Downloaded from UvA-DARE, the institutional repository of the University of Amsterdam (UvA)
http://dare.uva.nl/document/62637

File ID	62637
Filename	Chapter 6 Summary and conclusions

SOURCE (OR PART OF THE FOLLOWING SOURCE):

Type	Dissertation
Title	Essays on modeling nonlinear time series
Author	P.T. de Bruin
Faculty	Faculty of Economics and Business
Year	2002
Pages	133
ISBN	9051706413

FULL BIBLIOGRAPHIC DETAILS:
http://dare.uva.nl/record/104500

Copyright

It is not permitted to download or to forward/distribute the text or part of it without the consent of the author(s) and/or copyright holder(s), other then for strictly personal, individual use.

UvA-DARE is a service provided by the library of the University of Amsterdam (http://dare.uva.nl)

Chapter 6

Summary and conclusions

It is well-known that economic recessions tend to be shorter and more intense than expansions. This characteristic is often reflected in economic time series data. For these data nonlinear models are needed to describe this asymmetric behaviour adequately. Models that are used for this purpose here are the Self Exciting Threshold Autoregressive [SETAR] and the Smooth Transition Autoregressive [STAR] model.

In general, for minimum mean squared error forecasting with nonlinear models no closed form expressions of point forecasts can be determined. Therefore, approximating methods are needed. In Chapter 2, the Normal Forecasting Error [NFE] method is applied to various SETAR models. The NFE method assumes Gaussianity of the forecasting error of a point forecast for a certain number of steps ahead. This assumption is then utilized for determining the forecast one step further ahead. Accordingly, explicit approximate expressions are derived for point forecasts and for their variances. By simulation experiments, the approximations prove to be reasonably accurate as compared with other methods, like numerical integration techniques and Monte Carlo forecasting. An advantage of the NFE method is that it is easy to use and not computer intensive. However, only the case of SETAR models with Gaussian innovations has been considered. It would be of interest to investigate the NFE method for SETAR models with non-Gaussian disturbances. Also, the application of the NFE method to other models, like the STAR model, can be a topic for future research. Nevertheless, taking the conditional expected value as a forecast for STAR or SETAR models remains questionable, since these models may generate forecasts with a multimodal probability density. This topic is not further discussed here.

Most macroeconomic time series are transformed to stationarity before models, linear or nonlinear, are fitted to them. In Chapter 3 the interaction is examined between the Box-Cox transformation with different Box-Cox parameter values and different aspects of

nonlinear time series modeling. First, the influence of different Box-Cox parameter values on evidence of nonlinearity in the transformed data is examined. Empirical as well as simulated time series data are used for this purpose. The general finding is that evidence of nonlinearity depends on the data transformation. For instance, the transformation may introduce nonlinearity in otherwise linear data. Therefore, careful selection of the Box-Cox parameter value is advised. Another approach would be to include the Box-Cox parameter in the procedure of parameter estimation after selecting a specific model. This can be a topic for further research. We also showed that detecting nonlinearity in macroeconomic time series is best done for disaggregated data and that aggregated data are less useful. This confirms earlier findings in empirical work that monthly data are more convenient for fitting nonlinear time series models than quarterly data.

Forecasting with a STAR model with Box-Cox transformed data is also considered in Chapter 3. We conclude that levels should not necessarily be forecasted by a model for the levels, or log-transformed data forecasted by a model for the log-transformed data. In general, imposing a specific Box-Cox transform prior to a forecasting exercise leads to sub-optimal forecasts, even if the purpose is to forecast similarly transformed data. Therefore, selecting an appropriate Box-Cox transformation may be worthwhile. This conclusion also holds when one uses STAR models for the classification in distinctive regimes of various Box-Cox transformed time series data. The agreement on regime switches is evaluated by using the Kappa coefficient of agreement. The main result is that agreement is low in some cases. This means that different Box-Cox transformations of a given time series variable lead to (sometimes considerably) different opinions on regime switches in this variable. Moreover, the agreement decreases when the different Box-Cox data transformations diverge.

Apart from the Box-Cox transformation, seasonal adjustment is another transformation which may influence nonlinearity in time series data. This issue is studied in Chapter 4. Seasonal adjustment methods assume that seasonality can be separated from other sources of variation in the data. However, recent work has proven that in empirical time series data seasonal and nonlinear influences may interact with each other. We examine the impact of seasonal adjustment on the analysis of implied business cycle chronologies in empirical macroeconomic data. For this purpose the seasonal STAR [SEASTAR] model is introduced. This model describes seasonal behaviour and STAR-type nonlinearity simultaneously. The SEASTAR model is applied to seasonally unadjusted empirical data, while the STAR model is applied to the seasonally adjusted antipodes. The main finding is that for seasonally adjusted data recessionary periods tend to last longer. Therefore, seasonal adjustment of the data prior to fitting a model influences inference on behaviour of the business cycle, and

hence analyzing unadjusted data is to be recommended. Additionally, it may be interesting in itself to compare the forecasting performance of both the SEASTAR model and the STAR model. Especially, the question may be worthwhile which of the two models predicts recessions better. The empirical seasonal data in Chapter 4 are quarterly observations. Although we have noted before that monthly data show more evidence of nonlinearity, they are not subjected to SEASTAR modeling. The SEASTAR model contains seasonal dummies. Therefore, monthly data instead of quarterly data increases the number of model parameters in a SEASTAR model considerably, and one would expect that this affects the forecasting performance of the model. Modeling and forecasting monthly seasonal data by a SEASTAR model can thus be a topic for future research.

The SEASTAR model is examined in more detail in Chapter 5. The model representation, parameter estimation and residual diagnostics are discussed, as well as out-of-sample forecasting. SEASTAR models are applied to various quarterly empirical time series. We conclude that forecasting with these models in some cases outperforms forecasting with models nested within the class of SEASTAR models. In general, almost no evidence is found that seasonal fluctuations change with the business cycle. Finally, as in Chapter 4, SEASTAR models are compared with STAR models for corresponding seasonally adjusted series with the use of the Kappa coefficient of agreement. The main result is that the estimated business cycles from both models are sometimes quite different from each other. This supports the idea of modeling unadjusted data, as the SEASTAR model does.