The Current State of Commodity Price Forecasting Methods: An Appraisal

by

W. G. Tomek and T. D. Mount

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"A good forecaster is not smarter than anyone else, he merely has his ignorance better organized" [Granger, 1980, p. 135).

Forecasting methods range from informal (but perhaps informed) judgments to formal quantitative procedures. Forecasts that are actually used commonly rely on a combination of methods. The objective of this paper, however, is limited to an appraisal of quantitative approaches to forecasting, especially traditional (structural) econometric methods and, to a lesser degree, time-series procedures. Our emphasis is on the potential sources of forecasting errors rather than on methods of evaluating forecasts. But to say that a forecast is in error implies some underlying measure of the accuracy of the forecast, and the idea of a "standard error of a forecast" will be implicit in much of the discussion.

The paper begins with a review of the various sources of errors

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in forecasts. Why do forecasts go wrong, and what are the implications for selecting appropriate methods? This review provides the framework for much of the remainder of the paper. Current econometric practices, including time-series methods, are discussed and appraised, and the relationship between time-series and traditional structural models is explored. A final section contains attempts to draw conclusions for improving forecasting methods.

An important problem in drawing conclusions, however, is that the purpose of the forecast influences the models, data, and techniques used. For example, is the problem to make an investment decision based on how energy prices move relative to other prices over the next five to 10 years, or will the forecast be used by private decision-makers in making short-run sales, procurement, or storage decisions? No single model or technique is likely to be "best" for the broad range of questions which analysts might help to answer. We return to this issue before concluding.

Sources of Forecasting Error

The traditional confidence interval for an individual forecast assumes just two sources of error: the sampling error inherent in statistical estimation and the nonzero residual associated with the forecast of an individual value--in contrast to the mean--of the variable (see, e.g., Johnston,1972, p. 154). The model and associated estimation method are assumed to be correct, and the same model is assumed to be applicable to the forecast period, implying that the structure of the model does not change.

In practice, of course, the model, data, and estimation procedures may be inappropriate. There is great potential for specification errors. The data set may contain one or more outliers, and the variables used in the analysis may be poor measures of the appropriate concepts in the model. In addition, the estimation procedure may not be appropriate for the underlying specification.

All statistical procedures may have these problems. Structural econometric models have the additional problem that projections of the exogenous variables have to be supplied for the forecast period. Such projections are themselves subject to error. Hence, erroneous forecasts may merely be functions of errors in the levels of exogenous variables used for the forecasts.

For all of these reasons, it is not surprising that forecasts often differ greatly from actual outcomes and that traditional confidence intervals are poor guides to the size of forecasting errors. Fair (1980) and Feldstein (1971) have developed measures of the variability of forecasts which take account of such sources of error as the stochastic properties of the exogenous variables. These variances can be used to compute more realistic confidence intervals, but the resulting forecast intervals may be so large that they aren't useful for decision-making. In this paper, the different sources of forecasting error are used as a basis for appraising forecasting methodology.

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Current Econometric Practice

Econometric models have been characterized as being simultaneous, dynamic, and stochastic, and much attention has been devoted to developing estimators for simultaneous equations, specifying distributed lag models, and dealing with autocorrelated disturbances (for a review, see Judge, 1977). With the development of high speed computers, these methods can be applied to a wide range of data sets, and agricultural economists have been in the forefront of applying new techniques.

More recently, attention in econometrics has shifted somewhat to issues related to the quality of data. There also has been concern about the statistical implications of experimentation with a given data set in the search for the "best" model. These developments have had less chance to influence the empirical models used in forecasting. Some of these ideas are developed in greater depth in the next few subsections.

Appropriate models and estimators

Most models of agricultural product markets are basically equilibrium supply-demand models, and given the time lags inherent in the production process, the models often have a recursive feature. But correct models of agricultural subsectors sometimes involve simultaneity (Tomek and Robinson, 1977). In this context, multiple equation models are necessary and useful for simulating policy alternatives and for providing insights into the structure of particular agricultural product markets.

Cromarty and Myers (1975) have argued, however, that relatively simple single equation models are to be preferred to large simultaneous models for forecasting. A single equation, of course, may be a reduced form from a larger model, and in this sense the larger model is useful. But the importance of simultaneous equations bias as a source of error in forecasting has perhaps been exaggerated in the literature. We should remember that Waugh (1961) consistently advocated the use of least squares estimation of single equations as an appropriate procedure for forecasting, but his view was definitely in the minority through the 1950s and 1960s.

Our empirical knowledge is strongest with respect to the domestic demand for agricultural products, and numerous, useful price-dependent equations have been estimated. Our knowledge is less strong with respect to supply, inventory, and export relationships. This is partly related to the quality of data available, and in particular, to risk and expectations concepts that appear to be important for supply and inventory models. These concepts are not directly observable. Hence, they are commonly based on lagged values of observable variables, and it is difficult to discriminate among competing hypotheses. In fact, the autoregressive characteristics of the resulting structural models are similar to pure time-series models.

Distributed lag effects, whether related to expectations or to other factors, clearly are important in agricultural economics, and a large number of applications of a variety of models exists in the literature. But no single preferred lag specification or estimation procedure has emerged. Geometric-lag models remain popular; however, if the coefficient of a lagged dependent variable is approximately one with a large t ratio (a common result), then the model differs little from a naive, autoregressive model. Turning points are likely to be missed with a one period lag.

Applications of Almon-type specifications of lag structures have been disappointing (at least relative to the initial expectations about their contributions). Specifying the length of lag and degree of polynomial has turned out to be difficult; that is, although constraining the coefficients of the lagged variable to follow a smooth polynomial seems plausible, the possibility of serious specification error appears greater than first realized. Hence, relatively few examples of forecasting applications with polynomial lags exist in the literature (for one, see Meilke, 1977).

An idea somewhat associated with deriving lagged relationships from partial adjustment mechanisms is the disequilibrium of a market. That is, in the short run, quantity demanded may not equal quantity supplied. In the nonfarm sector, excess demand implies a draw-down in inventories and a build-up in unfilled orders while prices adjust little if at all. Excess supply has the opposite effect. Heien (1977) has suggested that an analogous idea might have value for agricultural markets, and observed adjustments in prices may be a reflection of the short-run, supply-demand imbalance. At present, there is insufficient evidence about the usefulness of the concept for agricultural products. In an application to the corn sector, Baumes and Womack (1979) found that a model based on an equilibrium specification was a better predictor than one based on a disequilibrium specification.

Model specification

In selecting variables for the model, the economic logic of the problem is, of course, important. Most empirical work, however, also depends on exploratory analysis of alternatives before picking the final model. The initial screening of variables usually involves examination of t-ratios (formal or informal tests of hypotheses) as well as signs of coefficients. Then, the modified model is refitted using the same set of data. Technically, the final model is based on a "pre-test estimator" which has a different sampling distribution than the distribution of the conventional, unrestricted least squares estimator applied once to the correct model (e.g., see Wallace, 1977). Other (Stein-type) estimators exist which dominate the pre-test and least squares estimator in a mean square error sense. Yet, these theoretically promising alternatives are rarely used. In one empirical study (Aigner and Judge,1977), the Stein-type estimators did not dominate the pre-test approach, apparently because of the collinearity that existed in the data used.

Experimentation with alternative model specifications is likely to continue. Obviously one would like to specify a correct model, but an implication of the recent literature is that "final" models may have t-ratios which are misleadingly large for some regressors. Experimentation can find associations among variables which appear important in the sample period but do not really exist. In such a situation, the computed confidence intervals for forecasts may be misleadingly small.

Functional forms are a potentially important question in forecasting. Explanatory variables often have trends, and forecasts may have to be made beyond the range of the data used to estimate the equation. Thus, while many alternative forms may fit the data reasonably well near the means of the variables, the basic question is, what constraint does the function place on the dependent variable as the explanatory variables grow (or decline)? Box-Cox procedures (Zarembka, 1974) perhaps have value in selecting functional forms, but these procedures also involve pre-test estimation, where the same data are used to estimate the functional form and then the final model. Moreover, the key question is the logic of the function over the plausible range of the data, not just over the observed range. A quadratic function, for example, may have an appropriate downward sloping curve for the observed data, but if the quantity variable becomes large enough, price will turn upward.

A huge literature exists on autocorrelation in the disturbances, but until fairly recently, this topic was not taken seriously in much of the applied, empirical literature. A common rationalization was that ordinary least squares provides unbiased, even if inefficient, estimates of the slope coefficients, <u>given</u> that the model is otherwise appropriate, and larger R^2's, were taken as a sign that the model is appropriate. But, as is now recognized, autocorrelated residuals are often a signal that something is indeed wrong with the model. Moreover, it is precisely when the residuals are autocorrelated that F-statistics and R^2-coefficients are biased upward (Granger and Newbold, 1976). Thus, if the residuals are autocorrelated, the model specification needs to be reviewed carefully, and if changes in specification do not eliminate the autocorrelation, then an estimator which takes account of autocorrelation should be used. In this case, the "best" forecast will include a correction for the effect of the lagged residual (Johnston, 1972, pp. 212-213).

Structural change

The deleterious effects of structural change for forecasts can come from two sources. First, the analyst may mistakenly fit a model to data from a structurally heterogenous period, and assuming no variables are included to accommodate the change in structure, the estimated coefficients will be "averages" which do not represent either the current or past structures. Second, of course, the structure may change during the forecast period. Hence, the fitted model is not directly applicable to the forecast period. Intuitively, changes in structure are probably important sources of mistaken forecasts. Numerous sources of structural change appear to exist. The acceleration of the rate of inflation in the Nixon administration resulted in a series of price control measures, which might be viewed as temporary changes in structure. Changes in lifestyles and concerns of consumers imply changes in the structure of demand, while changes in technology imply new supply relationships.[1]

Statistical techniques exist for testing for the constancy of the structure over the sample period (e.g., Brown et al.,1975; for a pioneering effort see Schultz,1938), and methods also exist for accommodating changes in structure within the sample period (e.g., Poirier, 1976). Yet, given the potential magnitude of the problem, little systematic research appears to have been done on it. Admittedly, many models have adopted zero-one variables to reflect war years, strikes, and similar events, but other types of structural change have received little attention.

Empirical evidence suggests, for example, that the structure of demand for poultry and red meats changed in the late 1950s (Goodwin et al., 1968; Tomek, 1965; Waugh, 1964), but other studies have continued to use data from the 1950s in estimating demand equations for meats. Hassan and Johnson (1979), using a CUSUM methodology suggested by Brown, et al. (1975), found reasonable structural stability for the demand for meats in the 1965-1976 period.[2] More analysis of possible changes in structure is needed as a foundation for improving forecasts.

Quality of data

Errors in variables are of two types: mistaken data points (e.g., enumeration or recording errors) and observed variables (e.g., proxy variables) that do not measure the underlying concept accurately. The problem of errors in variables often receives light treatment in econometrics textbooks as well as in empirical applications. This may be because the problem is difficult to solve. It is also argued, for example, that the errors from using proxy variables are small relative to other econometric problems in typical applications and hence can be ignored. Second, forecasts based on least squares estimates of a linear model with errors in variables are consistent estimates of the true conditional mean, and hence for forecasting, least squares estimates may be adequate even if the explanatory variables are proxy variables (Johnston, 1972, p. 290f). Or, as Goldberger (1972) has shown, one solution is to use the over-identifying restrictions in a system of simultaneous equations to identify the variances associated with measurement errors. Full information maximum likelihood can then be used to derive a consistent estimator of the structural parameters.

The advice to eliminate or minimize errors in variables is rather empty, as researchers obviously want to do exactly that. Recent developments in computer software, however, make it easier to identify certain problems, namely influential observations that may be mistaken data points. Influential observations do not always arise from data errors and are sometimes beneficial. Conversely, data errors may not appear as outliers, but nonetheless, we believe that the ability to identify influential observations (and sources of collinearity) is important to improved forecasts. Indeed, the payoff to identifying influential data points may be substantially larger than in other problem areas. Since the principle of least squares is to minimize the sum of squared residuals, an outlier clearly can have a large effect on a slope coefficient. Thus, it is important to know whether coefficients depend on the bulk of the data or are highly influenced by a few, possibly aberrant, points.

Prior to the development of high speed computers, regressions were costly to compute, and analysts tended to examine their data carefully prior to computations. Graphic analysis was common, and consequently unusual data points tended to be identified. The careful study of data prior to estimation probably became less common among analysts as modern computing facilities became available. It is easy to estimate numerous equations and to use large data sets, and the tendency has been to emphasize model specifications (via experimentation with alternatives) rather than to determine whether the data have peculiar attributes.

A large number of regression diagnostic procedures are now available at reasonable computational cost (e.g., see Belsley et al., 1980). These procedures help the analyst identify influential data points and to determine their effect on the slope coefficients and their standard errors. A particularly useful tool is the "partial-regression leverage plot," which is available in the TROLL, SAS, and

MINITAB packages. These scatter diagrams plot the partial (i.e., net) regression relationships between the dependent variable and each of the independent variables, taking account of the other explanatory variables. (It is analogous to the conventional scatter diagram of a simple regression.) Thus, the analyst can visualize whether a particular net slope coefficient in a multiple regression is distorted by one or two observations.[3]

Time-Series versus Structural Models

Contrasts in models

Specifying a time-series model is often viewed as an alternative to an econometric specification of a structural relationship. Sometimes the relative merits of these two approaches to forecasting are discussed in a manner that is almost as heated as the controversy between Bayesian and classical statisticians. Although both authors of this paper are unrepentent users of structural models, it is clear that structural and time-series models are closely related. The differences between the two approaches reflect the relative importance given various features of each specification, and these need not be mutually inconsistent.

A typical univariate time-series model, such as an ARMA (autoregressive moving average) process, relate the dependent variable only to lagged values of the dependent variable and a residual. This is an obvious contrast to a standard econometric model which typically includes one or more explanatory variables. The other main difference is that the properties of the residual in an ARMA model are generally more complex than in a standard econometric specification.

As a result, time-series models are often criticized for omitting important regressors, while econometric models are faulted for ignoring important interdependencies of the residuals through time (Granger and Newbold, 1976). Both of these problems can be remedied. More general time-series models, such as transfer function models, can include regressors (Box and Jenkins, 1976), and the properties of the residuals in an econometric model need not be limited to the classical assumptions or even to first-order serial correlation. Both kinds of generalizations tend to make the associated estimation procedures more cumbersome, but no serious conceptual problems exist with specifying such models. For example, the autoregressive form of a rational lag model, proposed by Jorgenson (1966), can be specified so that it is identical to a time-series model with one or more control variables.

Another important link between time-series and structural models is in the use of structural equations for forecasting. Since projected values of the exogenous variables must be provided, it is possible to use projections derived from time-series models for this purpose. As Wallis (1977) and others have shown, when the projection of each exogenous variable is generated by an ARMA process, the forecasts of the dependent variables can also be represented by ARMA processes even though the original model was estimated as a set of structural equations. The complexity of the resulting ARMA process for a dependent variable may, however, be considerably greater than if a "pure" time-series model was specified directly, and the structural relationships were ignored.

The absence of exogenous variables in a time-series model makes it easy to derive forecasts. Since projections of these variables are not needed, one major source of error is removed. An important question is whether this advantage over a structural model is offset to some extent by a greater vulnerability to structural change. In other words, is it reasonable to expect that the form of a time-series model of an economic variable will be stable over time? If one considers the quantity of oil consumed in the U.S. during the 1960s and 1970s, for example, a substantial change in the structure of this series occurred in 1973 and 1974. Hence, for time-series analysis, some kind of reformulation of the model would be required after 1974. Time-series models were, after all, developed primarily for applying to physical and biological processes that are not usually subjected to the sort of disruptions that lead to structural changes in economic data series.

Forecasts of the annual consumption of oil made, say, in 1972 for 1977, using a demand (structural) model, also would almost certainly have been wrong. This would have been largely due to failing to anticipate the large price increase in 1973. If this source of error is corrected, then the demand model, in principle, could still perform well for years after 1974 (implying that no structural change had occurred). From a strict forecasting point of view, this is being wise after the event. Nevertheless, the point is that if the structure of a model remains intact, the econometric model has the potential to provide accurate forecasts. It is also probably correct to assume that analysts who build econometric models hope to "explain" most apparent structural changes in the time series for a dependent variable within their model. Even if the structure changes, judgmental changes can be made in structural models prior to forecasting, which may not be possible in a time-series model.

Although the number of variables in a time-series model tends to be small compared to a structural model, the required number of observations is relatively large. This is due to losing observations when variables are lagged many periods and to the need for good time-series information when estimating complex ARMA processes. In some situations, information for estimating structural models can be obtained by pooling cross-section and time-series data (Maddala, 1971). In other words, many short time series can be used instead of one long time series. This is generally not the case with time-series models. Given the need for a long series and the problem of structural change, it is inevitable that time-series models are often estimated from monthly, weekly, or even daily observations.

While increasing the frequency of taking measurements of a variable does expand the sample size, some other problems are exacerbated. The variability of the series becomes more sensitive to short-run cyclical phenomena related to the days of the week or seasons of the year, for example. Although these may be interesting phenomena in some applications, they may also tend to obscure other important changes and to add to the complexity of the specification. As an illustration, it may be necessary to define a first difference as the change from four (twelve) periods earlier with quarterly (monthly) data (Nerlove et al., 1979) which, in turn, will tend to reduce the effective sample size.

When the frequency of measurement is less than monthly, however, the practicality of estimating a structural model is limited because many of the relevant exogenous variables may not be available at these high frequencies or, if available, may be measured very inaccurately. Hence, if daily or weekly forecasting is a required feature of a model, a time-series model is probably the most feasible approach.

Given the continued use of both time-series and structural models, it should be of no surprise that neither approach has demonstrated a clear superiority for forecasting. An early study by Leuthold et al. (1970) and a recent one by Schrader (this conference) both show that a structural model performs slightly better than a time-series model of an agricultural market. Other studies have found ARMA models with better forecasting performance than a structural model (e.g., Brandt and Bessler, 1981). The choice between the two approaches is often made for practical reasons rather than performance. If data are only available for a few variables of interest, for example, a time-series model may be necessary.

In any comparison of the two types of models, the results depend on how well the models are applied. Poor forecasts may reflect deficiencies of the application rather than of the method itself. For example, a structural model may be estimated ignoring serial correlations. This information about the residuals is often ignored when forecasts are derived, even though short-run forecasts would be more accurate if it had been used (Johnston, 1972, pp. 212-213).

In terms of the demands on an analyst, good structural models depend on having a sound perspective on the economic characteristics of the application as well as knowing about statistical methods. This economic knowledge is required for identifying which variables would be included in the model, and for imposing restrictions on the form of the relationships. In contrast, the use of time-series models places a greater emphasis on statistical methods. In practice, it is the importance and accuracy of knowledge about the underlying economic processes that determines whether or not a structural model will perform better than a time-series model.

Role of information

As the initial quotation from Granger suggests, an important issue is, how well do alternative forecasting methods use information? In considering this question, a distinction must be made between the correct use of current information, that may subsequently turn out to be mistaken, and the mistaken use of information that is indeed correct. In the context of markets, Working (1949) has called these errors "necessary inaccuracy" and "objectionable inaccuracy."

In principle, a variety of alternative forecasting methods should be able to make unbiased and efficient use of existing information.

Futures markets quotations, for example, may provide unbiased estimates of the maturity-month price.[4] Informed experts, by definition, also ought to make correct use of information.

Quantitative tools formalize the use of data. The distinction between objectionable and necessary inaccuracies is perhaps most clear in forecasts generated from structural econometric models. Errors may arise from the use of mistaken values of the exogenous variables for the forecast period, and errors also may be associated with "necessary" random events and sampling errors. But, clearly, inexact forecasts may arise from poor models and methods. In contrast, if expert opinion is wrong, it is less clear whether the expert used poor information or whether the individual just wasn't very expert.

Simple ARMA models use only the historical and current values of the variables that are being forecast, but if markets are efficient, then a single variable, such as price, may reflect existing information. Moreover, as discussed above, ARMA models of endogenous variables in a dynamic, simultaneous model can be interpreted as a form of solution to the structural equations. Hence, forecasts based on historical patterns may accurately reflect all that is known.

The limited evidence available suggests that most methods of forecasting have sources of objectionable inaccuracies. Just and Rausser (1981) found that futures markets tended to be better forecasters than large-scale econometric models, but other researchers have formulated econometric models that appear to forecast better than futures (e.g., Leuthold and Hartman, 1981) or have raised doubts about the degree of perfection of price formation in futures markets (e.g., Martin and Garcia, 1981). On balance, however, imperfections in futures markets typically appear to be small (Tomek, 1980).

Expert opinion sometimes has had systematic errors; that is, the errors in forecasts by experts were significantly related to observable variables (Brown and Maital, 1981). This implies that, at least in some cases, the experts did not make full use of the information available to them. In another study, the mean squared error of forecasts made by experts was larger than the mean squared errors for econometric and ARMA procedures (Brandt and Bessler, 1981).

If composite forecasts (i.e., combining several individual forecasts) perform better than any single forecast method, this implies that the individual methods are not fully using the information available; each component of the composite contains some useful information for forecasting that is not in the other component. For hog prices, certain types of composite forecasts tended to outperform the individual forecasts (Brandt and Bessler, 1981). Schrader (this conference) found no gain from composite forecasts for eggs, and Spriggs (1981) reports that ARMA forecasts combined with futures prices quotations did not outperform futures quotations alone for predicting the price of corn.

Two conclusions emerge from this discussion. First, improvements in forecasts will depend, in part, on better basic information--a better data base. ". . . progress in understanding economic laws depends strictly on the quality and abundance of statistical data. All improvements in methodology would be in vain if they had to be applied to mediocre data" (Malinvaud, 1966, p. 614). And the benefits of improved information could greatly exceed the costs (Nelson, 1961; Hayami and Peterson, 1972).

Second, existing methods to make errors which, in principle, are unnecessary. This paper has been concerned mainly with how quantitative methods might be improved.

Research Problem and Forecasting Method

No single method is likely to be best for all forecasting problems. Forecasts should be accurate, i.e., capture turning points and be "close" to the true value, but different users will place different weights on various aspects of accuracy. For example, a firm purchasing a raw farm product would like to know the seasonal low price each year, while an electric utility considering the expansion of capacity is interested in the relative prices of alternative sources of fuel over a long time frame. Other factors to consider in selecting a forecasting methodology are timeliness, cost, and knowledge of structural relations, and they also will vary in importance with the problem. Clearly, a firm has more time to consider major investment decisions than it does to make day-to-day operational decisions.

In considering short-run forecasts, each method appears to have advantages and disadvantages. Expert opinion has not compared well with quantitative procedures in the few appraisals which have been futures (e.g., Leuthold and Hartman, 1981) or have raised doubts about the degree of perfection of price formation in futures markets (e.g., Martin and Garcia, 1981). On balance, however, imperfections in futures markets typically appear to be small (Tomek, 1980).

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In considering short-run forecasts, each method appears to have advantages and disadvantages. Expert opinion has not compared well with quantitative procedures in the few appraisals which have been made of accuracy (as measured by mean squared error). But, in developing a quantitative model, numerous specifications may seem equally plausible, and it may be costly and time consuming to find a useful, quantitative model. If a firm has an employee with long experience on the payroll, the opportunity cost of the expert's opinion is small, although the cost of a wrong decision based on a poor forecast can be large.

Futures markets' prices have sometimes performed relatively well in terms of accuracy, and these price quotations are available at little cost. Of course, since organized markets operate only during fixed time periods, new information must be analyzed by non-market methods during times when the markets are closed. Moreover, USDA releases of new information typically occur during times when markets are closed, and the firm may want an analysis of the price effects of the new information before the markets open. Expert opinion or quantitative models can provide this timeliness.

Quantitative methods also have the advantage of formalized procedures; the analyst is forced to specify and estimate a specific model. This routine may be important in itself. In addition, structural models have the advantage of permitting adjustment for structural change during the forecast period (Marschak, 1953).

For long-run forecasts or simulations, structural models would seem to have a clear advantage. These models are designed to answer "if-then" questions in a causal framework, and it is the interrelationships among variables that is important in policy simulations.

Sources of Error--Their Importance

In appraising performance of a model in the forecast period, it is important to identify, if possible, sources of error. Are forecasts within the range of "normal" sampling error? Has an unusual circumstance contributed to a large residual? Is the structure changing? Does the original model have serious specification errors? Was the forecast made conditionally on mistaken data?

As we have seen, the standard error of forecast, as traditionally computed, is likely to be "too small." Furthermore, experimentation with a given data set to find the best model will tend to give a misleadingly small confidence interval. The major potential sources of problems for forecasting relate to model specification, data quality, and structural change, none of which are accounted for in the traditional standard error of forecast. Data errors and structural change can be problems both for the sample and the forecast periods.

Of these problems, model specification has received the most attention in forecasting. Analysts have tended to accept the sample period data and search for the "best" model. It is just as important to ask whether an anomalous result is the consequence of an aberrant data point as to ask whether it is the consequence of an inappropriate model. In the context of the sample period data, the full use of theory, logic, and available information is important. But, in addition, the analyst should make use of the techniques which are now available to test for structural change and to examine the possible impacts of influential observations and/or collinearity.

A balance between theory and empiricism is required in the search for a useful model. Structural models in agricultural economics have often been specified and estimated in the context of a PhD thesis problem. The problem rarely involves short-run forecasting; rather, the analyst had a policy simulation in mind. These models naturally tend to emphasize theoretical constructs; they tend to be large; and considerable emphasis is placed on selecting the appropriate estimator. The forecasting ability of such models is rarely tested with new data, nor are the models maintained or updated.

Quantitative analyses for short-run forecasting tend to be more empirical. Time-series models are usually developed with a forecasting application in mind. They are highly empirical, and they typically are tested in forecasting situations. Short-run forecasting from structural models often involves relatively "quick and dirty" types of analyses. The tendency is to use a single equation, often a reduced form-type equation derived from a fairly simple structural model. This equation is typically fitted by ordinary least squares.

A blend of time-series and structural analysis may, in several senses, improve forecasts. Analysts using a structural approach to forecasting have been prone to emphasizing statistical fit in the sample period and to placing little importance on the properties of the residuals. If the residuals are autocorrelated, then at a minimum the estimates of the variances are biased. But, more important, autocorrelation is an important sign of model misspecification, implying bias in the slope coefficients as well. Thus, the analyst should understand the time-series properties of the variables being used in the analysis, and the error term of model should be specified with care.

Proponents of time-series analysis sometimes argue that relatively simple ARMA models provide a good representation of economic time series (e.g., Granger and Newbold, 1976, p. 203). But prices and quantities of agricultural products often have important systematic components--trends, seasonals, and cycles. In addition, logical reasons exist for changes in these components with the passage of time; e.g., the seasonal component of prices and quantities may dampen. Thus, the specification of time-series models should benefit from knowledge about the nature and structure of the economic sector under study.

Forecasts from alternative empirical approaches can be blended formally into composite forecasts. This probably is a useful expedient for practical forecasting situations. The implication is that each individual forecast contains information not available in the other forecasts.

Given the best model, forecasts may still be made conditionally on incorrect values of exogenous variables. In 1979, for example, the preharvest estimates of the size of corn crop ranged from 6.7 billion to 7.6 billion bushels, and the associated prices for the December futures contract ranged from about $3.18 to $2.66 per bushel.

This emphasizes the role of accurate information in making forecasts, and the forecaster often has little control over the quality of information available. Perhaps, all the analyst can do is make clear the conditions which are used to make the forecast.

Summary

Both structural and time-series models have a role to play in forecasting. In principle, both approaches can provide accurate forecasts, but in practice, the particular application is likely to influence the selection of a method. Moreover, any quantitative procedure used for forecasting in economics is likely to be subject to a wide range of potential problems. The actual value of the variable, therefore, often falls outside the confidence interval computed for the forecast (i.e., based on classical statistical methods).

Analysts have tended to emphasize model specification and estimation methods to obtain better forecasts. More effort is needed to improve the data and other information that are the bases for forecasts. The quality of data is, to some extent, outside the control of the analyst, but techniques are now available to identify influential data points in the sample period. These techniques should be used. More resources also should be devoted to improving the "auxiliary forecasts" of exogenous variables, which are necessary for making forecasts beyond the sample period. Finally, attention should be given to the possible effects of structural change both during the sample and forecast periods.

Footnotes

[1]Schrader's paper presented at this conference mentions two possible structural changes which may influence the forecasts of egg prices: the control of Marek's disease in 1971 and the trend toward forced molting of the existing laying flock, which alters the relationship between number of chicks hatched and egg production.

[2]The Hassan and Johnson paper contains a few typographical problems, and we recommend the Brown et al. paper as the basic source for the CUSUM and CUMUMQ methodology.

[3]New software also has improved collinearity diagnostics. Multicollinearity is perhaps a less serious problem for forecasting than for the precision of the estimated coefficients. Nonetheless, with highly collinear data, a particular slope coefficient can be determined by one or two influential observations, and a large error in a coefficient can result in large forecast errors.

[4]A controversy has existed in the literature on futures markets about whether a risk premium is transferred from hedgers to speculators. If this were so, then futures quotes, at least for storable grains, would be biased downward. Empirical research has found little or no support for the idea of a downward bias.

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