, with the econometric model slightly better than the trend extrapolation model. None of the composite methods outperforms the time-series model, although in some cases the differences are slight. Nevertheless, the time-series trend extrapolation composite outperforms all other models in identifying turning points. Generally speaking, it would appear that ex-vessel prices for hard blue crabs possess strong time dependencies, and consequently, better forecasts occur with time-series models than with econometric models.

Introduction

Hard blue crabs are prevalent primarily on the East and Gulf coasts of the United States. The economic importance of hard blue crabs to these regions has long been recognized. In the last twenty years, the average annual production has been approximately 140 million pounds, valued at roughly 15 million dollars.

Hard blue crabs are more abundant in the Chesapeake Bay than elsewhere. Annual landings for hard blue crabs from 1960 to 1979 in the Chesapeake Bay have ranged from 45.2 to 94.1 million pounds, 0.4 to 6.4 million pounds in the Middle Atlantic, 27.4 to 52.0 million pounds in the South Atlantic, and 25.3 to 44.3 million pounds in the Gulf (Table 1). On average, the Chesapeake Bay region has accounted for 46 percent of the hard blue crab landings in the United States over this period. The average annual share of hard blue crab landings for the Middle Atlantic, South Atlantic, and Gulf regions has been 2, 28, and 24 percent, respectively (*Shellfish Market Review*).

Given the relative importance of the Chesapeake Bay hard blue crab fishery to the

U.S. blue crab fishery, this paper analyzes ex-vessel prices for hard blue crabs landed in this region. Ex-vessel prices are defined by the U.S. Department of Commerce as "prices received by harvesters for fish and shellfish landed at the dock." Except for the work of Cato and Prochaska (1980) and Rhodes (1981), little attention has been focused on ex-vessel prices for hard blue crabs. This study concentrates on hard blue crabs because the aggregate ex-vessel value of hard blue crab landings has constituted more than 80 percent of the aggregate ex-vessel value of total blue crab landings in the United States since 1952 (Rhodes 1981).

Harvesters in the aquacultural sector as well as producers in the agricultural sector make decisions in risky environments. Rational decision-making consequently requires information about the likelihood of many alternative outcomes. This information is generally available from both private and public sources in the way of price forecasts. In this light, the specific purpose of this paper is to evaluate alternative methods, both individual and composite, of forecasting ex-vessel prices for hard blue crabs in the Chesapeake Bay region. This research is likely to pay dividends in the way of assessment of price forecast information, to harvesters of hard blue crabs in the Chesapeake Bay region.

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Table 1. Annual Landings for Hard Blue Crabs by Region from 1960 to 1979

Year	Middle Atlantic ^a	Chesapeake Bay ^b	South Atlantic ^c	Gulf ^d	U.S. ¹
----- Million pounds -----					
1960	3.6	66.3	44.8	34.9	149.6
1961	1.4	70.6	40.4	35.3	147.7
1962	3.4	81.3	38.7	25.9	149.3
1963	1.4	63.1	50.8	26.5	141.7
1964	0.9	74.1	52.0	25.3	152.3
1965	1.5	82.6	46.0	37.0	167.0
1966	1.3	94.1	40.5	31.0	166.8
1967	0.8	79.4	37.3	27.5	145.0
1968	0.4	54.2	33.3	25.8	113.6
1969	1.1	56.7	41.3	33.2	132.3
1970	1.4	67.4	42.7	34.0	145.4
1971	2.1	73.9	39.6	33.5	149.1
1972	4.0	72.0	36.2	35.2	147.5
1973	4.9	56.3	31.8	43.5	136.5
1974	5.0	65.5	38.3	40.4	149.2
1975	6.4	59.1	30.5	38.7	134.7
1976	6.3	45.2	27.4	36.6	115.4
1977	1.3	56.4	30.7	44.3	132.7
1978 ²	1.2	52.6	47.1	38.2	138.2
1979 ²	1.3	64.2	49.2	38.2	152.8

¹ The U.S. total may include a very small amount of blue crabs landed in New England.

² Preliminary.

Note: Figures may not add to total because of rounding.

Source: *Shellfish Market Review*, various issues.

^a Delaware, New Jersey, and New York.

^b Maryland, Virginia.

^c Florida (East Coast), Georgia, North Carolina, South Carolina.

^d Alabama, Florida (West Coast), Louisiana, Mississippi, Texas.

The organization of this paper is as follows. The next section presents alternative models for generating forecasts of hard blue crab ex-vessel prices in the Chesapeake Bay. The third section provides an overview of the techniques of composite forecasting. The fourth section outlines the procedures used to obtain the composite forecasts. In the fifth section, alternative forecasts are evaluated. Concluding remarks and suggestions for further research follow in the sixth section.

Alternative Forecasting Models

Individual methods of generating forecasts include: (1) intuitive methods, such as trend extrapolation, seasonal adjustment, and smoothing methods; (2) econometric methods; and (3) time series methods. Intuitive methods concentrate primarily on trend and seasonal components and are predominantly deterministic in nature. Econometric methods rely on the specification of causal relationships among variables.

Similar to intuitive methods, time series methods attempt to discover patterns in historical data series and to extrapolate the patterns into the future. Unlike intuitive methods however, time series methods are stochastic in nature and employ statistical principles. Among the more common time-series models are the autoregressive integrated moving average (ARIMA) models suggested by Box and Jenkins (1972). Unlike econometric models, ARIMA models do not involve causal relationships.

In this paper, one model is selected from each of the above categories to generate forecasts of monthly ex-vessel prices for hard blue crabs in the Chesapeake Bay from August 1979 through June 1980. The three models are: (1) a quadratic trend extrapolation model; (2) an econometric model with seasonal (fall, winter, spring) dummy variables; and an ARIMA (1,1,0) × (1,0,1)₆. Each of the estimated models is presented and briefly described below. All models were estimated for the period January 1973 through July 1979.¹

Quadratic Trend Extrapolation Model

The estimated quadratic trend extrapolation model is presented in Table 2. The model was estimated using a centered three-month moving average of ex-vessel prices. The use of this smoothed series potentially reduces the impact of aberrant fluctuations in the original series. Alternative models were examined prior to selection of this centered moving average trend model. The alternatives in-

¹ The forecast period and the data period used for model estimation were dictated by data availability only.

Table 2. Monthly Quadratic Trend Extrapolation Model for Centered Three Month Moving Average of Ex-Vessel Price for Hard Blue Crabs (Live Weight) in the Chesapeake Bay Region, January 1973 to July 1979.

Variable	Parameter Estimate	Standard Error	T-Ratio	P-Value
Intercept	0.5396E-01	0.1835E-01	2.94	0.0044
TIME	0.4504E-02	0.9904E-03	4.55	0.0001
TIME**2	-0.3318E-05	0.1202E-05	-2.76	0.0073
Dummy	0.6170E-01	0.1063E-01	5.80	0.0001

Summary Statistics:

Durbin-Watson Statistic = 1.415

R² = 0.5801 \bar{R}^2 = 0.5629

F = 33.62 (P-Value = 0.0001)

cluded three and seven-month moving averages (centered and uncentered) with linear and quadratic trends. In all cases, the quadratic trend was judged to be statistically significant, and the centered moving averages provided the smallest forecast errors for the historical period.

The estimated model reported in Table 2 contains linear and quadratic trend variables as well as a dummy variable for the harvest season. This dummy variable is equal to 1 for the months January through June and zero otherwise. All of the estimated coefficients are statistically significant as indicated by the small *p*-values. The summary statistics for the model indicate that the model explains over 56 percent of the variation in the dependent series. The Durbin-Watson statistic indicates some evidence of positive serial correlation, thus it is expected that this model will yield suboptimal forecasts.

Econometric Model

The econometric model is given by:

$$\begin{aligned} \text{EXP}(t) = & B_0 + B_1\text{CBL}(t) + B_2(D2*\text{CBL}(t)) \\ & + B_3(D2*\text{CBL}(t)) \\ & + B_4(D3*\text{CBL}(t)) + B_5\text{LOCB}(t) \\ & + B_6\text{RMPW}(t) + B_7\text{WPFLM}(t) \\ & + B_8D1 + B_9D2 + B_{10}D3 + e(t), \end{aligned}$$

where:

$\text{EXP}(t)$ = ex-vessel price of hard blue crabs in the Chesapeake Bay region in month *t* (dollars/pound live weight basis, weighted average value of Maryland and Virginia landings),

$\text{CBL}(t)$ = Chesapeake Bay landings in month *t* (live weight basis, 1000 pound units),

$\text{LOCB}(t)$ = landings outside the Chesapeake Bay region (South Atlantic and Gulf) in month *t* (live weight basis, 1000 pound units),

$\text{RMPW}(t)$ = retail price of hard blue crabs in month *t* (dollars/pound meat weight basis, at Baltimore),

$\text{WPFLM}(t)$ = wholesale price of hard blue crabs in month *t* (dollars/pound meat weight basis, lump/flake mixed, at New York),

$D1$ = winter (dredge) season indicator ($D1 = 1$ for December,

January, February, March; $D1 = 0$ otherwise),

$D2$ = spring season indicator ($D2 = 1$ for April, May; $D2 = 0$ otherwise),

$D3$ = fall season indicator ($D3 = 1$ for October, November; $D3 = 0$ otherwise),

$e(t)$ = random disturbance term in month *t*.

The ex-vessel demand relationship, with some notable differences, is similar to that used by Prochaska (1978) to analyze the king mackerel marketing system, by Chui (1980) to analyze Gulf shrimp, by Capps and Shabman (1981) to analyze Virginia oysters, by Rhodes (1981) to analyze the U.S. blue crab fishery, and by Cato and Prochaska (1980) to analyze Florida blue crabs.

The seasonal indicators, $D1$, $D2$, $D3$, are related to biological factors governing the growth and development of hard blue crabs in the Chesapeake Bay. The binary variables in this model serve as both intercept and slope shifters. Based on economic theory, the price offered to hard blue crab harvesters is hypothesized to vary inversely with Chesapeake Bay hard blue crab landings in the fall, spring, summer, and winter months, as well as with monthly hard blue crab landings outside the Chesapeake Bay region. Hard blue crab landings outside the Chesapeake Bay region, from either the South Atlantic or the Gulf regions, the other major sources of U.S. hard blue crab landings, represent imports to harvesters in the Chesapeake Bay region. Consequently, the signs of the parameter coefficients B_1 , B_2 , B_3 , B_4 , and B_5 are hypothesized to be negative. The retail and wholesale prices of hard blue crabs reflect consumer demand and processor demand, respectively. As such, the signs of B_6 and B_7 are hypothesized to be positive. Due to the abundance of hard blue crabs in the summer months vis-à-vis the spring and winter months, the ex-vessel price of hard blue crabs is hypothesized to be higher in the spring and winter than in the summer. Hence, the signs of the parameter coefficients, B_8 and B_9 , are hypothesized to be positive. Since large hard crab inventories tend to exist in the fall months, the ex-vessel price of hard blue crabs is hypothesized to be lower in the fall than in the summer. Therefore, the sign of the parameter coefficient B_{10} is hypothesized to be negative.

Empirical estimates of coefficients and stan-

dard errors appear in Table 3. Slightly more than 80 percent of the monthly variation in the ex-vessel price of hard blue crabs was explained by the model. The monthly variation explained by the model was statistically significant at any reasonable level of significance. The signs of the estimated coefficients in the ex-vessel demand model conformed to the theoretical expectations. Serial correlation problems were not present in the empirical model.

Time Series Model

The time series model selected is a seasonal autoregressive integrated moving average model, ARIMA (1,1,0) \times (1,0,1)₆. This model contains one seasonal autoregressive parameter and one seasonal moving average parameter. The model was chosen from alternative specifications of ARIMA models for the ex-vessel price series. All models included first-differencing of the data series to obtain stationarity. Non-seasonal models were first examined, but spikes at the seasonal frequencies of 6, 12, 18, etc. were observed. Therefore, seasonal models were examined for both six and twelve month seasonal periods. The six month seasonal models performed best in terms of forecast errors for the sample period.

The estimated ARIMA model is presented in Table 4. The estimated seasonal parameters are each statistically significant, as indicated by the large t-statistics. Although the intercept

Table 3. Monthly Econometric Ex-Vessel Price Equation for Hard Blue Crabs (Live Weight) in the Chesapeake Bay Region, January 1973 to July 1979

Variable	Parameter Estimate	Standard Error	T-Ratio	P-Value
Intercept	-0.05316	0.04292	-1.239	0.2197
CBL	-0.4197E-05	0.3525E-05	-1.190	0.2380
D1CBL	-0.3012E-04	0.6705E-05	-4.363	0.0001
D2CBL	-0.9254E-05	0.5837E-05	-1.585	0.1175
D3CBL	-0.6814E-06	0.5465E-05	-0.125	0.9012
LOCB	-0.1609E-05	0.3267E-05	-0.493	0.6239
RPMW	0.02540	0.01035	2.454	0.0167
WPLFM	0.04135	0.01554	2.660	0.0077
D1	0.05177	0.02895	1.788	0.0782
D2	0.05140	0.02941	1.747	0.0051
D3	-0.04571	0.03286	-1.341	0.1687

Summary Statistics:

Durbin-Watson Statistic = 1.557
 $R^2 = 0.8469$ $R^2 = 0.8244$
 $F = 37.624$ (P-Value = 0.0001)

Table 4. Monthly ARIMA (1,1,0) \times (1,0,1)₆ Model for Ex-Vessel Price for Hard Blue Crabs (Live Weight) in the Chesapeake Bay Region, January 1973 to July 1979

Variable	Parameter Estimate	Standard Error	T-Ratio	P-Value
Mu	0.00125	0.00336	0.37	0.6437
AR1	-0.02216	0.11777	-0.19	0.4249
SAR1	-0.98655	0.05255	-18.77	0.0001
SMA1	-0.86667	0.21872	-3.96	0.0001

Summary Statistics:

Variance Estimate = 0.11264E-02
 Standard Error Estimate = 0.33563E-01
 Box-Ljung Q Statistic* = 7.14 (P-Value = 0.028)

* The Box-Ljung Statistic reported is a test for the randomness of residuals from the ARIMA model through lag 7.

estimate (Mu) and the first order autoregressive parameter are not significant, similar models without these parameters performed poorly. The diagnostic Q statistic for the model gives no reason to doubt the adequacy of the representation.

Composite Forecasting

Composite forecasting of economic variables has been studied by various researchers including: Bates and Granger (1969), Granger and Newbold (1977), Rausser and Just (1979), and Bessler and Brandt (1981). The notion underlying composite forecasting is that often alternative forecasts of the same data series are available, each of which contains information independent of others. Bates and Granger (1969, p. 451) point out that the prevalent reaction of analysts faced with alternative forecasts is to "attempt to discover which is the better (or best) forecast." The analyst, upon finding the "best" of the alternatives discards the remaining forecasts. Given the independent information which may be present in the alternatives, Bates and Granger suggest that if the objective is to make as good a forecast as possible the analyst should attempt to combine the forecasts. Researchers have demonstrated, empirically, that composite forecasting methods can provide forecasts which are preferred to the individual forecasts used to generate the composite (e.g. Bessler and Brandt).

Building composite forecasts requires that the analyst select weights to assign to the individual forecasts. Bates and Granger (1969) and Granger and Newbold (1977) discuss alterna-

tive procedures for selecting these weights. Three of these procedures are discussed here: (1) minimum variance weighting based on the observed errors over the history of the forecast period; (2) adaptive weighting also based on the observed errors over the history of the forecast period; and (3) simple averaging of the individual forecasts.

The method of simple averaging is useful when no information is available on the historical performance of each individual method. This method gives each forecast equal weight and involves relatively low computation costs. In cases where a history is available, minimum variance weighting, which minimizes the variance of the forecast errors over the historical period, and adaptive weighting, which reflects recent forecast errors more strongly than distant errors, are typically used. These methods select the weights to give more weight to those forecasts which have performed best historically (in terms of forecast errors). Minimum variance weighting is useful when the performance of each individual forecast method is consistent over the forecast period. The adaptive weighting scheme allows the weights to change from period to period and is useful if the individual forecast methods are not consistent over the forecast period. Given the relatively constant performance of the respective forecast methods over the historical forecast period in this study, the minimum variance weighting scheme is compared to the simple averaging weighting scheme as well as to the individual methods.

Generating Composite Forecasts

Two methods are employed to generate the composite forecasts. The first composite method is to average the forecasts from the three individual methods. The second composite method employs the minimum variance weighting approach. Granger and Newbold (1977) have extended this minimum variance scheme of weighting to more than two forecasts, but for simplicity only the bivariate case is considered. This approach yields three composites from the three individual methods: (1) ARIMA model with quadratic trend extrapolation model; (2) ARIMA model with econometric model; and (3) quadratic trend extrapolation model with econometric model.

To calculate the weights for the minimum variance approach, forecasts are generated

using each of the estimated models. The weights are then calculated from the following formulae (Granger and Newbold 1977):

$$A_1 = \frac{\sigma_1^2 - \rho_{12}\sigma_1\sigma_2}{\sigma_1^2 + \sigma_2^2 - 2\rho_{12}\sigma_1\sigma_2};$$

$$A_2 = 1 - A_1,$$

where σ_i^2 is the variance of the forecast errors for method i , σ_i is the square root of σ_i^2 and ρ_{ij} is the correlation coefficient between the forecast errors from methods i and j , ($i, j = 1, 2$).

The weights are consequently dependent upon the variances of the individual forecast errors and the covariances between the errors of the different forecasts. It can be easily shown that as the variance associated with one particular forecast goes to zero, the weight given to that method goes to one.

The calculated weights for the composites appear in Table 5. The weights for the ARIMA-quadratic case suggest the forecast error variances of the two methods to be approximately equal. In the cases of the ARIMA-econometric model and the quadratic-econometric model, the ARIMA and quadratic forecasts have smaller variances and therefore receive the larger weight. The small weights for the econometric model are a further indicator of the importance of time related components in ex-vessel prices for hard blue crabs.

Comparison of Forecasts

Using the individual models and the two composite methods, forecasts of ex-vessel prices for hard blue crabs in the Chesapeake Bay were calculated for the period August 1979

Table 5. Minimum Variance Weights for Composite Forecasts of Ex-Vessel Price for Hard Blue Crabs (Live Weight) in the Chesapeake Bay Region Using Quadratic Trend Extrapolation, ARIMA, and Econometric Models

ARIMA with Quadratic Trend	
$A_1 = 0.465701$	$A_2 = 0.534299$
ARIMA with Econometric Model	
$A_1 = 0.811493$	$A_2 = 0.188507$
Quadratic with Econometric Model	
$A_1 = 0.729961$	$A_2 = 0.270039$

through 1980. The results are presented and compared to the actual values in Table 6.

A relatively simple criterion for comparing forecasts is the use of squared error over the forecast period. Examining the mean squared errors for the individual methods, the ARIMA model performs the best, with the econometric model slightly better than the quadratic model. None of the composites outperforms the ARIMA model, although the difference is slight between the ARIMA model and the ARIMA-econometric composite. The mean squared forecast error for the simple average composite is approximately equal to the mean squared error for the ARIMA-quadratic composite. The quadratic-econometric composite is a slight improvement on either of the two individual methods, but is the worst of the three composites.

Forecast Evaluation

In addition to using the mean squared error criterion to evaluate alternative forecasts, it is important to examine how well the models correctly identify turning points. For this purpose, two by two contingency tables are constructed to examine turning point prediction of the alternative methods (Table 7).

Better performance is associated with larger numbers on the positive diagonal of each 2 × 2 matrix. The turning point analysis is in general consistent with the mean squared error analysis, except for the ARIMA-quadratic composite.

The ARIMA-quadratic composite outperforms all other models in identifying turning points. The two models perform identically as

Table 7. Evaluation of Alternative Prediction Models in Terms of Ability to Track Turning Points

Model	Observed	Predicted		Sum of Diagonal
		Change	No Change	
ARIMA	Change	0	3	4
	No Change	2	4	
Quadratic	Change	0	3	4
	No Change	2	4	
Econometric	Change	2	1	3
	No Change	5	1	
Simple Average	Change	2	1	3
	No Change	5	1	
ARIMA w/ Quadratic	Change	2	0	6
	No Change	3	4	
ARIMA w/ Econometric	Change	2	1	3
	No Change	5	1	
Quadratic w/ Econometric	Change	2	1	3
	No Change	5	1	

individual methods, although not as well as their composite. Although the ARIMA-econometric composite is second best in terms of mean squared error, it performs poorly in identification of turning points. The quadratic-econometric composite, the simple average composite, and the individual econometric forecasts are equally poor turning point predictors.

Concluding Remarks and Suggestions for Further Research

Several conclusions are suggested by the current research. In terms of recommendations to those interested in forecasting ex-vessel prices

Table 6. Comparison of Actual and Alternative Forecast Values for Monthly Ex-Vessel Prices for Hard Blue Crabs (Live Weight) in the Chesapeake Bay Region, August 1979 to June 1980

Time	Actual	ARIMA	Quadratic	Econometric	Simple Average	ARIMA-Quadratic	ARIMA-Econometric	Quadratic-Econometric
Aug 79	0.17	0.159680	0.202201	0.197635	0.186505	0.182399	0.166835	0.200968
Sep 79	0.16	0.156569	0.201405	0.214228	0.190734	0.180525	0.167438	0.204868
Oct 79	0.13	0.168956	0.200543	0.172172	0.180557	0.185833	0.169562	0.192882
Nov 79	0.14	0.173049	0.199614	0.182359	0.185007	0.187243	0.174804	0.194954
Dec 79	0.14	0.186475	0.198619	0.163655	0.182916	0.192964	0.182173	0.189177
Jan 80	0.24	0.239346	0.259386	0.256236	0.251656	0.250053	0.242530	0.258535
Feb 80	0.29	0.258496	0.258257	0.273371	0.263375	0.258368	0.261300	0.262338
Mar 80	0.28	0.264051	0.257060	0.290565	0.270559	0.260316	0.269049	0.266108
Apr 80	0.20	0.254316	0.255797	0.279975	0.263363	0.255107	0.259153	0.262326
May 80	0.21	0.252763	0.254467	0.287420	0.264883	0.253673	0.259296	0.263366
Jun 80	0.23	0.242004	0.253070	0.246888	0.247321	0.247917	0.242925	0.251401
Mean Squared Error		0.001005	0.002022	0.001923	0.001445	0.001407	0.001060	0.001896

for shellfish, the techniques of composite forecasting should be pursued, especially if the ability to better predict turning points is desirable.

If resources are limited and the forecast need only track the series, the current research suggests that seasonal ARIMA models do the best job on average. A composite of the ARIMA model and a quadratic trend extrapolation model aids in identifying turning points. In general it would appear that ex-vessel prices for hard blue crabs possess strong time dependencies and can be better modeled with time series or intuitive methods than with econometric models.

Finally, a few comments can be made regarding composite forecasting. Granger and Newbold (1977, p. 270) note "it is reasonable to expect in most practical situations that the best available combined forecast will outperform the better individual forecast—it cannot, in any case, do worse." Although this proposition seems sound, it is not empirically supported by the current research. The reason for the inconsistency lies in the fact that the calculation of the weights is from historical data, while forecast performance is evaluated outside the historical data. In other words, the variances of the forecast errors from which the weights are calculated may not be the same as the variances of the errors over the forecast period. Thus, composite forecasts can do worse than individual forecasts, as evidenced above.

Future researchers need to keep in mind the cautions noted above. Extension of the composite forecasting technique to include combinations of more than two forecasts may lead to better models for forecasting ex-vessel prices for hard blue crabs in the Chesapeake Bay region. Mean squared error comparisons could be made empirically using techniques suggested by Ashley, Granger and Schmalensee (1980) and implemented in Bessler and Brandt (1983). In cases where the differences are so small relative to the units of the forecast (such

as above), this procedure may need to be evaluated on a benefit/cost basis.

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