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Linear models, smooth transition autoregressions, and neural networks for forecasting macroeconomic time series: A re-examination

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Abstract

In this paper, we examine the forecast accuracy of linear autoregressive, smooth transition autoregressive (STAR), and neural network (NN) time series models for 47 monthly macroeconomic variables of the G7 economies. Unlike previous studies that typically consider multiple but fixed model specifications, we use a single but dynamic specification for each model class. The point forecast results indicate that the STAR model generally outperforms linear autoregressive models. It also improves upon several fixed STAR models, demonstrating that careful specification of nonlinear time series models is of crucial importance. The results for neural network models are mixed in the sense that at long forecast horizons, an NN model obtained using Bayesian regularization produces more accurate forecasts than a corresponding model specified using the specific-to-general approach. Reasons for this outcome are discussed.

JEL classification: C22; C53
Keywords: Forecast combination; Forecast evaluation; Neural network model; Nonlinear modelling; Nonlinear forecasting

1. Introduction

In recent years, numerous forecasting competitions between linear and nonlinear models for macroeconomic time series have been held. Comparisons based on a large number of variables have been carried out, and the results on forecast accuracy have generally not been particularly favourable to nonlinear models.

In a paper with impressive depth and a wealth of results, Stock and Watson (1999), henceforth SW, addressed the following four issues, among many others. First, do nonlinear time series models produce forecasts that improve upon linear models in real-

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time? Second, if they do, are the benefits greatest for relatively tightly parameterized models or for more nonparametric approaches? Third, if forecasts from different models are combined, does the combination forecast outperform its components? Finally, are the gains from using nonlinear models and combination forecasts over simple linear autoregressive models large enough to justify their use?[1]

In this paper, we re-examine these four issues. The reason for this, and the motivation for this paper, is the following. SW used two nonlinear models to generate their forecasts: a "tightly parameterized" model and a "more nonparametric" one. The former model was the (logistic) smooth transition autoregressive ((L)STAR) model, (see Bacon & Walts, 1971; Chan & Tong, 1986; and Teräsvirta, 1994) and the latter the autoregressive single hidden layer feedforward neural network (AR-NN) model; see Fine (1999) for a general overview of neural network models. SW applied these models to 215 monthly US macroeconomic time series. They considered three forecast horizons, 1, 6 and 12 months ahead, constructing a different model for each horizon. Furthermore, since they were interested in real-time forecasting, the models were re-estimated each time another observation was added to the information set. Repeating this procedure some 300 times for each of the series (as the (longest possible) forecasting period was January 1972 to December 1996) amounted to estimating a remarkably large number of both linear and nonlinear models.

Carrying out these computations obviously required some streamlining of procedures. Thus, SW chose to employ a large number of different specifications of STAR and AR-NN models, keeping these specifications fixed over time and only re-estimating the parameters each period. This simplification was necessary in view of the large number of time series and forecasts. But then, it can be argued that building nonlinear models requires a large amount of care. As an example, consider the STAR model. First, when the data-generating process is a linear AR model, some of the parameters of the STAR model are not identified. This results in inconsistent parameter estimates, in which case the STAR model is bound to lose any forecast comparison against an appropriate linear AR model. Hence, it is essential to first test linearity before considering a STAR model at all. Second, the transition variable of the STAR model is typically unknown and has to be determined from data. Fixing it in advance may lead to a badly specified model and, again, to forecasts inferior to those from a simple linear model.

Similar arguments can be made for the AR-NN model. The ones SW used contained a linear component, that is, they nested a linear autoregressive model. This is reasonable when NN models are fitted to macroeconomic time series because the linear component can in that case be expected to explain a large share of the variation in the series. But then, if the data-generating process is linear, the nonlinear "hidden units" of the AR-NN model are redundant, and the model will most likely lose forecast comparisons against a linear AR model. Testing linearity is therefore important in this case as well. Furthermore, if the number of hidden units in the AR-NN model is too large, in the sense that some of the units do not contribute to explaining the variation in the time series, convergence problems and implausible parameter estimates may occur. This calls for a careful modelling strategy for AR-NN models as well.

An important part of our re-examination concerns the potential benefits of careful specification of STAR as well as AR-NN models. Specifically, instead of examining the forecasting performance of multiple but fixed specifications of STAR and AR-NN models, we consider a single but dynamic specification of these nonlinear models. For this purpose, model building is carried out "manually" as follows. Linearity is tested for every series and a STAR or AR-NN model is considered only if linearity is rejected. The nonlinear models are then specified using available data-based techniques that will be described in some detail below. This would be a remarkable effort if, to approximate a real-time forecasting situation as closely as possible, it were done sequentially every time another observation is added to the in-sample period. In order to keep the computational burden manageable, the models are respecified only once every 12 months. Besides, we

[1] An advantage of this simulation approach is that forecast densities are obtained directly as a by product. These densities can in turn be used for constructing interval forecasts. It is sometimes argued that the strength of nonlinear models in macroeconomic forecasting lies in such interval and density forecasts; see for example Lundbergh and Teräsvirta (2002) and Siliverstovs and van Dijk (2003). Nevertheless, since useful methods for comparing density forecasts from different models are not as yet available, neither interval nor density forecasts are considered in this study.