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COMPOSITE FORECASTING METHODS: AN APPLICATION TO SPANISH MAIZE PRICES

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This paper investigates alternative forecasting methods when few observations are available. An illustration is provided by Spanish monthly maize prices after Spanish accession into the EC. Sophisticated multiple-equation models are difficult to specify in situations of limited data, and simpler models have to be considered. In this paper, several individual and composite forecasting methods are compared, based on 24 one-period-ahead forecasts generated from these models. Results based on different quantitative and qualitative measures show that composite forecasting methods are more accurate. In situations where severe multicollinearity exists, forecasting performance is improved by modelling this problem explicitly.

1. Introduction

Agricultural economists have devoted considerable effort to the methodology of commodity price forecasting. Consequently, a variety of methods, from sophisticated multiple-equation regression techniques to rather naive extrapolations or intuitive estimates, have been developed. In some situations, data availability is limited (e.g. short sample periods and information scarcity) and it is only possible to fit several relatively simple models. In such situations, combination of forecasts generated by different models takes advantage of error structures in the joint pattern of forecasts.

Composite forecasting methods have been studied for more than two decades. Applications to agricultural markets can be found in Bessler and Brandt (1979), Granger and Ramanathan (1984), Jolly and Wong (1987) and Skold (1989). The most common criticism of such methods is that, if there is room to improve a model's forecasts by combining them with some other sources, then the model has not been properly specified. Advocates of combining forecasts have generally accepted this up to a point, but have also pointed to the lack of comprehensiveness of any one modelling approach and the difficulties of model specification and identification in practice. Their theoretical perspectives have been backed up with strong statistical results. In terms of minimising forecast error variance, combining separate forecasts has been shown to be optimal and never worse than selecting the best individual model (Bunn, 1989).

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The objective of this paper is to evaluate different methods of combining forecasts when few observations are available. The organisation of the paper is as follows. Section 2 explains changes in the Spanish maize sector after joining the EC. Recent developments on composite forecasting techniques are outlined in Section 3. Three different price forecasting models are specified and estimated in Section 4. Section 5 develops several methods for combining the forecasts obtained in the previous section, and the results are evaluated using different quantitative and qualitative criteria. Finally, Section 6 describes the conclusions of the analysis.

2. The Spanish Maize Sector After EC Enlargement

Spanish maize production was approximately 2 million tonnes per year during the period 1970-79. In 1980 and 1981, production reached 3 million tonnes per year and continued at approximately the same level until Spanish accession to the EC, in 1986. As in other EC Mediterranean countries, the compound feed sector accounts for more than 85% of total maize consumption. Before joining the EC, Spain imported all the maize required by the compound feed sector, traditionally being a large net importer of this commodity, mainly from the United States and Argentina.

The intervention prices of Spanish maize were below EC levéis, and a seven-year transition period of price harmonisation was agreed. As a result, increased prices were expected, production went up to 3.5 million tonnes per year, the quantity of maize demanded by the feed sector was reduced, and self-sufficiency raised from 46.2% in 1984 to 80% in 1990. This situation was reinforced by the fact that imports from third countries were expected to be reduced as a consequence of adopting the protectionist Common Agricultural Policy. However, the United States pressed the EC in an attempt to maintain access to the Spanish market. In 1987, an agreement was signed by which Spain had to import, with levy reductions, 2 million tonnes of maize and 300,000 tonnes of sorghum yearly over the 1987-1990 period.

Thus, uncertainty about future prices has increased, and maize producers, traders and processors have to undertake risky short-run decisions in this new situation. The need to generate accurate short-run maize prices forecasts has become a significant issue.

3. Methods of Combining Forecasts

A key issue in composite forecasting techniques is to choose a set of weights for individual forecasts. A number of alternatives are available for deriving these weights. One rather intuitive method consists of calculating a simple average of individual forecasts, but this does not take into account information on the relative accuracy of individual forecasts. Bates and

Granger (1969) developed a weighted average scheme for two variables. Newbold and Granger (1974), Granger and Newbold (1986), Dickinson (1973, 1975) and Jolly and Wong (1987), among others, developed weighted schemes for several variables. In this minimum variance method, the composite forecast for period t (c_t) is given by:

$$c_t = a'F_t$$

where F_t is a $m \times 1$ vector of unbiased forecasts, m is the number of individual forecasts and a is a $m \times 1$ vector of weights. Newbold and Granger (1974) developed optimal minimum variance weights with larger weights assigned to more accurate forecasts.

Granger and Ramanathan (1984) have shown that optimal minimum variance weights have a regression interpretation with zero intercept and the sum of weights equal to unity. The relaxation of these conditions leads to a combined within-sample mean squared forecasting error which is smaller than the mean error obtained using the minimum-variance method.

In the regression approach, two problems have been pointed out: the possibility of serial correlation (Diebold, 1988) and the presence of near-collinearity among forecasts generated by individual methods (Guerard Jr., 1989). If serial correlation exists, Diebold (1988) developed a strategy to specify and estimate composite weights.

A common approach to deal with near-collinearity employs ridge regression, proposed by Hoerl and Kennard (1970). In our case, the ridge regression estimator has been defined as

$$p(\alpha) = (F'F + \alpha I)^{-1}F'X$$

where $F = (n-1) \times m$ matrix of individual forecasts

$X = (n-1) \times 1$ vector of the dependent variable $I = m \times m$ identity matrix ($\alpha = m \times 1$ vector of the ridge parameter estimates α = the shrinkage parameter, a constant greater than zero, in most applications lying between zero and one).

The method used in this study to estimate α has been proposed by Hoerl *et al.* (1975).

4. Individual Forecasting Methods

Available data covers monthly information on prices and international trade and quarterly data on consumption and stocks.* Quarterly data were transformed into monthly figures with the help of various experts from the most important trading firms in Spain. Monthly data from July 1986 to December 1990 were collected. The estimation period was taken from July 1986 to December 1988, and one-period-ahead forecasts were generated from January 1989 to December 1990.

Three individual forecasting methods are considered: exponential smoothing, ARIMA and an econometric model. The Holt-Winters exponential smoothing method was used

with level and trend being the only factors considered (Granger and Newbold, 1986). Parameters were estimated minimising the one-period-ahead forecasting error over the estimation period. The estimated model was:

$$X_t = 0.95 X_{t-1} + 0.05 (X_{t-1} - T_{t-1})$$

$$\underline{T_t = 0.7(X_t - X_{t-1}) + 0.3T_{t-1}}$$

The data source was: Servicio Nacional de Productos Agrarios (various years) *Mercados Nacionales*. Ministerio de Agricultura, Pesca y Alimentación. where X_t is the estimated mean of maize price in month t , X_t is the maize price in month t and T_t is the estimated trend term in month t .

ARIMA forecasts were obtained following the traditional Box-Jenkins (1970) approach. Maize prices were differenced once in order to achieve stationarity. Seasonality was considered but the results indicated that its inclusion did not contribute to increased forecast accuracy. In the estimation process, two outliers were detected (the months July-August 1987 and July-August 1988). These outliers are explained by difficulties of adjustment due to delay in the EC-US agreement in the first case, and exports at the beginning of the season following overestimation of barley production in the second. Both situations led to a considerable increase in maize prices. Two dummy variables were defined and adjusted by a MA(1) process in each case to take account of those problems. The resulting ARIMA (2,1,0) model applied to the monthly maize price series was:

$$(1 - 1.04B + 0.6B^2) (1 - B) PM_t = (3.73 + 0.74B) 10787 + (1.51 + 0.78B) 10788 + e_t$$

(5.66) (3.24)
(11.09) (2.22)
(4.61) (2.38)

$$R^2 = 0.95 \quad x^2_{18} = 12.46 (\text{not significant at the 5\% level})$$

–2

R = 0.94 $\delta = 0.57$ Figures in parentheses are t-statistics

where PM_t is the monthly maize price, B is the lag operator and 10787 and 10788 are the two dummy variables for periods July-August 1987 and July-August 1988, respectively. The chi-squared statistic implies that the hypothesis that the disturbance is a white noise is not rejected.

Econometric models and their forecasts are essentially structural representations of underlying behavioural systems for a particular commodity. If the goal, as in this case, is to predict only a single variable, a reduced-form model involving only a single equation seems appropriate. Lagged variables were chosen instead of current exogeneous variables, in order to make the econometric model truly predictive. Thus, future price movements can be predicted from currently available data.

The 1987 US-EC agreement significantly influenced maize prices during the season,

depending on the month that imports came to Spain. Cereal substitutes have been increasingly imported by the feed sector, but no significant relationship with maize prices has been found. Barley and wheat prices have been also considered. Wheat has been used in the feed sector very recently, so we have not found a strong relationship between maize and wheat prices.

The Schwarz criterion was chosen to determine the maximum lag for each variable, and the final estimated model was:

$$PM_t = 11.69 + 0.50PM_{t-1} - 0.27PM_{t-2} - 0.01FS_{t-1} + 0.47PB_{t-1} - 0.03M_{t-1} + 4.6410787 + 1.8510788$$

(3.64) (4.82) (-2.87) (-3.40) (5.34) (-2.45)

(7.84) (3.96)

$R^2 = 0.95$ $R^2 = 0.93$ $\sigma = 0.56$

where PM_{t-2} = monthly maize price lagged i (i = 1,2) periods (pta/kg)*
 FS_{t-1} = maize ending stock in month t-1 (1,000 kg)
 M_{t-1} = maize imports in month t-1 (1,000 kg)
 PB_{t-1} = barley price in month t-1 (pta/kg)

Godfrey's test (Godfrey, 1978) was used to check for serial correlation. This test is asymptotically valid in the presence of lagged endogeneous variables and is flexible enough to consider various orders of serial correlation. Serial correlation was not detected.

Maize price forecasts were generated over the period January 1989-December 1990. The first twelve forecasts were used to calculate weights for the different composite forecasting methods. The last twelve forecasts were used to evaluate both individual and composite method's forecasting ability.

Table 1: Estimated Weights of the Different Forecasts Combinations for the Five Composite Forecasting Methodsti

<i>Composite Model</i>	<i>Constant</i>	<i>Exp.</i>	<i>ARIMA</i>	<i>Econometric</i>
Simple Average (Method 1)				
AllThree	—	0.33	0.33	0.33
Exp.Smooth-ARIMA	—	0.50	0.50	—
Exp. Smooth-Econometric	—	0.50	—	0.50
ARIMA-Econometric	—	—	0.50	0.50
Minimum Variance (Method 2)				
AllThree	—	0.22	0.71	0.07
Exp. Smooth-ARIMA	—	0.22	0.78	—
Exp. Smooth-Econometric	—	0.83	—	0.17
ARIMA-Econometric	—	—	0.93	0.07
OLS Regression (Method 3)				
AllThree	14.28*	1.01*	0.21	-0.73*
Exp.Smooth-ARIMA	3.59*	0.35	0.51	—
Exp. Smooth-Econometric	16.35*	1.21*	—	-0.81*
ARIMA-Econometric	3.48	—	0.99*	-0.12
Regression with Serial (Method 4)				
AllThree	14.83*	1.06*	0.19	-0.79*
Exp. Smooth-ARIMA	6.04*	0.83	0.39	—
Exp. Smooth-Econometric	17.09*	1.25*	—	-0.88*
ARIMA-Econometric	4.67	—	0.92*	-0.09
Ridge Regression (Method 5)				
AllThree	2.50	0.31	0.48*	0.11*
Exp. Smooth-ARIMA	2.29	0.30*	0.61	—
Exp. Smooth-Econometric	5.33	0.72*	—	0.08*
ARIMA-Econometric	0.20	—	0.79*	0.20*

t Exponential Smoothing, ARIMA and Econometric RMSE were 0.69, 0.62 and 0.92, respectively, over January-December 1989. t An * indicates that the weight was significantly different from zero at the 5% level of significance.

5. Composite Forecasting Methods

Exponential smoothing, ARIMA, and econometric forecasts were combined in all possible ways using five different composite methods, and the results are shown in Table 1. The five methods were:

1: simple averaging of the results of the individual methods.

* National Currency: 1 US\$ = 100 pta over the 1986-1990 period.

t The x^2 values associated with testing serial correlation of order 1,2,3 and 4 were 1.17, 3.32,4.56 and 5.20, respectively. These values are well under the critical value at the 5% level of significance.

2: weights derived from the minimum variance criterion.

3: weights are the OLS estimated parameters regressing actual maize prices on the individual forecasts.

4: the Diebold (1988) procedure was used to detect possible autocorrelation in the previous method and the disturbance process approximated by a finite autoregressive representation. Using the Akaike (1974) criterion, the optimal order for the autoregressive approximation was AR(1). Weights are estimated as in method 3 using GLS.

5: the ridge-regression method.

As expected, the minimum variance criterion assigned higher weights to forecasting models with less Root Mean Squared Error (RMSE) values. The OLS regression analysis revealed evidence of severe multicollinearity. That is, the rather high correlation between exponential smoothing and ARIMA forecasts (0.95), exponential smoothing and econometric (0.89) and ARIMA and econometric (0.80) tended to produce unstable regression coefficients. The weight assigned to the econometric forecast was always negative and the ARIMA one was statistically insignificant in most cases. The regression with serial correlation hardly differed from the OLS regression. The application of ridge regression techniques tended to produce positive and statistically significant coefficients on the ARIMA and econometric forecasts.

Twelve one-period-ahead out-of-sample forecasts were generated from the different composite methods and compared with those obtained from individual models. Two types of measures were considered to evaluate the forecast accuracy of different models: the Mean Absolute Percentage Error (MAPE) and the RMSE. Results are shown in Table 2.

Table2 Out-of-Sample RMSE and MAPE for the Different Composite Forecasting Methods (January-December 1990)*t

Simple Average	0.49	1.55	0.62	1.79	0.50	1.55	0.53	1.67
Minimum Variance	0.57	1.71	0.62	1.79	0.58	1.59	0.58	1.75
OLS Regression	0.86	0.22	0.59	1.69	0.91	2.40	0.64	1.87
Regression with Serial Correlation	0.89	2.31	0.60	1.78	0.92	2.54	0.63	1.82
Ridge Regression	0.48	1.55	0.58	1.70	0.52	1.56	0.52	1.66

* Exponential Smoothing, ARIMA and Econometric RMSEs/MAPEs were 0.69/1.88, 0.62/1.84

and 0.92/3.10, respectively. t The underline indicates that differences in RMSE were statistically significant at the 5% level

with respect to the minimum RMSE in each column.

The ARIMA model generated the most accurate forecasts among individual models (see

footnote * in Table 2) and the econometric model was the worst. Composite method performance ranked quite similarly independently of the different ways of grouping individual models: in all cases studied, "the simple average, the minimum variance and the ridge-regression methods outperformed the best individual forecast. Ridge-regression composite forecasts generally were the most accurate. The other regression-based composite methods provided poor forecasting performance because multicollinearity was a severe problem.

Granger and Newbold (1986) developed a method for testing Mean Squared Error (MSE) equality across forecasting models, and proposed the test

$$Z = [\ln(1 + r) - \ln(1 - r)] (T - 3)^{1/2}$$

where r is the sample correlation between $(e^1 + e^2)$ and $(e^1 - e^2)$ [e^i ($i = 1, 2$) is the forecast error of model i] and T is the number of out-of-sample forecasts. Under the null hypothesis of no correlation, Z is approximately distributed $N(0,1)$.

Pairwise comparisons were made between the model with minimum RMSE (ridge regression) and the rest. Significant differences were found between ridge regression and econometric forecasts in all cases. The ridge regression method performed significantly better than the OLS regression and the regression with serial correlation methods in two cases of grouping individual forecasts (exponential smoothing-econometric and exponential smoothing-ARIMA-econometric).

Finally, as a qualitative measure, a turning point (TP) criterion was used. The criterion relies on a (4x4) contingency table, developed by Naik and Leuthold (1986) and Kaylen and Brandt (1988), distinguishing a 'peak TP' (PTP) from a 'trough TP' (TTP), and an 'upward non-TP' (UNTP) from a 'downward non-TP' (DNTP). From this table, two measures of interest are defined (Naik and Leuthold, 1986): the ratio of accurate forecasts (RAF) and the ratio of inaccurate forecasts (RÍF).

In general, the turning point evaluation (Table 3) shows the same results as those obtained from the quantitative evaluation. Ridge regression and the simple average follow the actual data movements most closely. When considering the three individual models, any composite method performs as well as or better than individual models. Combining only the ARIMA and econometric models provides slightly better results from the qualitative point of view.

6. Discussion

When data availability is limited and there is a short sample period, composite forecasting methods are an alternative to selecting the best single forecast.

Table 3 Out-of-Sample Turning Point Evaluation for One-Month-Ahead Forecasts of the Different Composite Models (January-December, 1990)

<i>Composite Methods</i>	<i>Different Ways of Grouping Individual Forecasts</i>							
	<i>All Three</i>		<i>Exp. AR1MA</i>		<i>Exp. Econometric</i>		<i>ARIMA-Econometric</i>	
	<i>RAr</i>	<i>RIF*</i>	<i>RAF</i>	<i>RIF</i>	<i>RAF</i>	<i>RIF</i>	<i>RAF</i>	<i>RIF</i>
Simple Averaget	0.92	0.08	0.92	0.08	0.92	0.08	0.92	0.08
Minimum Variance	0.83	0.17	0.83	0.17	0.83	0.17	0.83	0.17
OLS Regression	0.75	0.25	0.92	0.08	0.67	0.33	0.83	0.17
Regression with Correlation	0.75	0.25	0.75	0.25	0.67	0.33	0.83	0.17
Ridge Regression	0.83	0.17	0.83	0.17	0.92	0.08	0.92	0.08

* RAF and RIF are the ratio of accurate and inaccurate forecasts to the total, respectively. t Exponential Smoothing, ARIMA and Econometric RAF/RIF were 0.67/0.33, 0.75/0.25 and 0.75/0.25, respectively.

Even with simple averaging, when no prior information about the forecasting performance of different models exists, it is possible to remove the likelihood of introducing large errors when relying only on one model. When prior information exists, the user can weight future forecasts.

The results in this paper show that simpler methods, such as simple average or minimum variance, yield good out-of-sample forecasts. With more time-consuming (regression-based) composite methods, several problems may appear. In our case, multicollinearity was a serious problem and its explicit modelling provided the best forecasting results in all cases considered.

The results reported here apply to the series analysed during the evaluation period considered. Further research on other price series and other evaluation periods is needed. Also, in order to improve forecasting tools, additional comparisons among different individual and composite models should be performed (e.g. forecast of probability distributions).

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