A Note on Forecasting with Econometric Models

P. Geoffrey Allen

Forecasts made by econometricians are typically conditioned on actual values of explanatory variables, even when at the time of the forecast, such variables might not be available. As a first step, one might test the adequacy of econometric specification by comparing conditional post sample forecasts with those of a univariate ARIMA model. Second, when explanatory variables must themselves be forecast, those for which this can be done only badly, should be omitted from the final model. A better forecast will result. An example of screening out badly forecasted explanatory variables is presented.

Introduction

Forecasting of agricultural time series, particularly prices, appears to be gaining in popularity, as judged by the number of such articles appearing in the agricultural economics literature, including recently this *Journal* (Hudson and Capps, Taylor and Tomek). Most business forecasters use simple extrapolative models but in academic circles the more general univariate autoregressive integrated moving average (ARIMA) and econometric approaches are favored. Econometricians have been making conditional predictions for years, an implicit recognition of the forecaster's problem: in order to forecast a dependent variable in future time t one must know the value of any contemporaneous explanatory variable. The term contemporaneous is used here in a slightly broader sense than usual for any explanatory variable that is not available as data at the time one makes an h-step ahead forecast of the dependent variable. In the example presented later, where yield is assumed to depend on weather variable values during the growing season, forecasts made early in the season must rely on forecasted weather variables.

A badly misspecified econometric model will have a worse conditional predictive performance than a simpler ARIMA model. And a well specified econometric model, when used for forecasting, may encounter two related and frequently ignored problems, (1) the need to forecast all contemporaneous explanatory variables, and (2) the usefulness of such forecasts in making the dependent variable forecast. These issues will be discussed below, followed by an application illustrating a possible solution. Anticipating the conclusions of this effort, it will be noted that it is generally not a good plan to insert forecasted explanatory variables into an optimal econometric model. Optimal is used in the sense of the best fitting model discovered after the usual kinds of testing, re-specification and re-estimation.

The author is Associate Professor, Agricultural and Resource Economics, University of Massachusetts, Amherst. Helpful comments were received from two anonymous reviewers.

Forecasting Using Econometric Models

As any econometrician knows, the paradigm governing choices of variables and functional forms allows considerable room for individual experimentation. A rather misleading classification has grown up between explanatory models and predictive models. In the latter such "non-economic" explanatory variables as lagged dependent variables were common and were employed because they improved the goodness of fit. However, as pointed out most extensively by Mizon and Hendry, and by Sargan, the dynamic specification of an economic relationship may justify testing for the inclusion of various lagged dependent and independent explanatory variables. This approach specializes the transfer function or multivariate ARIMA model to an expression that can be estimated by least squares regression.

With unidirectional causality, the usual assumption in a single equation econometric model, the complete system for a bivariate model is

(1) $$Y_t = \frac{\omega(B)}{\delta(B)} X_t + \frac{\theta(B)}{\phi(B)} u_t$$

(2) $$a(B)X_t = b(B)e_t$$

where

u_t, e_t are mutually stochastically uncorrelated normally distributed disturbances.
B is the backward difference operator, e.g. $BX_t = X_{t-1}$
ω, δ, θ, ϕ, a, b are finite lag polynomial functions, e.g. $\omega(B) = \omega_1 + \omega_2 B + \ldots + \omega_n B^n$, and the ω_i are parameters to be estimated.
Y_t, X_t are the time series variables, differenced if necessary to make them stationary.

Equation (1) is a transfer function, equation (2) an ARMA model. If $\delta(B) = \phi(B)$ then (1) becomes an ARMAX model and if also $\theta(B) = 1$ then (1) is an autoregressive distributed lag equation in a form that can be estimated by ordinary least squares. Not all explanatory variables, X_t, are stochastic. For example, time itself is often used as an explanatory variable and can be forecast perfectly.

The recent paper by Hudson and Capps fails to recognize the need for equation (2) in performing actual forecasts. A comparison of forecasting performance of econometric and ARIMA models therefore requires that forecast explanatory variables be used. Generally these would be one-step ahead forecasts either within the sample time period or, preferably, post sample, from a model such as (2). In fact Hudson and Capps find that the post sample predictive ability (measured as mean square error) is worse for their econometric model than their ARIMA model. Accepting as correct their list of explanatory variables, this is, as Hendry and Richard point out (p. 129), *prima facie* evidence of incorrect dynamic specification of their econometric model. Further confirmation of misspecification is provided by the Durbin-Watson statistic value of 1.56, which is in the inconclusive range. Since the econometric predictions are conditioned on a potentially larger data set than are the univariate ARIMA, they should be no worse than predictions from an ARIMA model.

The second problem is that econometric predictions using forecasted explanatory variables may indeed be worse than forecasts from a univariate ARIMA model. Models with contemporaneous explanatory variables need to be checked for this. The situation is not as gloomy as Taylor and Tomek imply (p. 101).

> "... a standard error that takes account of the errors in the regressors is difficult to compute and typically gives [a] confidence interval so large that it is not useful for decision making."

First, a mean square error of forecast (MSE), either within or post sample, is more useful than a standard error of forecast. Second, such a statistic is not difficult to compute. In common with the forecasting literature, the definition of mean square error used in this paper, when it refers to forecast errors, is the residual sum of squares divided by the number of observations forecast.

The problem can be restated in a slightly different way: "Will the forecast of a dependent variable, $\hat{y}_t$, be improved or not by the incorporation of a forecasted explanatory variable, $\hat{x}_t$?" If the answer is negative then an econometric model intended for forecasting should be re-estimated with the x_t dropped from its specification. The criterion adopted is a within sample goodness of fit measure. The relative importance of different criteria, including ability to predict turning points, is a matter of judgment, and post-sample performance is the ultimate test. The question posed above can be answered using a theorem by Ashley. Recognizing that forecasts, $\hat{x}_t$, of an explanatory variable, x_t, from a misspecified model may have $MSE(\hat{x}_t) > Var(x_t)$, Ashley shows that whenever this occurs, the MSE of a forecast for y_t ignoring its relationship with x_t will not exceed the MSE of a forecast including x_t. This is true for both econometric and multivariate ARIMA models. There seems to be no reason why a complex or judgmental forecast, for example, the USDA planting time crop estimate of corn production in the U.S. (Taylor and Tomek) should not be subject to the same screening test.

The converse to the theorem is not true. That is, just because a variable passes the screening test above does not guarantee that its inclusion in an econometric model will improve the predictability of the dependent variable. Ashley performs some testing which indicates that if the ratio $MSE(\hat{x}_t)/Var(x_t)$ is greater than about 0.7 there is always room to doubt the improvement from including x_t. The screening test will eliminate candidates whose forecasted values are sufficiently bad; beyond that the best forecasting model can only be found empirically.

An Example

The process of finding the best empirical model is illustrated using results from a study designed to forecast cranberry yields. Data are for production in Massachusetts from 1932–79 and meteorological values from Plymouth, Massachusetts over the same time period. More information can be found in Morzuch, Kneip and Smith.

Based on statements from biologists about the impact on yields of deviations from normal temperature and precipitation, the maintained production function model included precipitation in May, August and September and average monthly temperatures in February, May, July and the previous December. After the usual econometric data mining a restricted model was developed as

$$
\begin{aligned}
(3)\quad Y_t = &-1092.81 + 0.58T - 2879.51D_1 \\
&\ \ (343.88) \quad (0.18) \quad\ (827.03) \\
&+ 1.47D_1T + 16.75D_2 + 0.34TDEC \\
&\ \ (0.42) \qquad\ (4.27) \qquad (0.31) \\
&+ 0.92TFEB - 1.24TJUL \\
&\ \ (0.33) \qquad\ \ (0.67) \\
&R^2 = .91 \qquad d = 2.34 \qquad n = 48
\end{aligned}
$$

where

Y = Massachusetts average yield per acre (barrels).
T = time 1932, . . . , 1979.
D_1 = 1 if sprinkler irrigation in use, i.e. if $T \geq 1962$; 0 otherwise.
D_2 = 1 if wet harvesting in use, i.e. if $1969 \leq T \leq 1971$, $T \geq 1978$; 0 otherwise.
TDEC = December temperature, previous year.
TFEB = February temperature, crop year.
TJUL = July temperature, crop year.

All meteorological variables are in deviations from the 1932–79 mean for that month. Standard errors are in parentheses.

The motivation for this forecasting exercise is to provide the cranberry grower's cooperative, Ocean Spray, with information to make storage bin leasing decisions. The yield forecast (and given the fixed acreage of this perennial crop, the production forecast) is updated through the crop year which ends in November. As an example consider a forecast made in December. No actual weather data are available.

Examination of table 1 reveals that forecasts for July temperature will be too bad to be of any use in forecasting yield. The forecasts for February temperature made in December (using temperatures through November) will be 3 steps ahead and will have a somewhat higher MSE than the tabulated value. Suitable candidates for a December forecasting model are December and February temperatures. Time and the dummy variables can, of course, be forecast perfectly. Table 2 shows some results. Again it should be remembered that mean square error values are based on the assumption that yields are being forecast one step ahead using the data specified in the left-hand column for 48 time periods.

The econometric model with time and dummy variables only has a lower within-sample MSE than the univariate ARIMA model, indicating that the dynamic specification of the former is not grossly distorted. This result and others in table 2 are confirmed by forecasting performances in 1980–83, not presented here. Inclusion of December and February temperature variables improves MSE further, again suggesting the appropriateness of this specification. However, when the coefficients estimated from this model are applied to forecasted values of December and February temperatures the predictive ability is worse than the simpler model with time and dummy variables alone.[1]

To answer the question, "Is the poor forecasting performance the result of bad forecasts of December temperature or February temperature or both," models must now be estimated that drop one or the other of these variables. These results are shown in table 2 also. A forecasted weather variable is used in place of an actual weather variable with the coefficients appropriate to that specification. The problem is clearly the inability to forecast February temperature sufficiently well, although it must be noted that the only thing which saves the December forecast from the same charge is the small coefficient attached to it when it stands as the sole weather variable.

An appropriate strategy for this particular problem is now revealed. When no tempera-

[1] One reviewer suggested that forecast values of the explanatory variables should be used to estimate coefficients. These coefficients would then be used with forecasted weather variables to predict yield. And if the forecasts of the explanatory variables are bad, their estimated coefficients would tend to be nonsignificant, causing them to be eliminated from the final model. I have not found such an approach described anywhere in the literature. If the forecasts are unbiased the result would seem to be the same as with the screening method used here.

Table 1. Meteorological Forecasts, One Step Ahead 1932–83

Month and Type	Forecast Error Mean	Forecast Error Variance	$(\text{Bias})^2$	Forecast MSE	Data Variance
Dec. temperature	−0.277	13.79	0.08	13.87	14.81
Feb. temperature	−0.017	15.71	0.00	15.71	17.19
July temperature	0.212	3.16	0.04	3.20	2.98

Monthly temperature was estimated from the model $\underset{(.039)}{(1 - .216B)}(1 - B^{12})X_t = \underset{(.0095)}{-.0455} + (1 + \underset{(.007)}{.962}B^{12})e_t$

where X_t is mean temperature in month t. Standard errors are in parentheses.

ture data are available, the econometric model with time and dummy variables only will be the best single forecasting model. Later, when December temperature data are available, a slight improvement can be gained by using them in a model specified for December temperatures. Likewise, when the latest February weather data become available a further improvement is possible. No weather variable can be forecast well enough to justify its inclusion in a forecasting model.

Conclusions

The example presented above, if it is typical, suggests that the econometrician's usual explanatory model may be a poor prospect as a forecasting tool. Since long-range weather forecasts are notoriously difficult to make, the conclusions drawn from the example may not have wide generality. However, they do illustrate one point of practical significance: any econometric model that incorporates through lagged dependent and explanatory variables, some information on the stochastic process that generated the data ought to be able to out-perform its naive competitor, the univariate ARIMA model. This requires the kind of screening and testing described here. If the final econometric model is still hopelessly misspecified and requires contemporaneous explanatory variables that can be forecast only extremely badly then a forecaster must revert to the naive competitor. But, however large the confidence interval on the forecasts, surely any decision maker will accept the result as better than nothing.

Table 2. Goodness of Fit of Various Models, 1932–79

Model	Mean Square Error (n = 48)
Univariate ARIMA (0, 1, 1)[a]	97.08
Econometric	
Time and dummy variables only	57.32
Plus December temperature	57.27
Plus December forecast temperature	57.32
Plus February temperature	49.87
Plus February forecast temperature	60.52
Plus December, February temperatures	48.94
Plus December, February forecast temperatures	62.07
Plus December temperature, February forecast temperature	64.65
Plus December, February, July temperatures	45.07

[a] $(1 - B)Y_t = \underset{(.369)}{1.425} + (1 + \underset{(.092)}{.772}B)e_t$

Standard errors in parentheses.

References

Ashley, R. "On the Usefulness of Macroeconomic Forecasts as Inputs to Forecasting Models." *Journal of Forecasting* 2(1983):211–223.

Hendry, D. F., and J-F. Richard. "The Econometric Analysis of Economic Time Series," *International Statistical Review* 51(1983):111–147.

Hudson, M. A., and O. Capps. Jr. "Forecasting Ex-Vessel Prices for Hard Blue Crabs in the Chesapeake Bay Region: Individual and Composite Methods." *Journal of the Northeastern Agricultural Economics Council* 13(1984):112–118.

Mizon, G. E., and D. F. Hendry. "An Empirical Application and Monte Carlo Analysis of Test of Dynamic Specification." *Review of Economic Studies* 47 (1980):21–45.

Morzuch, B. J., J. Kneip, and D. C. Smith. *An Econometric Approach to Modeling the Effects of Weather and Technology on Cranberry Yields*. Res. Bull. No. 683, Agr. Exp. Sta., Univ. of Massachusetts, May 1983.

Sargan, J. D. "The Consumer Price Equation in the Post War British Economy: An Exercise in Equation Specification Testing." *Review of Economic Studies* 47(1980):113–135.

Taylor, P. D., and W. G. Tomek. "Forecasting the Basis for Corn in Western New York." *Journal of the Northeastern Agricultural Economics Council* 13 (1984):97–102.