International Journal of Forecasting 30 (2014) 616–631

Contents lists available at ScienceDirect

International Journal of Forecasting

journal homepage: www.elsevier.com/locate/ijforecast

Forecasting performances of three automated modelling techniques during the economic crisis 2007–2009

Anders Bredahl Kock, Timo Teräsvirta *

CREATES, Aarhus University, Fuglesangs Allé 4, DK-8210 Aarhus V, Denmark

ARTICLE INFO

Keywords:
Autometrics
Economic forecasting
Marginal Bridge estimator
Neural network
Nonlinear time series model
QuickNet
RETINA
Root mean squared forecast error

ABSTRACT

In this work we consider the forecasting of macroeconomic variables during an economic crisis. The focus is on a specific class of models, the so-called single hidden-layer feed-forward autoregressive neural network models. What makes these models interesting in the present context is the fact that they form a class of universal approximators and may be expected to work well during exceptional periods such as major economic crises. Neural network models are often difficult to estimate, and we follow the idea of White (2006) of transforming the specification and nonlinear estimation problem into a linear model selection and estimation problem. To this end, we employ three automatic modelling devices. One of them is White's QuickNet, but we also consider Autometrics, which is well known to time series econometricians, and the Marginal Bridge Estimator, which is better known to statisticians. The performances of these three model selectors are compared by looking at the accuracy of the forecasts of the estimated neural network models. We apply the neural network model and the three modelling techniques to monthly industrial production and unemployment series from the G7 countries and the four Scandinavian ones, and focus on forecasting during the economic crisis 2007–2009. The forecast accuracy is measured using the root mean square forecast error. Hypothesis testing is also used to compare the performances of the different techniques.

1. Introduction

Economic crises provide a useful testing ground for time series models which are designed for forecasting. It is generally not possible to forecast a crisis well in advance, unless the data include information about past crises of the same type, which is usually not the case. Nevertheless, it is useful to investigate how well models based on quantitative time series forecast during a crisis and in its aftermath. This puts models to a severe test, because, in quantitative terms, an economic crisis involves strong decreases (in production) or increases (in unemployment), while the reverse occurs in the aftermath.

In this paper, our attention is restricted to a well-defined class of flexible models, the so-called single hidden-layer feed-forward neural network models. Neural networks or multilayer perceptrons are universal approximators that can arbitrarily accurately approximate any function satisfying rather mild regularity conditions. In a recent study, Ahmed, Atiya, El Gayar, and El-Shishiny (2010) compared the forecasting abilities of several 'machine learning' tools, including various neural network models. They applied them to the forecasting of 1045 time series from the M3 forecasting competition, see Makridakis and Hibon (2000). The series were monthly and each contained at least 80 observations. It turned out that a neural network model of the type we shall consider in this paper was the overall winner of the comparison. Our aim is to study how well this model forecast during the recent economic crisis and to compare its performance with that of a linear autoregressive model, a nonparametric model, and a simple 'no change' forecast.

One problem with these multilayer perceptrons is deciding how to specify their structure and estimate

* Corresponding author.
E-mail address: tterasvirta@econ.au.dk (T. Teräsvirta).

0169-2070/$ – see front matter © 2013 International Institute of Forecasters. Published by Elsevier B.V. All rights reserved.
http://dx.doi.org/10.1016/j.ijforecast.2013.01.003

the parameters. Recently, White (2006) presented a solution that amounted to converting the specification and nonlinear estimation problem into a linear model selection problem. This leads to a somewhat atypical situation, at least in time series econometrics, where the number of variables may vastly exceed the number of observations. The second aim of this paper is to compare three model selection methods which are capable of handling this situation. One is White's QuickNet, which Ahmed et al. (2010) mentioned as a possible extension to their study. The other two are the Marginal Bridge Estimator, see Huang, Horowitz, and Ma (2008), and Autometrics, from Doornik (2009). White (2006) proposed comparing QuickNet with other approaches, and we take up his suggestion.

In this study we shall consider multiperiod forecasts. There are two main ways of generating them. One is to specify and estimate a single model and generate the forecasts recursively from this model. It is also possible to build a separate model for each forecast horizon and use it for obtaining the forecasts. For a discussion of these methods, see for example Teräsvirta, Tjøstheim, and Granger (2010, Chapter 14). Marcellino, Stock, and Watson (2006) compared these two methods in a linear framework, and the third aim of this paper is to do the same when the set of models consists mainly of neural network and nonparametric models, but also contains linear autoregressive ones.

Nonlinear models, such as the neural network model, sometimes generate unrealistic or 'insane' forecasts, see Swanson and White (1995, 1997a,b) for discussion. This problem can be remedied at least partly by adjusting such forecasts towards more realistic values. Our fourth aim is to consider this possibility, which will be called filtering, and see whether it can be useful in our forecasting situation.

These problems have already been considered by Kock and Teräsvirta (2011b). The novelty of the present paper is its focus on the recent economic crisis and its aftermath. We shall consider forecasting two monthly macroeconomic variables that have been strongly affected by the crisis: industrial production and the unemployment rate. The plan of the paper is as follows. The neural network model is presented in Section 2 and the modelling techniques in Section 3. The generation of the forecasts is discussed in Section 4. The time series, which come from 11 different countries, are presented in Section 5. Section 6 is devoted to empirical results, and final remarks can be found in Section 7.

2. The model

The focus of this paper will be on forecasting with a flexible model during the recent economic crisis, when the macroeconomic series to be forecast showed exceptionally large fluctuations. Following Kock and Teräsvirta (2011b), our model is the so-called single-hidden-layer feedforward autoregressive neural network (ANN) model, or single-hidden-layer perceptron

$$y_t = \boldsymbol{\beta}_0'\mathbf{z}_t + \sum_{j=1}^{q} \beta_j(1 + \exp\{\boldsymbol{\gamma}_j'\mathbf{z}_t\})^{-1} + \varepsilon_t \qquad (1)$$

where $\mathbf{z}_t = (1, y_{t-1}, \ldots, y_{t-p})'$, $\boldsymbol{\gamma}_j = (\gamma_{j0}, \gamma_{j1}, \gamma_{j2}, \ldots, \gamma_{jp})'$, $j = 1, \ldots, q$, $\boldsymbol{\beta}_0 = (\beta_{00}, \beta_{01}, \ldots, \beta_{0p})'$, and $\varepsilon_t \sim \mathrm{iid}\mathcal{N}(0, \sigma^2)$. As is well known, the ANN model is a so-called universal approximator. Suppose that there is a functional relationship between y and $\mathbf{z}$: $y = H(\mathbf{z})$. Then, for all $\delta > 0$, there exists a positive integer $q < \infty$ such that $|H(\mathbf{z}) - \sum_{j=1}^{q} \beta_j(1 + \exp\{\boldsymbol{\gamma}_j'\mathbf{z}\})^{-1}| < \delta$, where $|\cdot|$ is an appropriate norm. As was explained by Kock and Teräsvirta (2011b), Eq. (1) is a flexible functional form which can be used for approximating various unknown nonlinear processes.

In this work, we follow Kock and Teräsvirta (2011b) and linearise the nonlinear specification and estimation problem, as White (2006) originally suggested. The idea is that assuming the parameter vectors $\boldsymbol{\gamma}_j$ in Eq. (1) to be known makes the model linear. The ensuing linear model selection problem is the one of choosing a subset of variables for Eq. (1) from the set

$$S = \{y_{t-i}, i = 1, \ldots, p; (1 + \exp\{\boldsymbol{\gamma}_j'\mathbf{z}_t\})^{-1},$$
$$j = 1, \ldots, M\}, \qquad (2)$$

where M is large. It is clear that the quality of the estimates depends on the size of S. For this reason, in a typical macroeconomic application of White's approach, the number of elements in S is likely to exceed the number of observations. This requires model selection techniques which can handle such a situation.

3. Modelling with three automatic model selection algorithms

In this section, analogously to Kock and Teräsvirta (2011b), we consider three model selection algorithms that apply to our modelling problem, where the number of variables exceeds the number of observations. These are (i) Autometrics, which is a development of PcGets, see Krolzig and Hendry (2001), Hendry and Krolzig (2005) and Doornik (2009); (ii) the Marginal Bridge Estimator (MBE, see Huang et al., 2008); and (iii) QuickNet (White, 2006). Autometrics has been built on the principle of proceeding from general to specific, which means beginning with a large model and gradually reducing its size. QuickNet may be characterised as a specific-to-general-to-specific procedure, although we will also report results on the performance of a simplified specific-to-general version. The starting-point of MBE also involves all variables, but the process of selecting the final model is very different to Autometrics. We will now describe these three techniques in more detail, beginning with Autometrics.

3.1. Autometrics

The algorithm is described in detail by Doornik (2009). Modelling begins with a linear model called the General Unrestricted Model (GUM). When the number of variables is less than the number of observations, GUM contains all candidate variables. The model is subjected to significance tests. If all variables have statistically significant coefficient estimates, GUM is the final model. Otherwise, because