speech synthesis are known to be not only of autoregressive moving average type but also with additional impulsive input; see also Basseville and Nikiforov (1993). My question would thus be: are piecewise constant models still of interest in econometrics, and of lower or higher interest than STR models?

- Of course, this also raises the issue of the purpose of the (possibly non-linear) modelling. My own experience (on monitoring industrial processes) is that there is no unique model for a given set of time series, and that the choice of the model should basically be governed by the goal of the processing. For a given application, the best model for simulation has no reason to be the same as the best one for prediction, or for control, or for monitoring. My second question would thus concerns the underlying purpose of the modelling which is discussed in the chapter.

D. VAN DIJK AND P.H.B.F. FRANSES

The chapter by Timo Teräsvirta gives a comprehensive overview of the state of the art concerning various aspects of smooth transition regression (STR) models. Teräsvirta pays particular attention to tests for STR and diagnostic tests to examine the empirical adequacy of an estimated STR model. Teräsvirta (1994) and Granger and Teräsvirta (1993) incorporate these statistical tools into a sequential specification procedure for STR models, which consists of the familiar stages of testing, estimating and diagnostic checking.

Given the availability of this specification procedure, nothing seems to prevent a widespread application of this class of non-linear time series models. In our comment, we will elaborate on some practical issues, which any empirical researcher who seeks to apply STR models may wish to consider. To be more precise, we focus on the possible 'observational equivalence' of outliers and non-linearity in small samples and we provide some comments on evaluating forecasts from STR models.

Smooth transition models have been applied almost exclusively to study possible non-linearity of business cycles; see Teräsvirta and Anderson (1992), Teräsvirta, Tjøstheim and Granger (1994), and Öcal (1995), among others. At first sight, these studies seem to suggest that STR models are indeed useful in describing, for example, different properties of recessions and expansions. It has to be kept in mind, however, that many macroeconomic variables which reflect business cycle patterns are sampled only quarterly or monthly. Consequently, usually only series of moderate length are available, i.e. more than 100 observations is the exception rather than the rule. Possible non-linear properties in the data may then be most pronounced in only a small number of observations. For example, recessions often occur only once per decade and tend to last for not more than two or three quarters. From a practical point of view, one may then be tempted to regard these, say, 'non-linear data points' as aberrant observations, which can simply be removed by including dummy variables. If the primary goal of the econometric time series model is merely describing a time series, one may even justify this option by noting that estimating STR models often is not straightforward since several parameters in nonlinear functions are added. On the other hand, removing apparent outliers may destroy intrinsic nonlinearity, which could have been exploited to obtain better forecasts. Therefore, there seems to be a need for modelling strategies and tests which can distinguish nonlinearity from outliers and vice versa. A first step towards such a strategy is given in Van Dijk, Franses and Lucas (1996), where LM-type tests against smooth transition non-linearity are designed which are less sensitive to outlying observations. In short, these robust tests are obtained by estimating the linear model under the null hypothesis using a robust estimator.

As an example, consider Figure 4.A, which shows the seasonal differences of the quarterly index of US industrial production over the period 1962(iii)–1986(iv). Teräsvirta and Anderson (1992) model this series by a logistic smooth transition autoregressive (LSTAR) model, which seems to render an adequate description of the asymmetries observed between recessions and expansions. The circled observations indicate the recession periods as determined by the value of the transition function in their estimated model. When the LM-type tests as described in Teräsvirta's chapter are applied to this series, linearity is rejected

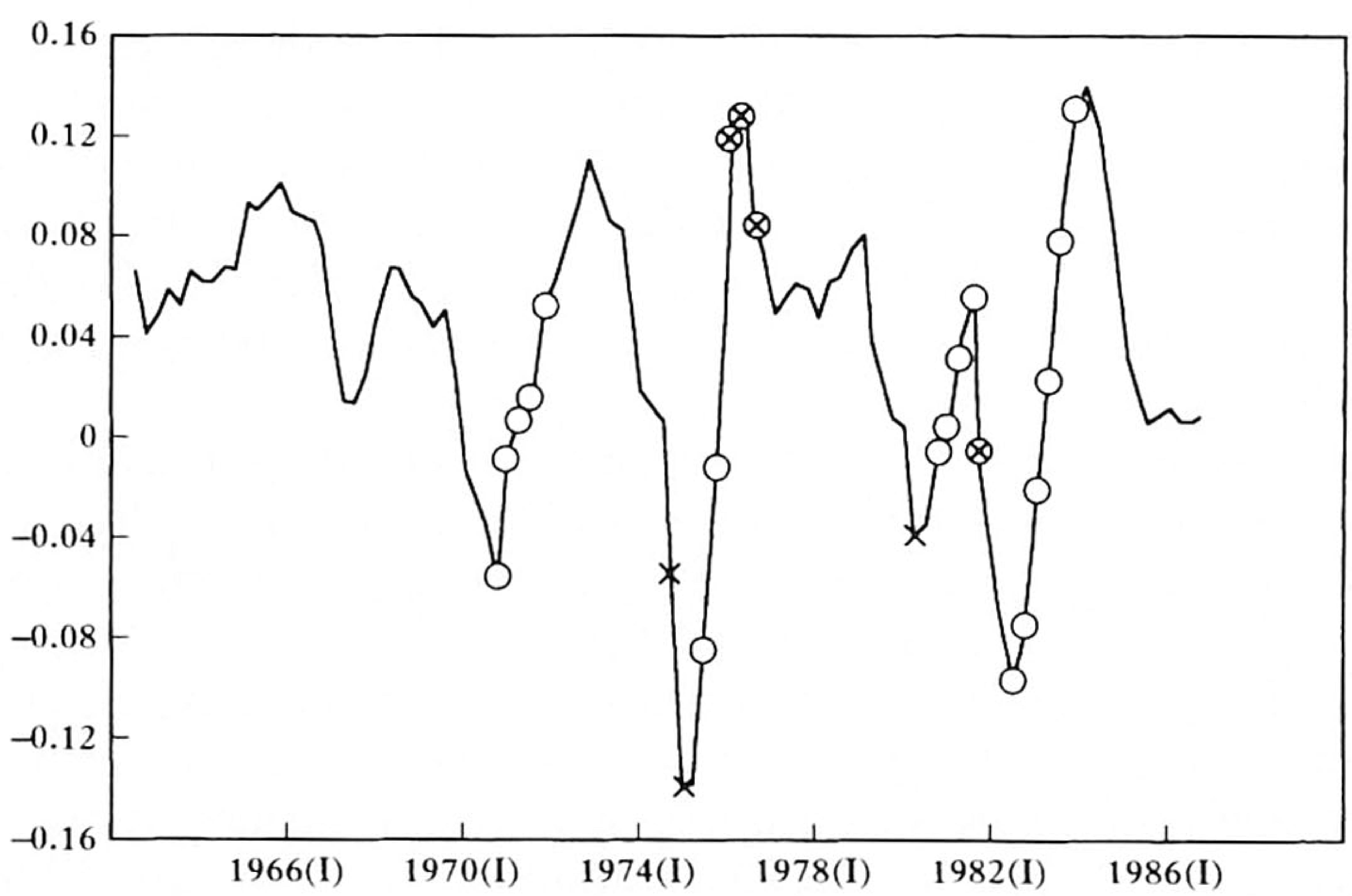

Figure 4.A US industrial production. Seasonal differences of quarterly index of US industrial production 1962(iii)–1986(iv). Circles indicate observations for which the estimated transition function is zero, crosses are observations that are identified as outliers in a robust estimation procedure

quite convincingly. The robust tests, on the other hand, do not reject the null hypothesis. The robust estimation procedure indicates that seven observations might be considered as outliers, marked by crosses in the figure, and that these observations roughly correspond with the recession periods around 1975 and 1981; see Van Dijk, Franses and Lucas (1996) for more details. Notice that these findings do not imply that STR models should not be used for these data. We merely find that any practitioner should make a decision whether or not to estimate complicated non-linear models of which characteristic features may only be reflected in a small number of observations.

Our second comment concerns the evaluation of forecasts from STR models, which, in a sense, is related to the issue of outliers. It is common practice to evaluate the adequacy of competing time series models by comparing their out-of-sample forecasting performance. If non-linearity is reflected by only a small fraction of observations, it may accidentally happen that the non-linear features do not become apparent in the period chosen (or available) for forecasting. Traditional measures of forecasting accuracy, such as the root mean squared forecasting error, treat all observations equally and, hence, may suggest that a linear model generates better forecasts, even though the non-linear model truly excels in forecasting data in specific regimes. Hence, an important topic for further research is the design of forecast evaluation criteria for non-linear time series models, which can incorporate this data-dependence.

M. CAMPBELL

The chapter by Teräsvirta is largely devoted to describing technical aspects of this class of non-linear models, statistical inference, testing for linearity, etc. Models are built for two Swedish data series, industrial production and employment and as a further application these techniques are used to test Granger non-causality.

The series for annual industrial production in Sweden runs from 1862 to 1988. Teräsvirta estimates a univariate smooth transition model for this series on the basis that the data are found to be non-linear. The non-linear model is an improvement on a linear autoregressive model of the same order, for example the residual variance of the non-linear model is 85% of the residual variance of the linear model. Nevertheless the standard error of the nonlinear model, which is 0.065, comes very close to the standard deviation of the data series itself, which is 0.070.

A similar non-linear model for employment is also reported which achieves a larger reduction in the residual variance but the estimated residual error of 0.038 is still a significant fraction of the standard deviation of the series 0.051.

In each case a single model is assumed to account for a very long period of time. It is far from clear either that this is a reasonable assumption to make, or