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Forecasting Seven Components of the Food CPI

An Initial Assessment

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Forecasting Seven Components of the Food CPI: An Initial Assessment. By Mark Denbaly, Charles Hallahan, Fred Joutz, Albert Reed, and Robert Trost. U.S. Department of Agriculture, Economic Research Service, Food and Consumer Economics Division. Technical Bulletin No 1851.

Abstract

This report makes the price forecasting procedure used by the Food and Consumer Economics Division of the Economic Research Service transparent to users, and evaluates the quality of the forecasts. After documenting and interpreting FCED's procedure, we evaluate it using the seven monthly food CPI series for which FCED computes forecasts. Based on the first subset of the sample, we compute a best-fitting, alternative ARIMA model for each series. The second subset of the data is used to compute out-of-sample forecast errors for both the FCED model and the alternative ARIMA models. We then compare the bias and the reliability of both sets of forecasts for each price series. The results show that forecasts computed using the alternative ARIMA model are more reliable than forecasts computed using the FCED model.

Keywords: food price forecasts, forecast evaluation, rolling forecasts, ARIMA models.

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Introduction

The Economic Research Service (ERS) of the U.S. Department of Agriculture (USDA) computes forecasts for a number of components of the Consumer Price Index (CPI) for food. The U.S. Federal Reserve uses ERS's food price forecasts when making policy decisions, and the President's annual budget relies on these forecasts when allocating funds to the Food Stamp Program. Given the use of ERS's forecasts, it is important to evaluate their reliability.

The Food and Consumer Economics Division (FCED) of ERS computes forecasts for seven components of the food CPI: (1) Fish and Seafood, (2) Fats and Oils, (3) Sugar and Sweets, (4) Cereals and Bakery Products, (5) Other Prepared Food, (6) Dairy Products, and (7) Nonalcoholic Beverages. This study evaluates the FCED procedure by comparing its forecasts of the seven CPI series with forecasts from competing models.

Description of the Data

The U.S. Bureau of Labor Statistics provides ERS with monthly data on individual components of the food CPI. The sample data used in this study are the seasonally unadjusted monthly series from January 1986 through February 1996. Of the seven series forecasted by FCED, all share a pronounced upward trend over the sample period, yet display different patterns (figs. 1-7).

The prices used to construct the Fish and Seafood component are: canned fish or seafood, fresh or frozen fish and seafood, shellfish, and fish. Between 1986 and 1995, this component rose nearly 48 percent. Despite some volatility around the trend, the trend appears constant and easily identified (fig. 1).

The prices used to construct the Dairy Products index are: fresh whole milk, other fresh milk and cream, cheese, ice cream and related products, butter, and other dairy products. The dairy price series increased by 30 percent over the sample period. It increased by 10 percent between 1986 and 1989, by 15 percent in 1990, and increased slightly from 1990 to 1995 (fig. 2).

The prices used to construct the Fats and Oils component are: other fats and oils, nondairy cream substitutes, and peanut butter. Between 1986 and 1988, this index displayed no trend. In 1989, the index increased by about 15 percent, and rose by about 10 percent in 1990. The Fats and Oils price index fell slightly between 1991 and 1993 and rose by about 3 percent from 1993 to 1995 (fig. 3).

The prices used to construct the Cereal and Bakery Products index are: flour, prepared flour mixes, cereal, rice, macaroni and similar products, and cornmeal. Of the seven component series, this price index rose most over the sample period--over 50 percent. There appears to be little volatility of the series around a linear trend (fig. 4).

The prices used to construct the Nonalcoholic Beverage price index are: cola drinks, carbonated drinks other than cola, coffee, tea, and other noncarbonated drinks. The index rose by 3-4 percent between 1986 and 1994. The sharp 15-percent increase during April and May of 1994 reflects a shortage of coffee caused by a drought and an early frost in Brazil. Following this increase, the Nonalcoholic Beverage price index showed little trend (fig. 5).

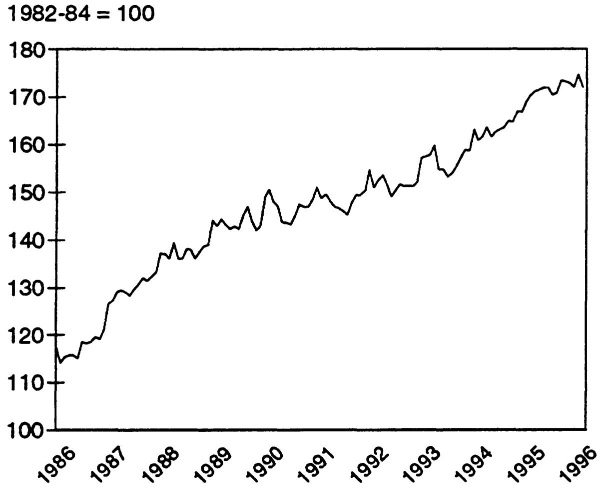
The prices used to construct the Sugar and Sweets index are: candy and chewing gum, other sweets, and sugar and other sweeteners. The Sugar and Sweets index increased by about 30 percent over 1986-95. From 1988 to 1992 the series closely follows a linear trend. After 1992, the series appears more volatile (fig. 6).

The prices used to construct the Other Prepared Foods index are: canned and packaged soup, frozen prepared foods and meals, potato chips and other snacks, nuts, salt and other seasonings and spices, olives, pickles and relishes, sauces and gravies, other condiments, canned or packaged salads and desserts, baby food, and other canned or packaged prepared foods. This series increased steadily by 41 percent over the sample (fig. 7).

While the seven components of the food CPI display a pronounced upward trend over the sample period, each series appears to grow at different rates. The Dairy Products, Fats and Oils, and Sugar and Sweets components display different and more volatile trends in the 1990's than in the 1980's.

Figure 1

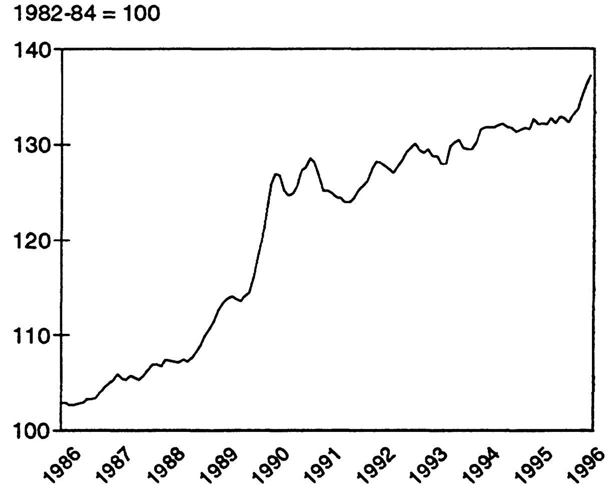
Consumer price index: fish and seafood, 1986-96



Source: ERS/USDA.

Figure 2

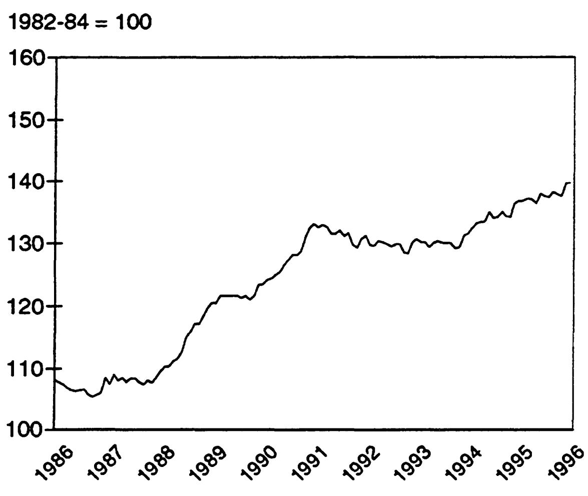
Consumer price index: dairy products, 1986-96



Source: ERS/USDA.

Figure 3

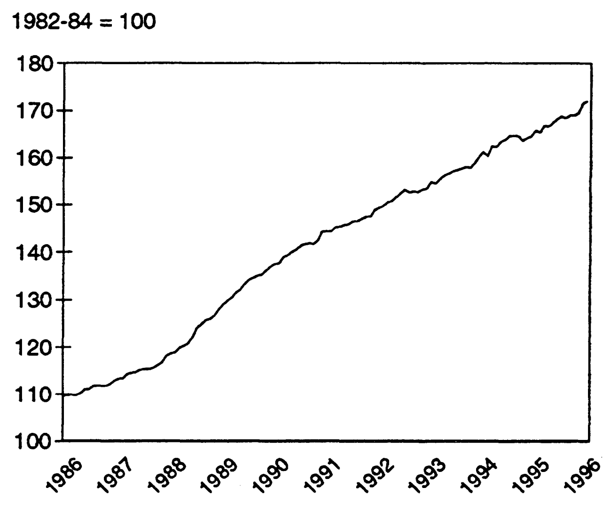
Consumer price index: fats and oils, 1986-96



Source: ERS/USDA.

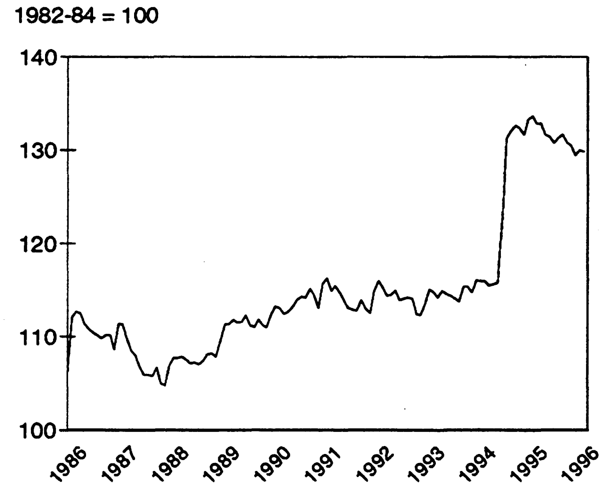
Figure 4

Consumer price index: cereal and bakery, 1986-96



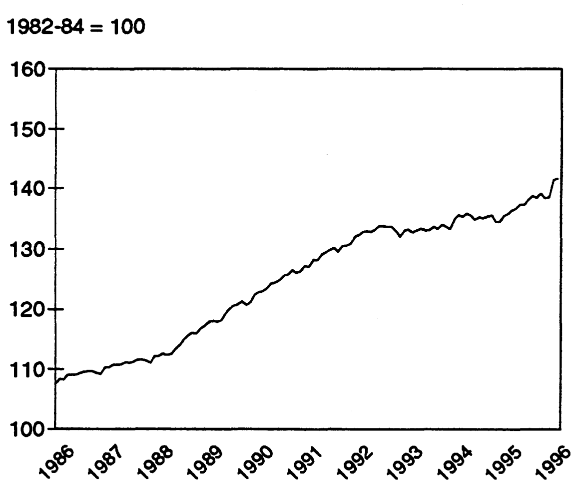
Source: ERS/USDA.

Figure 5
Consumer price index: nonalcoholic beverages, 1986-96



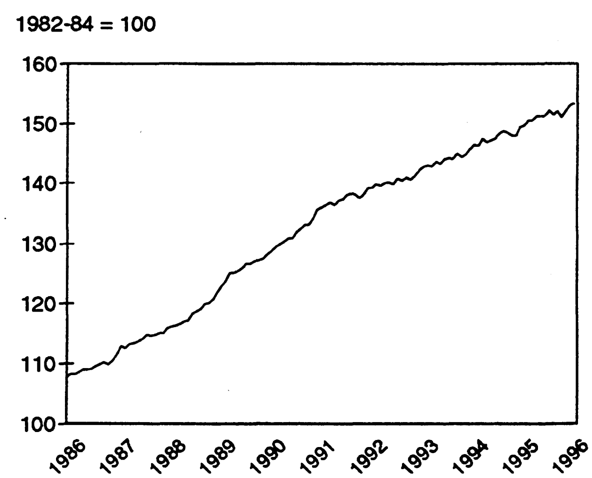
Source: ERS/USDA.

Figure 6
Consumer price index: sugar and sweets, 1986-96



Source: ERS/USDA.

Figure 7
Consumer price index: other prepared foods, 1986-96



Source: ERS/USDA.

Any changes in food price patterns between the 1980's and the 1990's would have occurred amid profound changes in the food industry.[1] In the 1980's, food processors shifted away from mass-produced foodstuffs and toward higher value-added products. Mass media may have helped shift consumers' preferences for convenience, safety, and health attributes of food; and marketers lured shoppers with national brand names such as Nabisco, Campbell, and Kelloggs. The willingness of consumers to pay for these attributes led to sharp increases in the price of nationally branded food products and to the profits of national-brand food firms. The leveraged buyouts of national firms in the late 1980's represented a demand for more brand names, and the magnitudes of some of the buyouts reflected firms' expectations that more brand names would translate into ever-increasing profits.

These expectations were not realized. Since the recession of 1991, thriftier consumers appeared to dump expensive brands for cheaper store brands. The 1980's price increases among nationally branded food products left national firms vulnerable to less costly competitors. Store-brand processors produced food products of reliably high quality, and marketed their products without the expense of advertising. Adding to the competition among processors was competition among retail outlets. Since the beginning of the 1990's, traditional outlets such as Kroger and Safeway have been challenged by warehouse clubs such as Sam's (Wal-Mart) and Pace (K-Mart). Thriftier and more quality-conscious consumers and more intense competition may have flattened price increases in the 1990's.

The Current FCED Forecasting Procedure

The FCED forecasts seven CPI series up to 12 months in advance. The FCED bases its forecasts on the assumption that the annual proportionate change in a series follows a random walk. 'Annual proportionate' refers to the ratio of the level of the CPI component in a given month divided by its level for the same month in the previous year. The discussion in this section describes the way in which the FCED incorporates annual proportionate changes into its forecast formula, illustrates the way in which FCED uses its formula to make various step-ahead forecasts, and cites the advantages the FCED approach may have over other forecast approaches.

Let y_t represent a CPI component observed in month t. The annual proportionate change in month t is simply $p_t = y_t / y_{t-12}$. Let '^' denote the predicted or forecasted value up to 12 months into the future. The FCED forecasts are based on the assumption

[1] This brief discussion relies on a series of articles in the *Economist* (December 4, 1993). The reader is referred to these articles for more detail.

$$\left(\frac{\hat{y}_{t+j}}{y_{t+j-12}}\right) \equiv \hat{p}_{t+j} = \left(\frac{y_t}{y_{t-12}}\right) \equiv p_t \tag{1}$$

for j = 1,...,12. Equation 1 describes the pattern of the proportionate change (p) in the price series over the 12-month forecast horizon. Equation 1 assumes the proportionate change in the series remains fixed at the level measured one month prior to the forecast period. In other words, the proportionate change of the price series is assumed to follow a random walk over the forecast horizon. Rearranging equation 1 gives

$$\hat{y}_{t+j} = \hat{p}_{t+j}\, y_{t+j-12} = p_t\, y_{t+j-12} = \left(\frac{y_t}{y_{t-12}}\right) y_{t+j-12} \tag{2}$$

for j = 1,2,..., 12. Equation 2 states that a given month's price forecast over the 12-month horizon is the last annual proportionate change observed multiplied by the level of the index observed 12 months before the month to be forecast. FCED uses equation 2 to generate forecasts of CPI components for food.

One advantage of using the FCED model is its simplicity. The j-step-ahead forecast of y is the product of the most recently observed annual proportionate change (p_t) and y_{t+j-12}. The one-step-ahead prediction of a March 1996 price index, for example, is the product of the proportionate change observed in February 1996 and the April 1995 level of the series. The two-step-ahead prediction (that is, the April 1996 index) is the product of the same proportionate change and the May 1995 level. It is routine to use equation 2 to generate sets of forecasts for many different time series.

Another advantage of computing forecasts using the FCED model is that large amounts of historical data are not needed to construct a forecast. Like the exponential smoothing models, equation 2 does not rely on historical correlation to describe the data. No parameter estimates are needed to implement equation 2.

Some Alternative Forecasting Models

While numerous forecasting procedures exist, they can be divided broadly into (1) statistical models with constant parameters, and (2) statistical models with time-varying parameters. Constant-parameter models include the Autoregressive Integrated Moving Average (ARIMA) models and econometric models. Time-varying parameter models include the Markov Switching Regression (MSR) models and state-space models. This section reports on the method used to identify a possible alternative to the FCED model.

Constant-parameter and time-varying parameter models describe different data-generating mechanisms. Constant-parameter models assume the distribution of the stochastic time series and forecast errors remain fixed over the sample. The widely used ARIMA models assert that each point (or vector) of a time series depends on previous points in the series and current or previous forecast errors. Fixed-parameter econometric models allow an endogenous time series to depend on exogenous time series. For both the ARIMA and the fixed-parameter econometric model, correlations are fixed and are based on the presumed fixed statistical distribution of the time series. In contrast, the time-varying parameter models assume that the distribution of the time series changes over the sample. The MSR model assumes a series is generated from one of two distributions or regimes, with a Markov chain describing the probability that the system moves from one regime in the current time period to the other regime in the next period. State-space models describe a changing distribution of a time series by allowing parameters to change systematically over the sample.

We narrow our search for an alternative model to the class of ARIMA models. Our choice is motivated by the relative ease of estimating and implementing ARIMA models, and because the FCED model is itself a restricted ARIMA model. Since the parameters of an ARIMA model completely describe the distribution of a time series, and its parameters are fixed, the historical dependencies observed in the data are reflected in forecasts generated by ARIMA models. Future research will be devoted to expanding the class of models considered as viable alternatives to the FCED model.

ARIMA models have been widely used for forecasting since they were first popularized by George Box and Gwilym Jenkins (1970). Box and Jenkins suggest four basic steps in implementing an ARIMA model for forecasting: (1) identification of a tentative model, (2) estimation of the model, (3) diagnostic checking (if the model is found inadequate, go back to step 2, and (4) use of the model for forecasting and control.

Our method of identification and estimation differs from Box and Jenkins' original suggestions. We used the Economic Time Series (ETS) procedure in SAS to identify an alternative candidate that best fits the observations from January 1986 to July 1990. Observations from January 1986 to February 1996 are used to measure the model's forecast performance. Prior to selecting the alternative model, ETS identifies the appropriate transformation of the data. It first performs a test of the log transformation, and if the log transformation cannot be rejected, the logged data are analyzed. Next, it performs a Dickey-Fuller test of the presence of a unit root in either the logged or unlogged data. Next, the procedure tests the statistical significance of seasonal dummies within an autoregressive model of large order. If the set of seasonal dummies cannot be rejected, each candidate model contains seasonal dummies. ETS's preliminary tests are consistent with the suggestions of Joutz, Maddala, and Trost (1995). Once the data are transformed, the model selected to compete with the FCED model is the one with the smallest root-mean-squared error (RMSE) among the alternative ARIMA models.[2]

The ARIMA (0,1,1) model with seasonal dummies minimized the RMSE for all price series but dairy. If y_t denotes the original time series, the ARIMA (0,1,1) model is

$$\Delta y_t = \theta\epsilon_{t-1} + \sum_{k=1}^{k=12} d_k S_k + \epsilon_t \qquad (3)$$

where $\Delta y_t = y_t - y_{t-1}$, ϵ_{t-1} is last month's forecast error, ϵ_t is the current month's forecast error, S_k are monthly seasonal dummies defined in the usual way, and θ and the d_k are parameters to be estimated.

The ARIMA (1,1,0) model minimized the RMSE criterion for the dairy price data. This model is given by

$$\Delta y_t = \alpha\Delta y_t + \epsilon_t \qquad (4)$$

where α is a parameter to be estimated. Equation 4 states that the monthly change in the dairy price component of the CPI depends only on the previous month's change.

Comparison of Forecast Accuracy

In this section we compare the forecast accuracy of the FCED and ARIMA models by generating out-of-sample forecast errors, computing four accuracy statistics, and performing a statistical test of forecast reliability. The forecasts evaluated are out-of-sample forecasts in the sense that the points of the time series forecasted are separated from the points used to estimate model parameters. In generating and evaluating rolling forecasts,[3] we are simulating a forecaster updating a model in light of new information.

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[2]The particular parameter estimates of the identification stage are not reported.

[3]See Joutz, Maddala, and Trost (1995) for more details of the rolling forecast procedure.

The rolling forecasts are generated as follows. The parameters of the ARIMA model are estimated using the January 1986-July 1990 observations. Based on the parameter estimates, predictions of the August 1990-July 1991 observations are computed. FCED predictions for the same period are computed, but are based on no estimated parameters. Next, the August 1990 observation is added, and ARIMA model parameter estimates are recomputed using the January 1986-August 1990 observations. The revised parameter estimates are used to forecast the September 1990-August 1991 observations. The new set of FCED forecasts requires no re-estimation. This process is repeated until the March 1995 observation, when forecasts are limited to 11 months ahead. In each succeeding update, the forecast horizons are reduced by 1 month until the January 1996 observation is added to the sample, and a single forecast is generated for February 1996. For our data, the rolling forecast procedure results in 67 1-month forecasts, 66 2-month forecasts, 65 3-month forecasts, and so forth to 56 12-month forecasts.

The relative forecast error of a j-month forecast made in month t is

$$RE_{t,j} = \frac{e_{t+j}}{y_{t+j}} \qquad for\ j = 1,2,...,12$$

where

$$e_{t+j} = y_{t+j} - \hat{y}_{t,t+j} \tag{5}$$

is the j-month forecast error, y_{t+j} is the actual observation, and $\hat{y}_{t,t+j}$ is the j-month forecast made in time t. Because the forecast errors are normalized by the data series, relative errors associated with more or less variable series are comparable. The relative errors of the ARIMA model are consistently lower than the relative errors of the FCED model across the seven series.

Summary measures of forecast performance are computed using the following four statistics: the mean error (ME),

$$ME_j = \frac{1}{n_j} \sum_t (y_{t+j} - \hat{y}_{t,t+j}) \tag{6}$$

the mean absolute error (MAE),

$$MAE_j = \frac{1}{n_j} \sum_t |y_{t+j} - \hat{y}_{t,t+j}| \tag{7}$$

the mean absolute percent error (MAPE),

$$MAPE_j = \frac{100}{n_j} \sum_t \left| \frac{y_{t+j} - \hat{y}_{t,t+j}}{y_{t,t+j}} \right| \tag{8}$$

and the root-mean-squared error (RMSE),

$$RMSE_j = \sqrt{\sum_t \frac{(y_{t+j} - \hat{y}_{t,t+j})^2}{n_j}} \tag{9}$$

for $j = 1, 2, ..., 12$, where n_j denotes the number of j-step-ahead forecasts. The mean error and the mean absolute error are indicators of the bias of the forecast. The mean error measures how close the average value of the forecast is to the average value of the observations. The mean absolute error and the root-mean-squared error measure forecast error dispersion. Both the MAE and the RMSE reflect the potential unreliability of a forecast. The larger the MAE or the RMSE, the more unreliable is a single forecast. The summary measures are reported in tables 1-4 for the 1-, 2-, 6-, and 12-month forecasts generated by both the FCED and the ARIMA models.

Table 1 reports a 1-month ME value for Fish and Seafood of -0.011 for the FCED model forecasts and -0.143 for the ARIMA model forecasts. The ME measures forecast bias, and positive forecast errors are offset by negative forecast errors. On the other hand, the MAE is always positive since it is the cumulate sum of the absolute values of forecast errors. An ME value roughly the same magnitude as an MAE value suggests systematic forecast bias. Both the FCED and ARIMA models generate forecasts with generally small bias, and the differing magnitudes of the MAE statistic (table 2) suggest no significant systematic bias.[4]

The mean absolute percent error (MAPE) associated with the 1-month forecast of the Fish and Seafood series is 0.988 for the FCED model and 0.697 for the ARIMA model (table 3). The ARIMA models' forecasts seem more reliable than FCED's. Except for one set of forecasts (12-month, other prepared food), the MAPE values associated with the ARIMA models are lower.

Like the MAPE, the root-mean-squared error (RMSE) is a measure of dispersion; unlike the MAPE, the RMSE is measured in the same units as the data series. Because the RMSE is a monotonic transformation of the mean squared error, and the mean squared error is one measure of the cost of making a forecast error, the RMSE is conceptually a more convenient measure of dispersion than the MAPE. For example, if the true model is known, an optimal forecast of a

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[4]Preliminary tests suggest both models deliver optimal forecasts, in the sense the forecasts correctly incorporate historical information. The statistical tests for optimality of the forecasts will be presented in an upcoming report.

series is the mathematical expectation of the model; and the optimal forecast will minimize the RMSE. Table 4 suggests the 1- and 2-month forecasts associated with the ARIMA model are more reliable than those associated with the FCED model. Furthermore, the FCED model outperforms the ARIMA model in only two instances.

Granger and Newbold (1977) propose a statistical test designed to compare the one-step-ahead forecast reliability of two competing models. The test presumes the forecasts are unbiased and the forecast errors from each model are serially uncorrelated. Since the forecast errors associated with j-step-ahead forecasts are generally serially correlated from $j > 1$, Granger and Newbold's test can only be applied to compare the reliability of one-step-ahead forecasts.[5]

Since the one-step-ahead forecasts from each model are presumably unbiased, and the RMSE of the forecast errors is a monotonically increasing function of the variance of the forecast errors, the variance of the forecast errors is a measure of forecast reliability. The null hypothesis is the variance, σ_1^2, of the one-step-ahead FCED forecast errors, e_1, equals the variance, σ_2^2, of the one-step-ahead ARIMA forecast errors, e_2. The test assumes the vector (e_1,e_2) is randomly drawn from a bivariate normal distribution with parameters σ_1^2, σ_2^2, and correlation coefficient, ρ. Under the null hypothesis, $\sigma_1^2 = \sigma_2^2$, the correlation between the variables $(e_1 - e_2)$ and $(e_1 + e_2)$ is zero; and the estimate of the coefficient, r, in a regression of $(e_1 - e_2)$ on $(e_1 + e_2)$ is also zero. Hence the statement $r=0$ is equivalent to $\sigma_1^2 = \sigma_2^2$, which means the two models' one-step-ahead, unbiased forecasts are equally reliable. The statement $r \neq 0$ is equivalent to the statement $\sigma_1^2 \neq \sigma_2^2$, implying that the models' forecasts are not equally reliable. The statement $r>0$ is equivalent to the statement $\sigma_1^2 > \sigma_2^2$ (ARIMA more reliable than FCED). Finally, the statement $r<0$ is equivalent to the statement $\sigma_1^2 < \sigma_2^2$ (FCED more reliable than ARIMA).

The t-values reported in the second column of table 5 are associated with the null hypothesis that $r=0$, or that the two models' 1-month forecasts are equally reliable. Point estimates of r are reported in column 1. The p-values reported in the last three columns are associated with three alternative hypotheses: the 1-month forecasts are not equally reliable ($r \neq 0$), FCED forecasts are more reliable than the ARIMA forecasts ($r < 0$), and the ARIMA forecasts are more reliable than the FCED forecasts ($r > 0$). The p-value measures the probability of incorrectly accepting the particular alternative hypothesis when the null hypothesis of equally reliable forecasts is true. The p-value of 0.0004 in the third column for Fish and Seafood, for example, means that by accepting that the forecasts are not equally reliable, the analyst will be wrong with probability 0.0004. By accepting that the FCED model is more reliable than the ARIMA model, the analyst will be wrong with probability of (almost) 1.0. By accepting that the ARIMA model is more reliable than the FCED model, the analyst will be wrong with probability 0.0002. The p-values

[5]The optimal j-step-ahead forecast errors follow an MA(j-1) process, and hence, for greater than one-step-ahead forecasts, violate the uncorrelated requirement necessary to apply the Granger and Newbold test. Diebold and Mariano (1995) propose statistical tests that can be used to compare the greater than one-step-ahead predictions generated from competing models. Future work will report other statistical tests designed to compare the reliability of greater than one-step-ahead forecasts.

reported in table 5 clearly suggest the 1-month forecasts generated by the ARIMA models are more reliable than the FCED model's.

Conclusions and Future Research

This report attempts to assess the benefits of incorporating historical correlation of prices into FCED's food price forecasts. FCED's current procedure is well-suited to situations in which historical correlation of food prices is either nonexistent or unreliable. Results indicate that at least some of FCED's forecasts would improve significantly by incorporating an estimate of the historical correlation into its food price forecasts.

Forecasts generated from ARIMA models fit to each sample series performed better than forecasts generated by the single FCED model. ARIMA models are well-suited to situations in which ample historical data are available and the correlation structure of the time series can be readily identified from the data. Not only do the ARIMA forecasts result in smaller relative forecast errors, but they also appear to be more reliable than the forecasts generated by the FCED model. In terms of one-step-ahead forecasts, this difference is statistically significant.

It is important to remember that the FCED forecast *procedure* and *not* the FCED forecasts are being evaluated. In generating the ARIMA models' forecasts, estimates of the correlation of the time series are revised as new information becomes available. Because the FCED model is not based on estimates of statistical correlation, new data do not lead to better parameter estimates and to, presumably, better forecasts. What is surprising is how well the FCED model performs despite this limitation. It is important to remember that FCED *forecasters* revise the model's forecasts in light of new information.

In terms of the ARIMA forecast comparisons, the next step is to evaluate the statistical difference in reliability of greater than one-month-ahead forecasts. Also, it is relatively straightforward to test whether one or both models generate optimal forecasts. Both results are forthcoming. In terms of other comparisons, it would be useful to compare ARIMA or FCED forecasts with Kalman's (1960) procedure of incorporating new information. Even at this stage of development, however, we feel our exercise could be extended in evaluating other food price series forecast by ERS.

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Table 1--Mean error forecast comparison (August 1990 to February 1996)

	Month-Ahead Forecast							
	1		2		6		12	
	FCED	ARIMA	FCED	ARIMA	FCED	ARIMA	FCED	ARIMA
Fish & Seafood	-0.011	-0.143	0.054	-0.248	0.237	-0.616	0.965	-0.797
Dairy	-0.113	0.059	-0.274	0.138	-0.758	0.439	-0.695	1.300
Fats & Oils	-0.042	-0.165	-0.090	-0.284	-0.426	-0.904	-1.044	-1.443
Cereals & Bakery	-0.033	-0.063	-0.057	-0.137	-0.265	-0.485	-0.632	-1.050
Non Alcohol	-0.109	0.055	-0.246	0.111	-0.730	0.534	0.175	1.726
Sugar & Sweets	0.008	-0.059	0.015	-0.120	-0.119	-0.508	-0.462	-1.251
Other Prep.	-0.032	-0.098	-0.067	-0.190	-0.293	-0.623	-0.699	-1.347

Table 2--Mean absolute error comparison (August 1990 to February 1996)

	Month-Ahead Forecast							
	1		2		6		12	
	FCED	ARIMA	FCED	ARIMA	FCED	ARIMA	FCED	ARIMA
Fish & Seafood	1.553	1.101	2.112	1.609	2.035	1.994	2.683	2.656
Dairy	0.836	0.552	1.416	0.917	2.926	1.865	3.745	2.420
Fats & Oils	0.699	1.000	1.008	1.280	2.236	1.726	3.785	2.198
Cereals & Bakery	0.502	0.388	0.650	0.443	1.047	0.785	1.510	1.237
Non Alcohol	1.161	0.820	1.882	1.307	4.757	3.013	7.368	5.075
Sugar & Sweets	0.488	0.370	0.669	0.511	1.354	1.046	2.002	1.773
Other Prep.	0.505	0.354	0.499	0.377	0.863	0.826	1.290	1.473

Table 3--Mean absolute percent error comparison (August 1990 to February 1996)

	Month-Ahead Forecast							
	1		2		6		12	
	FCED	ARIMA	FCED	ARIMA	FCED	ARIMA	FCED	ARIMA
Fish & Seafood	0.988	0.697	1.342	1.020	1.276	1.267	1.667	1.687
Dairy	0.649	0.426	1.100	0.707	2.287	1.444	2.916	1.868*
Fats & Oils	0.532	0.503	0.766	0.689	1.695	1.462	2.874	1.896*
Cereals & Bakery	0.319	0.248	0.414	0.284	0.661	0.500	0.949	0.783*
Non Alcohol	0.947	0.674	1.511	1.057	3.750	2.386	5.769	3.981*
Sugar & Sweets	0.365	0.277	0.499	0.382	1.004	0.780	1.483	1.319*
Other Prep.	0.351	0.248	0.350	0.264	0.608	0.578	0.907*	1.000

Table 4--Root mean squared error comparison (August 1990 to February 1996)

	Month-Ahead Forecast							
	1		2		6		12	
	FCED	ARIMA	FCED	ARIMA	FCED	ARIMA	FCED	ARIMA
Fish & Seafood	1.939	1.412	2.548	1.920	2.568	2.389	3.045	3.130
Dairy	1.192	0.682	2.125	1.133	4.370	2.341	5.274	2.759
Fats & Oils	0.910	0.822	1.336	1.062	2.994	2.090	4.888	2.676
Cereals & Bakery	0.620	0.504	0.766	0.542	1.265	0.868	1.678	0.960
Non Alcohol	2.199	1.464	3.846	2.620	7.944	5.349	10.71	7.345
Sugar & Sweets	0.598	0.489	0.831	0.662	1.649	1.198	2.457	1.815
Other Prep.	0.610	0.418	0.609	0.445	1.101	0.728	1.679	0.863

Table 5--Statistical comparison of forecast accuracy of the FCED and ARIMA models

	$\hat{r}$	t-value	p-value for FCED ≠ ARIMA	p-value for more accurate FCED forecasts	p-value for more accurate ARIMA forecasts
Fish & Seafood	0.183	3.724	0.0004	1.000	0.0002
Dairy	0.357	5.437	8.8 E-7	1.000	4.4 E-7
Fats & Oils	0.059	1.168	0.247	0.877	0.123
Cereal & Bakery	0.119	2.445	0.017	0.991	0.009
Non Alcohol	0.235	4.700	0.000	1.000	7 E-6
Sugar & Sweets	0.114	2.552	0.0131	0.993	0.006
Other Prep.	0.211	4.841	8.3 E-6	1.000	4.1 E-6

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