Time series analysis under model uncertainty

Summary

Econometricians are faced with the challenge of finding suitable models for the data to be analyzed. They face model uncertainty since the true data generating model is not known, and use model selection criteria or model averaging methods to deal with it. In this thesis we extend the range of applicability of some model selection and model averaging criteria to multivariate stationary time series models by providing their theoretical properties, and we show their usefulness for the field of macroeconomic policy analysis.

Claeskens and Hjort (2003) enriched the concept of model selection by introducing the focused information criterion. We extend the theory about its asymptotic properties in regression settings as described by Liu (2015) to autoregressive models in Chapter 2. We offer a basis for defining stationary parameter regions for the locally misspecified framework and we discuss the role of the misspecification parameter, which cannot be estimated consistently: The estimator of the misspecification parameter converges to a normally distributed random vector centered around the true misspecification parameter in the limit. This means that the estimate is still random in the limit, and the FIC expression does not converge in probability to the asymptotic MSE that it is intended to estimate. The chapter illustrates that point by including the infeasible estimator in the simulations, which corresponds to the FIC estimator, but with the estimate of the misspecification parameter replaced by the true misspecification parameter. The infeasible estimator is shown to have a lower MSE than the FIC estimators for large ranges of the simulations' parameter space. It is shown that the FIC estimator performs similarly to both AIC and BIC selection procedures. A plug-in average estimator (that also suffers from the fact that the misspecification parameter cannot be estimated consistently) is also discussed in that chapter.

In Chapter 3 we then similarly extend the results about the asymptotic properties of the smoothed AIC (sAIC) and smoothed BIC (sBIC) averaging methods, that Zhang (2015) derived, to dynamic regression settings. While for model selection based on the Akaike information criterion, the model with the lowest AIC score is selected, the smoothed AIC averaging estimator is defined as the weighted sum of the estimators from all models in the model set under consideration, with weights defined by the models' AIC scores. The chapter illustrates that the calculation of the weights as given by Zhang (2015) and in other publications, is actually only one representation of the set of smoothed AIC estimators, that is defined by a certain weight scaling parameter, cf. Section 3.3.1. We extend the

results by Zhang (2015) for a time series setting by showing root-T consistency of the averaging estimators for specific ranges of the weight scaling parameter in Section 3.3, and propose a bootstrap method to estimate the distributions of the averaging estimators in Section 3.4. Using results of Bose (1988) we also show its asymptotic validity. In simulations we show the benefits of using sAIC-based instead of AIC-based estimators for estimating impulse response coefficients.

In Chapter 4 the model selection criteria and model averaging methods of Chapters 2 and 3 are applied in structural VAR analyses of empirical data. Structural VAR models are a central tool in macroeconomic and monetary policy analysis and we offer a comparison of the FIC and smoothed model averaging estimators with other commonly used model selection estimators in this setting. We find that AIC-based model averaging yields smoother and more precise estimates of impulse response functions than AIC-based model selection. In order to make our results more relevant we use the data from three different previous studies, Christiano et al. (1999), Stock and Watson (2001), and Uhlig (2005), which have been carefully selected for their similar analyses: They all estimate exogenous monetary shocks for US data sets of similar time periods, and apply the same structural parametrization for identifying impulse response functions. But the data sets do differ in sampling frequency and number of variables, and this allows us to compare the performance of the estimators across the different sampling frequencies of the data sets and to make suggestions on sampling frequency based on a comparison of estimator precision across the different data sets. We find that sampling data at a higher frequency (monthly) leads to higher precision than sampling at lower frequencies. At the same time, the results drawn from lower frequency (quarterly) data are more robust to the choice of model selection method.