Journal of Macroeconomics 24 (2002) 495–497

Journal of
MACROECONOMICS

www.elsevier.com/locate/econbase

Comments on 'The state of macroeconomic forecasting'

Kenneth D. West

Department of Economics, University of Wisconsin, 1180 Observatory Drive, Madison, WI 53706-1393, USA

Received 14 September 2000; accepted 7 March 2001

I enjoyed reading this useful survey. But I think it was a little too negative about the quality of economic forecasts. And there is one recommendation for future research that I think deserves a little more emphasis.

I like to tell students that they should take the Henny Youngman approach to evaluation of economic models or forecasts. I am referring to the old comedy routine in which a straight man asks Henny Youngman, "How's your wife?" And Youngman replies, "Compared to what?"

Similarly, when one is told that an economic forecast does well, or poorly, I believe that one should ask "Compared to what?" Complaints that forecasts are biased (or are too tied to current conditions, or imply serially correlated forecast errors...) are best made while offering alternative forecasts that suffer less from these failings. Of course, it is useful as well to compare a forecast to an ideal one–one that is unbiased, uncorrelated with information known when the forecast is made, has serially uncorrelated forecast errors...

In general, I think the authors have been a bit too negative about the record of economic forecasters, in part because of an unfair, or too narrow, standard of comparison. Two examples. First, I am not as sure as the authors are that a profession-wide tendency to underestimate growth or inflation when either accelerates, or to overestimate when either declines, is in and of itself a sign of serious trouble. In Section 2.1.1, the authors cite the well-known Samuelson (1996) point that such a tendency to under- or overestimate is a property of optimal forecasts. But they dismiss this point a bit too quickly. Of course, one would like to have advance warnings of recessions or of a resurgence in inflation. But insofar as either event is caused by a large unpredictable shock, we have to reconcile ourselves to the inability of statistical procedures to reliably produce a warning. As well, it is incumbent upon us to educate

E-mail address: kdwest@factstaff.wisc.edu (K.D. West).

PII: S0164-0704(02)00059-9

the users of our forecasts of that fact. More importantly, one needs to ask whether there are alternative, feasible forecasts that would to better.

Second, I think we economists should take credit not only for good forecasts from large, structural models that we develop, but also for good forecasts from small reduced form or time series models. Hence I interpret much of the survey in Section 3.3 as comparing two different types of economic forecasts rather than comparing economic forecasts to non-economic ones. In this survey, some studies are cited in which structural models fare better, while other cited studies find better performance in time series models. In either case, the winner is an economic forecast.

A final point, unrelated to the ones just made, relates to directions for future research. One such topic, which has been central to my recent theoretical econometric research on forecasting, concerns statistical inference about forecast accuracy when one has a time series (rather than just one or two observations) of forecasts and forecast errors. Such inference can and should be used to improve forecast accuracy, by helping us get a feel for whether one or another model has worked well, or better than another model, simply because of chance. I believe that the authors and I are in agreement on this point; for example, in the last paragraph of Section 1.4, they recommend that differences between competing forecasts be tested for statistical significance. The authors mention this only in passing, and do not give the reader guidance about how to do so. While it would not be appropriate for them to devote enormous space to the issue, I do think it deserves more attention.

The type of inference I have in mind helps first of all to compare a forecast to an ideal one, by answering questions such as: Are one step ahead forecast errors serially uncorrelated? Are a model's forecast errors uncorrelated with its predictions? Does a model have zero mean forecast errors? It also helps us compare two feasible forecasts, by answering questions such as: If one model has a lower mean-squared or mean-absolute forecast error than another, or has forecasts that have yielded higher utility or profit than another, is this likely due to sampling error, rather than a systematic tendency for one model to outpredict another?

My impression (hope?) is that it is obvious why it is useful to answer such questions, and that the reason most studies do not supply measures of uncertainty is that the techniques to do so are not obvious or well-known. The good news is that a recent literature has developed such techniques. Comparative advantage dictates that I take my remaining space to outline some basic results.

A key question is how to account for the two conceptually distinct sources of uncertainty that are present in most forecasting exercises: uncertainty about the "true" value of regression parameters used to make forecasts, and uncertainty that would be present even if (counterfactually) one knew the regression parameters. Sometimes, one can ignore uncertainty about regression parameters. This happens in particular when the size of the sample of forecast errors is very small relative to the size of the samples used to estimate regression parameters needed to form forecasts. (This point was noted informally by Chong and Hendry (1986) in the context of tests of forecast encompassing, and was established formally and more generally in West (1996).)

West (1996) shows that one can usually ignore uncertainty about regression parameters when testing for (1) zero mean of forecast errors or (2) for equality of mean squared prediction errors, when predetermined variables are used to make the predictions. For testing for zero mean of (presumptively serially uncorrelated) one step ahead forecast errors, the standard error is just: sample standard deviation of forecast errors, divided by square root of number of forecast errors used in constructing the sample mean. For equality of mean squared prediction errors, and more generally for a wide range of tests when the tests are applied to data in which the size of the sample of forecast errors is very small relative to the number of observations used to form regression estimates used in forecasting, the procedures described in Diebold and Mariano (1995) or West and Cho (1995) are applicable.

Unfortunately, it will often be the case that both types of uncertainty matter. Techniques to properly account for both types inevitably are more complicated than those described in the preceding paragraph, though no more complicated than those used in estimation of economic models. Instead of plowing through examples, let me egotistically suggest that the reader consult the McCracken and West (2002) survey, or somewhat more technical papers such as: Clark and McCracken (2000), Corradi et al. (1999), McCracken (1999, 2000), West and McCracken (1998) and West (1996, 2001a,b). Try it, you may like it, and I think it will help us learn how to forecast better.

Acknowledgement

I thank the National Science Foundation for financial support.

References

Clark, T.C., McCracken, M.W., 2000. Tests of equal forecast accuracy and encompassing in nested models. Manuscript, Louisiana State University.

Chong, Y.Y., Hendry, D.F., 1986. Econometric evaluation of linear macroeconometric models, Review of Economic Studies LIII, 671–690.

Corradi, V., Swanson, N.R., Olivetti, C., 1999. Predictive ability with cointegrated variables. Manuscript, Texas A and M University.

Diebold, F.X., Mariano, R.S., 1995. Comparing predictive accuracy. Journal of Business and Economic Statistics 13, 253–263.

McCracken, M.W., 1999. Asymptotics for out of sample tests of causality. Manuscript, Louisiana State University.

McCracken, M.W., 2000. Robust out of sample inference. Journal of Econometrics 99, 195–223.

McCracken, M.W., West, K.D., 2002. Inference about predictive ability. In: Clements, M., Hendry, D. (Eds.), Companion to Economic Forecasting. Blackwell, Oxford.

Samuelson, P.A., 1976. Optimality of sluggish predictors under ergodic probabilities, International Economic Review 17, 1–7.

West, K.D., 1996. Asymptotic inference about predictive ability. Econometrica 64, 1067–1084.

West, K.D., 2001a. Encompassing tests when no model is encompassing. Journal of Econometrics 105, 287–308.

West, K.D., 2001b. Tests of forecast encompassing when forecasts depend on estimated regression parameters. Journal of Business and Economic Statistics 19, 29–33.

West, K.D., Cho, D., 1995. The predictive ability of several models of exchange rate volatility. Journal of Econometrics 69, 367–391.

West, K.D., McCracken, M.W., 1998. Regression based tests of predictive ability. International Economic Review 39, 817–840.