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OxMetrics™

OxMetrics news

AUGUST 2009 ISSUE 9

Announcing OxMetrics™ 6

OxMetrics™ 6 starts shipping on the 1st August 2009. This is a major upgrade of the software. However not all modules offer major improvements - STAMP™ and Ox™ only provide minor improvements and bug fixes. SsfPack™ has not been upgraded. The Macintosh and Linux user interfaces have been improved. The price for new copies remains constant and the price lists can be found on www.timberlake.co.uk.

1. New Features in OxMetrics™ 6

OxMetrics Enterprise Edition™ is a single product that includes and integrates all the important components for theoretical and empirical research in econometrics, time series analysis and forecasting, applied economics and financial time series: Ox Professional™, PcGive™, STAMP™ and G@RCH™. Purchasing the OxMetrics Enterprise Edition™ will provide users with a very powerful and cost effective tool to use during their modelling work. In addition to the usual features in modern econometric software, OxMetrics Enterprise includes Autometrics™ (in PcGive), a powerful Automatic Model Selection procedure.

1.1 PcGive™ 13

PcGive™ is an essential tool for modern econometric modelling. PcGive™ Professional is part of OxMetrics Enterprise Edition™ and provides the latest econometric techniques, from single equation methods to advanced cointegration, static and dynamic panel data models, discrete choice models and time-series models such as ARFIMA, and X-12-ARIMA for seasonal adjustment and ARIMA modelling. PcGive™ is easy to use and flexible, making it suitable both for teaching and research. Very importantly, PcGive 13 includes Autometrics™, a powerful automatic model selection procedure. It also includes extensive facilities for model simulation (PcNaive™). PcGive™ 13 now incorporates Markov Switching Models.

New features in PcGive™ 13

by Jurgen A. Doornik

Regime switching models:
Markov Switching (see detailed exposition in Section 2).
Diagnostic testing (single and multiple equations modelling). There are some new tests, the degrees of freedom have changed on the Heteroscedasticity and ARCH tests, and some further changes:

- Added RESET23 and Vector RESET/RESET23 tests. The RESET23 uses squares and cubes, and replaces RESET (just using squares) in the test summary.
- Added p-values for the Portmanteau statistic; Portmanteau is omitted from the system test summary if it has an open lag structure.
- The Hetero-test now removes variables that are identical when squared (these were already removed from the output, now they are removed from the calculations - this is useful when many dummies are present). Also removed are observations with (almost) zero residuals, removing implicit dummy variables from the set of regressors. For 4 or more equations the rotated form is used (n equations instead of $n(n+1)/2$). The unrestricted/fixed variables are now always included in the test.
- The Hetero and ARCH degrees of freedom in the denominator now exclude k, the original regressor count. The Hetero test changed from F(s, T-s-1-k) to F(s, T-s-1), while the ARCH test changed from F(s, T-2s-k) to F(s, T-2s).
- Added Index and Vector Index test. The Index test removes variables that are identical when cubed. The Index test is a powerful new low-dimensional test for non-linearity developed by Jennifer L. Castle and David F. Hendry.
- Added Hetero, Index and RESET23 to PcNaive
- Multiple equation modelling: the single equation AR and Hetero tests only use variables with non-zero coefficients in the reduced form. The single equation diagnostic are now ordered by equation.

Automatic model selection using Autometrics

- Autometrics added to cross-section modelling
- Autometrics for binary logit/probit and for count data
- Autometrics can impose sign restrictions on the search space. In a dynamic model these are long-run restrictions. Effectively, models with 'the wrong signs' can be omitted from the search space. Optionally, variables can be forcefully removed if they are significant with the wrong sign.
- PcNaive can now run with Autometrics and impulse saturation, but dummies are not reported in the output.
- Small change to Autometrics output: stages more clearly identified; now including coefficients of terminal models as well as p-values. Added sigma to the Autometrics single equation output (Not Adj.R^2, but note that highest Adj.R^2 corresponds to smallest sigma).

Robust standard errors (single and multiple equations modelling): Selection of robust standard errors (HCSE, HACSE) has moved from Options to the estimation dialog (it is different covariance estimator). Now it is remembered when it is used, and also part of the generated Ox code. The tabular output with different robust standard errors is still available from Further Output; this can be switched on permanently through Options. The part of the Options dialog that is below the maximization settings now purely relate to output options.

1.2 G@RCH™ 6

G@RCH 6.0 is a module dedicated to the estimation and the forecasting of univariate and multivariate (G)ARCH models and many of its extensions.
The available univariate models are all ARCH-type models. These include ARCH, GARCH, EGARCH, GJR, APARCH, IGARCH, RiskMetrics, FIGARCH , FIEGARCH , FIAPARCH and HYGARCH. They can be estimated by approximate (Quasi-) Maximum Likelihood under one of the four proposed distributions for the errors (Normal, Student-t , GED or skewed-Student). Moreover, ARCH-in-mean models are also available and explanatory variables can enter the conditional mean and/or the conditional variance equations. G@RCH 6.0 offers some multivariate GARCH specifications including the scalar BEKK, diagonal BEKK, full BEKK, RiskMetrics, CCC, DCC, DECO, OGARCH and GOGARCH models.
Finally, h-steps-ahead forecasts of both equations are available as well as many univariate and multivariate miss-specification tests (Nyblom, Sign Bias Tests, Pearson goodness-of-fit, Box-Pierce, Residual-Based Diagnostic for conditional heteroscedasticity, Hosking's portmanteau test, Li and McLead test, constant correlation test, …).

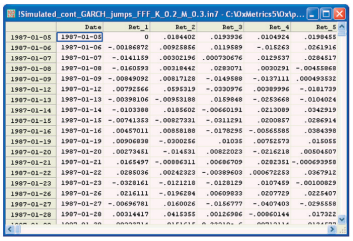
New features in G@RCH™ 6

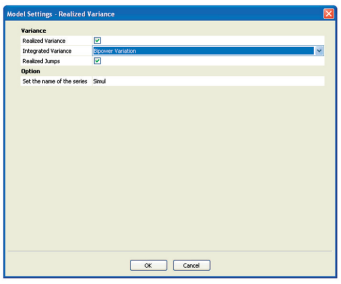
by Sebastien Laurent

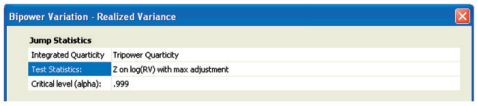
G@RCH™ 6.0 is not only a bug-fix upgrade but includes a new module, called RE@LIZED. The new version includes:

Bug fixed: G@RCH experienced convergence problems when returns were not expressed in %. This is now fixed.

G@RCH proposes a new module called RE@LIZED whose aim is to provide a full set of procedures to compute non-parametric estimates of the quadratic variation, integrated volatility and jumps using intraday data. The methods implemented in G@RCH 6.0 are based on the recent papers of Andersen, Bollerslev, Diebold and coauthors, Barndorff-Nielsen and Shephard and Boudt, Croux and Laurent. They include univariate and multivariate versions of the realized volatility, bi-power-variation and realized outlyingness weighted variance. Daily and intradaily tests for jumps are also implemented. The `Realized' class allows to apply these estimators and tests on real data using the Ox programming language. Importantly, they are also accessible through the rolling menus of G@RCH. Interestingly, like for the other modules, an Ox code can be generated after the use of the rolling menus. The Model/Ox Batch Code command (or Alt+O) activates a new dialog box called `Generate Ox Code' that allows the user to select an item for which to generate Ox code. Here are some screenshots and graphs obtained with the new module as well as an example of code generated after the computation of Lee and Mykland (2008)'s test for intraday jumps detection.








```
Z Jump Statistic on log(RV) with max adjustment using Tripower Quarticity
Expected number of spurious detected jumps (under H0=no jump): 3
Number of detected jumps: 405
Proportion of detected jumps: 0.135
Critical level: 0.001
Critical value: 3.09023
```

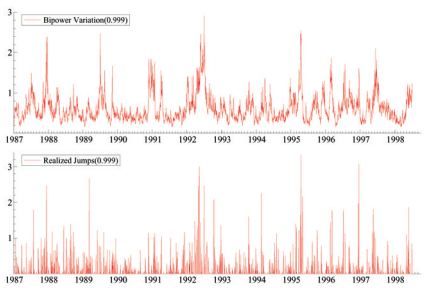


Figure 1: BV_t and significant jumps with $\alpha = 0.999$

```
#include <oxstd.h>
#import <packages/Garch6/garch>
#include <oxdraw.h>

main()
{
//--- Ox code for RE@LIZED
decl model = new Realized();

model.Load("C:\\Data\\Simulated_cont_GARCH_jumps_FFF_K_0.2_M_0.3.in7");
model.Deterministic(-1);

model.Select(Y_VAR, {"Ret_1", 0, 0});
...
model.Select(Y_VAR, {"Ret_288", 0, 0});

model.SetModelClass(MC_RV);
model.RV(1);
model.IV(1);
model.OPTIONS_JUMPS_TEST_BV(1,0,2,0.999);

model.SetSelSampleByDates(dayofcalendar(1987,1,5),dayofcalendar(1998,7,3));
model.Estimate();
model.Graphs_RV(0,0,1,0,0,0,0,1,1,0,0,10,0,0.999);
model.Append_in(model.m_vIV,"BV");
model.Append_in(model.m_vRJ,"RJ_BV");
model.Save("C:\\Data\\Simulated_cont_GARCH_jumps_FFF_K_0.2_M_0.3.in7");

delete model;
}
```

Non-parametric and parametric intraday periodicity filters are also provided. Figure 2 plots the true periodicity (dotted line) and the estimated periodicity (solid line) obtained by applying four non parametric filters on 3000 days of 5-min simulated returns (288 returns per day). The data generating process is a continuous time GARCH(1,1) with jumps and periodicity in the spot volatility. Importantly, occurrences of jumps are concentrated on the parts of the day when volatility is periodically very low. The first graph corresponds to Taylor and Xu (1997)'s periodicity filter which is not robust to jumps. The next three estimators, respectively the MAD, Shortest Halves and Weighted Standard Deviation periodicity filters are all robust to jumps (see Boudt, Croux, and Laurent, 2008). It is clear from this graph that the three robust estimators do a good job in estimating the periodicity factor in the presence of jumps.

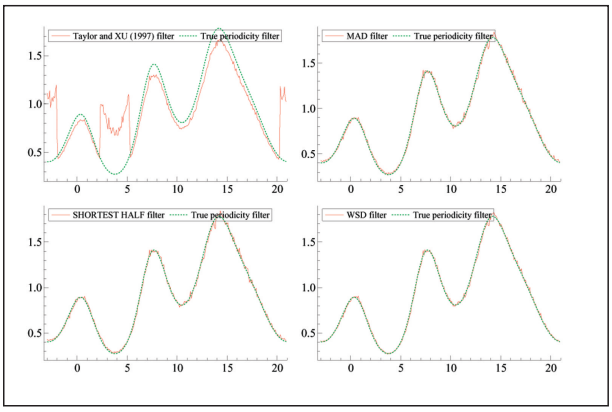


Figure 2: Non parametric periodicity filters.
DGP=periodic GARCH (1,1) = jumps

The DCC-DECO model of Engle and Kelly (2008) is now documented in the manual.

Conditional means, variances, covariances and correlations of MGARCH models can now be edited in a basic matrix or array editor.

Bug fixed (thanks to Charles Bos). Several functions of the MGarch class had not been included in the oxo file, e.g. GetVarf_ vec, Append_ in, Append_ out, etc.

Bug fixed. DCC models: the empirical correlation matrix used when applying 'Correlation Targeting' was computed on the residuals and not the devolatilized residuals as it should be.

References

Boudt, K., C., CROUX, S., Laurent, 2008. Robust estimation of intraweek periodicity in volatility and jump detection. Mimeo.
Engle, R.F., B.T., Kelly, 2008. Dynamic Equicorrelation. Mimeo, Stern School of Business.
Lee, S. S., P.A., Mykland, 2008. Jumps in Financial Markets: A New Nonparametric Test and Jump Dynamics. Review of Financial Studies, 21, 2535–2563.
Taylor, S.J., X., XU, 1997. The incremental volatility information in one million foreign exchange quotations. Journal of Empirical Finance, 4, 317–340.

1.3 STAMP™ 8.2

STAMP™ is a module designed to model and forecast time series, based on **structural time series modelling**. Structural time series models find application to a variety of fields including macro-economics, finance, medicine, biology, engineering, marketing and many other areas. These models use advanced techniques, such as Kalman filtering, but are set up in an easy-to-use interface - at the most basic level all that is required is some appreciation of the concepts of trend, seasonal and irregular components. The hard work is done by the program, leaving the user free to concentrate on model formulation and forecasting. STAMP includes both univariate and multivariate models and automatic outlier detection. STAMP is part of OxMetrics Enterprise Edition™.

New features in STAMP™ 8.2

STAMP 8.2 is a minor upgrade bringing bug fixes and minor improvements only.

1.4 Ox Professional™ 6

Ox Professional™ is an object-oriented matrix programming language. It is an important tool for statistical and econometric programming with syntax similar to C++ and a comprehensive range of commands for matrix and statistical operations. Ox is at the core of OxMetrics. Most of the other modules of OxMetrics (e.g. PcGive™, STAMP™, G@RCH™) are implemented with the Ox language. Ox Professional belongs to the OxMetrics Enterprise Edition™.

New features of Ox Professional™ 6

The major improvement in Ox is the support of recession shading in graphs. Other improvements are minor or bug fixes.

2. Regime Switching Models in PcGive™

by Jurgen A. Doornik

The main addition in the new version of PcGive™ is estimation and forecasting with Markov-switching models. Such models allow coefficients to be regime dependent, which is combined with the estimation of transition probabilities between regimes. In light of the current recession, which ended a long period of stability in the macro economy, it is likely that such models will see renewed interest.

PcGive™ distinguishes between two types of Markov-switching models: *Markov-switching dynamic regression models (MS or MS-DR)* and *Markov-switching autoregressions (MS-AR or MS-ARMA).*

In MS-DR the lags of the dependent variable are added in the same way as other regressors. An example is:

$$y_t = \nu(s_t) + \alpha y_{t-1} + \mathbf{x}_t'\beta + \epsilon_t, \epsilon_t \sim \mathsf{N}[0, \sigma^2], \qquad (1)$$

where s_t is the random variable denoting the regime. If there are two regimes, we could also write:

$$\begin{aligned} \text{Regime 0:} \quad & y_t = \nu(0) + \alpha y_{t-1} + \mathbf{x}_t'\beta + \epsilon_t, \\ \text{Regime 1:} \quad & y_t = \nu(1) + \alpha y_{t-1} + \mathbf{x}_t'\beta + \epsilon_t, \end{aligned}$$

which shows the regime dependent intercept more clearly.

In the MS-AR model the lag polynomial is applied to the dependent variable in deviation from its mean:

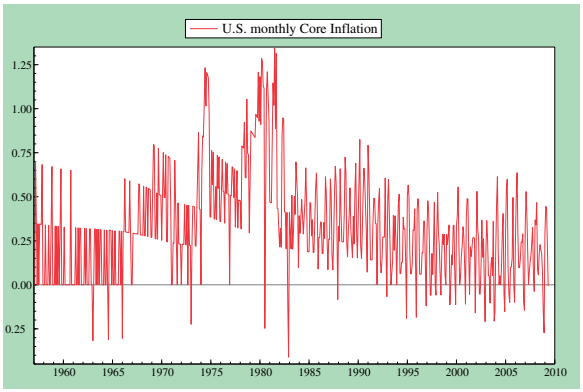
$$y_t - \mu(s_t) - \mathbf{x}_t'\gamma = \rho\left(y_{t-1} - \mu(s_{t-1}) - \mathbf{x}_t'\gamma\right) + \epsilon_t. \qquad (2)$$

Without regime switching both specifications are identical: one can be rewritten as the other. This is not the case for Markov-switching models. The MS-AR model is sometimes called the Hamilton model.[1]

PcGive™ allows any parameter to be regime dependent, including the variance. In an MS-ARMA model all ARMA parameters are either regime dependent or not.

The new chapter in PcGive™ Volume III illustrates the regime-switching models to estimate business-cycle models for U.S. quarterly GNP. Here we use U.S. core inflation (Urban CPI excluding energy and food, not seasonally adjusted).

The following graph shows monthly percentages of core inflation:



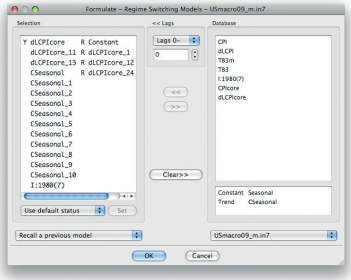
Unfortunately, the CPI is only reported with one decimal point, and there is very limited information in the early part of the sample.

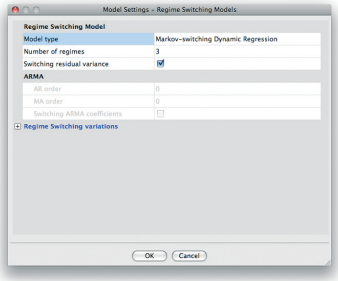
The graph shows that U.S. core inflation displayed persistent changes in the post war period. Periods with high means and low means, high persistence and low persistence, high volatility and low volatility followed each other. The significance of these changes is the subject of an intensive and ongoing debate among practitioners and academics.[2]

Markov regime switching models provide an elegant way to summarize the evolution of changing characteristics of time series processes. Specification, estimation, testing, interpretation and forecasting for Markov-switching models only requires a minimum effort using the new PcGive™ as we show in this note.[3] Some older models for seasonally adjusted inflation estimate an MS-AR model with three regimes and two lags.[4] However, we find that we need to allow for lags up to 24 months, which rules out the MS-AR specification.[5] We use centred seasonals, one dummy variable for July 1980, and some of the lags have a regime dependent coefficient. Finally, the variance is also regime dependent:

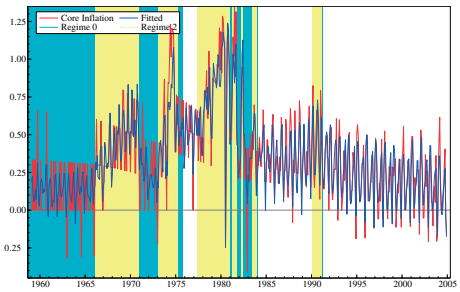
$$\begin{aligned} y_t = & \alpha_0(s_t) + \alpha_1(s_t)y_{t-1} + \alpha_{11}y_{t-11} + \\ & \alpha_{12}(s_t)y_{t-12} + \alpha_{13}y_{t-13} + \alpha_{24}(s_t)y_{t-24} + \\ & \text{dummy} + \text{seasonals} + \epsilon_t, \epsilon_t \sim \mathsf{N}[0, \sigma^2(s_t)]. \end{aligned}$$

Estimation is over 1959(2) to 2004(12). The following two screen captures show model formulation under OS X:

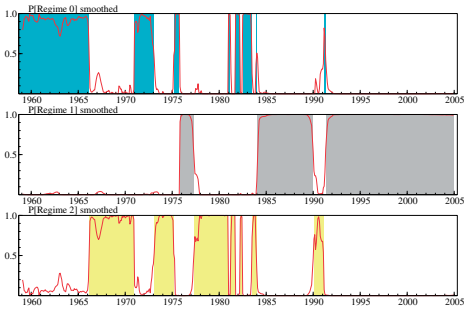




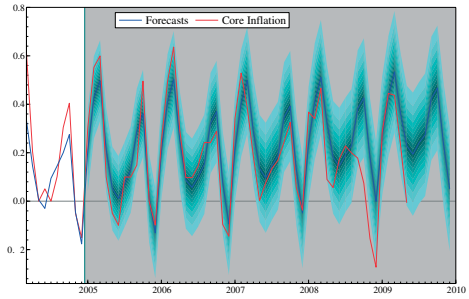
The next figure shows the actual and fitted values from the estimated model, as well as the regime classification based on the smoothed transition probabilities. Regime 0, in light blue, corresponds to periods of stable and low inflation, predominantly in the early part of the sample. Regime 2, in yellow, are periods of rising and persistent inflation in the period of Great Inflation, while regime 1, the remainder, covers most of the sample after the Great Moderation of the 1980s with low and less volatile inflation. The residual standard error in regime 1 is about 60% of that of the other two regimes, while the intercept in regime 1 is less than half that of the other two.



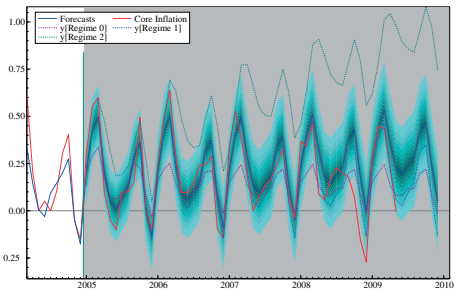
The smoothed transition probabilities for this MS-DR(3) model can also be graphed separately, with regime 1 in grey:



The five-year ahead forecast performance of this model is shown in the next figure:



For about 3 and a half year ahead the model forecasts very well. After July 2008 the forecasts start to break down, before recovering in early 2009. An over-estimate for mid 2009 looks then again likely.
Within each regime the model is linear, and the forecasts are a weighted average of the forecasts for the three regimes. This is depicted in the next figure, where the regime-specific forecasts are shown with dotted lines. The probability to be in regime 1 is high, but somewhat diminishing further into the future.



[1] See Chapter 22 in Hamilton (1994), *Time series Analysis*, Princeton University Press. Further references are given in PcGive™ Volume III.

[2] Cecchetti, Hooper, Kasman, Schoenholtz, and Watson (2007), Understanding the evolving inflation process; *Report U.S. Monetary Policy Forum*) evaluate findings in the literature for the period preceding the credit-crisis.

[3] PcGive Regime Switching models are not based on the MS-VAR class for Ox 3.4 (Krolzig, 1994). The PcGive interface provides some additional flexibility and new algorithms, but only for single equation modelling.

[4] See, e.g., Garcia and Perron (1996), An Analysis of the Real Interest Rate under Regime Shifts, *Review of Economics and Statistics.*

[5] The dimension of the state vector would be.

3. Finding statistical evidence of a crisis in the European car industry using STAMP 8.20

by Siem Jan Koopman

3.1 Introduction

Time series analysis is an exciting field of research. Economic and financial crises, as the ones we are experiencing today, are not phenomena that we welcome but they do deliver interesting time series. The time series with non-standard features allow us to reflect on methodological issues. It also may lead to interesting challenges for econometricians and time series analysts generally. It further provides us with possible new ideas in the way we carry out our analyses in practice. A basic illustration of such challenges may be given below. The financial crisis of the last and current years has been felt severely by many industries of importance including the car industry. An illustration of the problems in the car industry can be found in the time series of new passenger car registrations for the Euro-zone countries (source: European Central Bank). The series is adjusted for trading days and is transformed into logs. The monthly observations from January 1990 towards April 2009 are presented in Figure 1.

3.2 A STAMP analysis

The time series is clearly subject to seasonal effects. The smallest numbers of new registrations occur in August and December as these are months associated with the summer and Christmas holidays. Most registrations take place in the period March–June. The times series is further subject to the cyclical behavior of economic activity but the series is somewhat too short to identify trend and cycle dynamics separately. Therefore, we consider the basic structural model for a time-series decomposition. It is the default model in STAMP and consists of a level component (its associated slope component is not necessary), a seasonal component and the irregular. The graphical representation of the STAMP decomposition is presented in Figure 2.

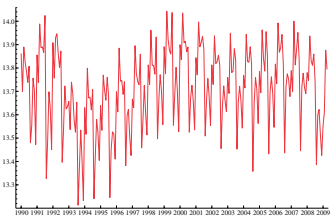


Figure 1: New passenger car registrations in the Eurozone: Monthly time series in logs, 1990M1–2009M4. Source: ECB

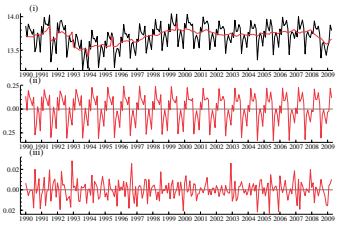


Figure 2: Decomposition of the new passenger car registrations in the Eurozone into (i) trend, incl. breaks and outliers, (ii) seasonal and (iii) irregular.

The residual diagnostic statistics for normality, heteroskedasticity and serial correlation are satisfactory once STAMP has selected some outliers and breaks using the"automatic" option. The three level breaks occur in the year of 1992 or are close to it. These breaks indicate the intricacies of interpreting this part of the time series in a period when the Euro-zone did not exist as an official entity and Germany experienced its post-reunification boom in car sales.
The seasonal component is somewhat changing over the years but is at least in the more recent years quite stable. The most interesting feature of the STAMP decomposition is the decline of the level component after the final months of 2007. The decline is severe but we should also point out that the estimated level in the last months has not gone beyond the low levels during the recession period in the first years of the 1990s.
We would like to investigate the recent decline in more detail and we question whether some statistical evidence can be given of the decline. The standard diagnostics are somewhat or partly helpful in this respect. In Figure 3 we present the standardized one-step ahead prediction errors (observation minus its forecast based on past observations only). The standardized residuals remain strictly within their 95% confidence interval and are therefore not significantly different from zero. However, 9 out of 12 forecast errors are negative. The negative bias of this set of residuals is more clearly observed from the cumulative sum of the residuals in the second panel of Figure 3, with a 95% confidence interval. We may conclude that at the end of 2008 the yearly level has significantly been subject to a structural break. We verify this by presenting the last 16 auxiliary residuals for the level innovation in the last panel of Figure 3. They can be interpreted as the t-test statistic for a level break at its corresponding time-point. It is confirmed that all potential level breaks in 2008 are negative but that a specific month cannot be associated with a clear significant level break. It is therefore not evident whether a level break in 2008 should be introduced and, if yes, nevertheless, at what time point the break should start to take effect.

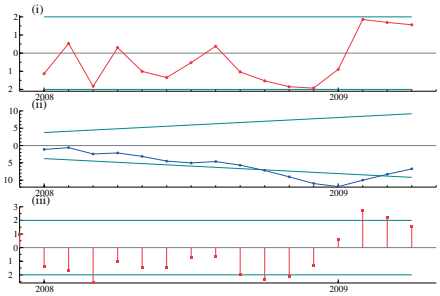


Figure 3: Some diagnostic plots for our analysis of the new passenger car registrations in the Eurozone for the last 16 observations (2008M1–2009M4): (i) standardized one-step ahead prediction errors; (ii) the cumulative sum of residuals; (iii) t-test statistic for a level break at each particular time point.

3.3 Forecasting

From a forecasting point of view, the impact of the financial crisis can be presented in a clear and transparent way. The new car registrations in the period 2000–2007 is a rather stable time series. To illustrate this, we have estimated the parameters of the basic model using the observations up to December 2005. We then forecast the 12 monthly observations in 2006. The realizations together with their forecasts are presented in the upper panel of Figure 4. The 68% confidence band for the multi-step forecasts is sufficient to keep almost all realizations within their forecasts certainty levels. When we repeat this for other windows, a similar picture is obtained. However, a very different picture emerges when we repeat this exercise by estimating the parameters using the observations up to December 2007 and then forecast the remaining 16 observations in the period 2008M1 – 2009M4. The forecasts and the realizations in the lower panel of Figure 4 clearly illustrate the depth of the crisis for the car industry and its challenges for the months ahead.

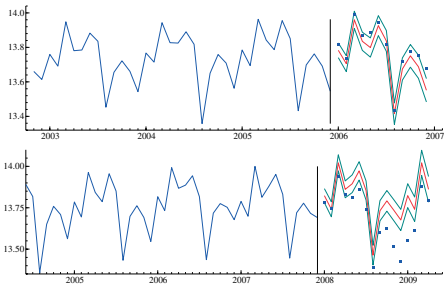


Figure 4: Forecasts of new passenger car registrations in the Eurozone for 2006 (upper panel) and for the period 2008M1 – 2009M4 (lower panel).

4. Estimating parameters in state space models using SsfPack™ 3

by Siem Jan Koopman

4.1 Introduction

Estimation for the linear Gaussian state space model usually relates to the state vector (linear in the observations) and to some vector of parameters (usually nonlinear in the observations). Explicit (or analytical) expressions for the optimal estimates of the state vector exist and are known as the Kalman filter and smoother. These computationally efficient recursions are implemented in SsfPack™, see Koopman, Shephard and Doornik (2008). Together with related functions for Kalman filtering and smoothing, SsfPack also includes more intricate functions that can be useful for a state space analysis. In case of estimating parameters of the state space model, other than those inside the state vector, we usually rely on the numerical maximization of the loglikelihood function. Given specific values for the parameter vector, the function *SsfLikEx()* implemented in SsfPack™ 3 computes the exact loglikelihood function in a computationally efficient and numerical stable manner. The maximization of the loglikelihood function is then carried out using one of the optimization function of Ox such as *MaxBFGS(), MaxSimplex()* and *MaxSQP()*. For most purposes of practical interest in state space analysis, using MaxBFGS() suffices. It has proven to work well, even for some complex and large dimensional models in state space. However, in some occasions we do encounter problems of a practical nature. An illustration of such a problem is discussed below.

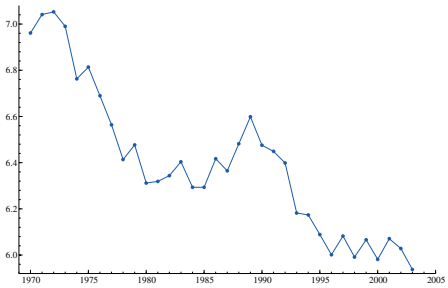


Figure1: Yearly number of fatalities in road accidents in Finland, 1970 – 2003.

4.2 Local linear trend model

In Figure 1 the time series of the yearly number of road traffic fatalities in Finland from 1970 to 2003 is displayed. In Commandeur and Koopman (2007), we analyze this series by means of the celebrated local linear trend model that decomposes a time series y_t into a trend component μ_t and an irregular noise component ε_t with the trend component being a random walk process with drift or slope β_t that also varies over time as a random walk process. In more formal terms, the model is given by

$$y_t = \mu_t + \varepsilon_t, \quad \mu_{t+1} = \mu_t + \beta_t + \eta_t, \quad \beta_{t+1} = \beta_t + \zeta_t,$$

for $t = 1,\ldots,n$, where the disturbances ε_t, η_t and ζ_t are mutually and serially uncorrelated disturbances, and are normally distributed with mean zero and variance $\sigma_\varepsilon^2, \sigma_\eta^2$ and σ_ζ^2, respectively. The time-varying trend and slope components, μ_t and β_t, can be extracted from the observations (or estimated) using the Kalman filter and smoother as implemented by SsfPack™. The estimation of the variances $\sigma_\varepsilon^2, \sigma_\eta^2$ and σ_ζ^2 takes place as described in the Introduction. Since *MaxBFGS()* yields unrestricted parameter estimates, we estimate the log-variances rather than the variances themselves (the non-negative restriction).

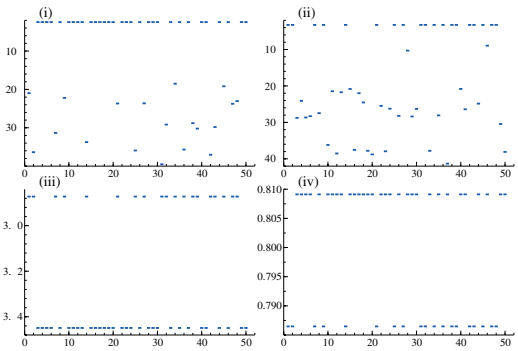


Figure 2: Fifty maximum likelihood estimates of the three log-variances of the local linear trend model applied to the time series displayed in Figure 1 and obtained by choosing initial parameter values randomly 50 times: (i) log σ_η^2, (ii) log σ_ζ^2, (iii) log σ_ε^2; panel (iv) displays the maximized loglikelihood values for these estimates.

4.3 Parameter estimation

In a numerical optimization method, estimation starts with a set of initial values for the parameters. Sometimes, depending on the shape of the likelihood function, the optimization can lead to different estimates when different initial values are used. A nice illustration of this problem is given for the estimation of the three log-variances in the local linear trend model when applied to the time series presented in Figure 1. We randomly choose 50 different sets of initial values for the estimation of the log-variances. The resulting 50 maximum likelihood estimates of the three variances are graphically displayed in Figure 2. The fourth panel of this figure displays the maximized loglikelihood values for these 50 estimation trials. The picture emerges that in most cases the (supposedly) maximized value of the loglikelihood function is found at 0.8091. In this case, the maximum likelihood estimate of σ_ζ^2 is effectively zero since its log-variance is estimated in most cases below the value of -20. It implies that the trend component in the local linear trend model reduces to a random walk with (fixed) drift process ($\beta_t = \beta_1$ is fixed for all t). However, in a substantive number of cases, the loglikelihood function is maximized at the local optimum value of 0.7865. In this case the model is a so-called smooth trend model where the variance of the level innovation, σ_η^2, is estimated as zero (effectively, since all these estimated log-variances are below -20). We can conclude that the estimation process may find it hard to choose between these two special cases of the local linear trend model for this particular data set. However, it is also interesting to conclude that on the basis of this simple exercise, we are able to detect such multi-modality problems quite easily. This illustration may be used as a benchmark to determine whether other estimation strategies converge to the global optimum. The Ox/SsfPack code is available upon request or check http://www.ssfpack.com.

References

Koopman, S.J., N., Shephard, J.A., Doornik, 2008. Statistical Algorithms for Models in State Space Form: SsfPack 3.0. London: Timberlake Consultants Ltd.

Commandeur, J.J.F., S.J., Koopman, 2007. An introduction to state space time series analysis. Oxford: Oxford University Press.

5. Other modules of OxMetrics™

5.1 SsfPack™

SsfPack™ is a suite of C routines for carrying out computations involving the statistical analysis of univariate and multivariate models in state space form. It requires Ox 4 or above to run. SsfPack™ allows for a full range of different state space forms: from a simple time-invariant model to a complicated multivariate time-varying model. Functions are provided to put standard models such as ARIMA, unobserved components, regressions and cubic spline models into state space form. Basic functions are available for filtering, moment smoothing and simulation smoothing. SsfPack can be easily used for implementing, fitting and analysing Gaussian models relevant to many areas of econometrics and statistics. Furthermore it provides all relevant tools for the treatment of non-Gaussian and nonlinear state space models. In particular, tools are available to implement simulation based estimation methods such as importance sampling and Markov chain Monte Carlo (MCMC) methods.

5.2 DCM™ v2.0 - An Ox Package for Estimating Demand Systems of Discrete Choice in Economics and Marketing

by Melvyn Weeks

DCM™ v2.0 (Discrete Choice Models) is a package, written in Ox, for estimating a class of discrete choice models. DCM represents an important development for both the OxMetrics and, more generally, microeconometric computing environment in making available a broad range of discrete choice models, including standard binary response models, with notable extensions including conditional mixed logit, mixed probit, multinomial probit, and random coefficient ordered choice models. Developed as a derived class of ModelBase, users may access the functions within DCM by either writing Ox programs which create and use an object of the DCM class, or use the program in an interactive fashion. New developments in v2.0 include a contraction mapping that facilitates the estimation of highly disaggregate models over a choice set with thousands of choices. Endogeneity of attributes is handled via an inversion procedure that casts the endogeneity problem within a linear model.

5.2.1 Two Flavours of DCM

With the release of DCM v2.0 there are now two flavours of DCM. The differences depend upon the nature of the observed data.

Class of Models C_1

We let C_1 represent a class of discrete choice models that are typically used in situations where there are no alternative-specific attributes. In this instance a generic specification might be written as:

$$U_{ij} = \alpha_j + \mathbf{x}_i' \beta_j + \varepsilon_{ij}, \qquad j \in \Omega_J$$

where U_{ij} denotes the utility of the ith individual for the jth alternative; Ω_J denotes the choice set. α_j denotes *mean utility*, and ε_{ij} is an iid error term. $\mathbf{x}_i$ is a $k \times 1$ vector of observed individual characteristics. Examples of these type of models include binomial and multinomial (logit and probit) models of occupational choice.

Class of Models C_2

We consider C_2 as representing a class of discrete choice models that are typically used in situations where there exists a combination of alternative-specific attributes and either observed and/or unobserved individual characteristics. In this instance a generic specification might be written as:

$$U_{ij} = \mathbf{v}_j' \omega + \xi_j + H_{ij}(\mathbf{t}_i, \mathbf{v}_j) + \varepsilon_{ij} \qquad (1)$$

where $H(\mathbf{t}_i, \mathbf{v}_j)$ denotes an individual-specific deviation from the mean utility, $\mathbf{t}_i$ denotes a vector of observed and unobserved individual characteristics, and $\mathbf{v}_j$ denotes an $L \times 1$ vector of observed attributes for the jth alternative. Mean utility is given by $\alpha_j = \mathbf{v}_j \omega + \xi_j$. Observed mean utility is given by $\mathbf{v}_j \omega$, and ξ_j denotes a composite unobserved alternative-specific attribute.
In DCM v2 the use of a contraction mapping facilitates greater differentiation over alternatives, and as a result it is possible to estimate advanced discrete choice models with hundreds, and in some cases thousands of alternatives. These type of models have been used in empirical industrial organisations. A large choice set may allow us to isolate and deal with endogeneity stemming from the covariance between observed and unobserved product attributes. In many instances these models are much more structural as they are derived from the profit maximisation decisions of oligopolistic firms with Bertrand-Nash prices.

5.2.2 Models of Differentiated Demand Systems

Over the last ten years what has been coined the new empirical industrial organization literature has made significant contributions to our understanding of markets. This literature, which synthesises microeconomic theory, marketing and recent advances in econometric inference, has enabled academics, consultants and policy makers to evaluate a large number of interesting issues such as:

1. the measurement of market power
2. eliciting consumer preferences for differentiated products
3. the impact of new, yet to be introduced, products
4. determine the impact of a tax on product demand
5. the impact of a merger on prices

In building models that are capable of addressing these type of issues, the demand system is an integral component. The principal characteristic of these demand systems is that for a large number of cases the assumption that consumers purchase at most one unit of a given product is consistent with observed behaviour. In this respect, the type of products we have in mind are consumer durables, such as motor vehicles. As a consequence we see that the specification of many demand systems over differentiated products involves the modelling of a discrete choice over a well-defined choice set. Using DCM v2.0 analysts have at their disposal a set of tools enabling estimation of demand systems over differentiated products, when demand is manifest as a discrete choice.

5.2.3 Model Specification

In briefly demonstrating a number of the features of DCMv2.0 a convenient point of departure is the benchmark model

$$U_{ij} = \sum_l^L v_{jl}\omega_l - p_j\omega_p + \xi_j + \varepsilon_{ij} \qquad (2)$$

where v_{jl} denotes the lth attribute for the jth alternative, p_j denotes price, ξ_j represents an unobserved attribute, and $\omega = \{\omega_l\}$ denotes a vector of unknown parameters. (2) is additive in attributes and i.i.d consumer preferences. Assuming that the error terms ε_{ij} are distributed independently and identically across both individuals and alternatives type 1 extreme value, we have the benchmark logit model.
Subsequent models introduced below allow interactions between attributes of alternatives and characteristics of individuals either through observed or unobserved.

Mixed Logit

The mixed logit model is a central feature of DCM v2.0 and can incorporate taste heterogeneity due to observed and unobserved characteristics in a relatively parsimonious fashion. In cases where observed demographics are available but perhaps limited, then a general model may be written as:

$$U_{ij} = \sum_l^L v_{jl}\omega_l - p_j\omega_p + \xi_j + \sum_l^L v_{jl}\omega_{i,l}^u - p_j\omega_{i,p}^u + \sum_l^L v_{jl}\omega_{i,l}^o - p_j\omega_{i,p}^o + \varepsilon_{ij} \qquad (3)$$

(3) incorporates both observed and unobserved preferences, the latter facilitated by a parametric distribution over the preferences for one or more product attributes. Using (3) it is instructive to decompose the utility into the following components.

- **Mean Utility** A weighted average of taste weights that are invariant across individuals, $\sum_l^L v_{jl}\omega_l - p_j\omega_p$ plus an unobserved attribute ξ_j
- **Deviation from Mean in Observed Characteristics** Deviation from mean preferences captured by observed demographics is denoted by $\sum_l^L v_{jl}\omega_{i,l}^o - p_j\omega_{i,p}^o$. $\omega_{i,l}^o = \sum_k x_{i,k}\omega_{lk}$, the taste weight for the ith individual for the lth attribute.
- **Deviation from Mean in Unobserved Characteristics** Deviation from mean preferences captured by unobserved demographics - $\sum_l^L v_{jl}\omega_{i,l}^u - p_j\omega_{i,p}^u$
- **Deviation from Mean in an i.i.d error term** Deviation from mean preferences captured by ε_{ij}

DCM v2.0 has a large number of options that enable the user to model choice behaviour over a large choice set, allowing for the influence of observed and unobserved characteristics, and the capabilities to address the endogeneity problem which may arise due to unobserved attributes.

5.3 TSP/OxMetrics™

TSP™ is an econometric software package with convenient input of commands and data, all the standard estimation methods (including non-linear), forecasting, and a flexible language for programming your own estimators. TSP is available as an add-on to OxMetrics™. TSP and TSP/OxMetrics™ offers a wide variety of facilities, such as: single-equation estimation (using a variety of techniques), non-linear 3SLS, GMM and FIML, time series methods (Box-Jenkins, Kalman-filter estimation, vector autoregressive models, etc.), financial econometrics (ARCH, GARCH, GARCH-M, including logarithmic versions), general maximum likelihood, qualitative dependent variable estimation, and panel data estimation. Extensive libraries of TSP procedures are available free of charge.

5.3.1 New Features in TSP/OxMetrics™ 5.1

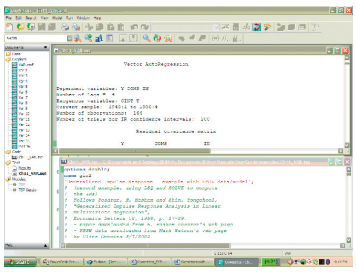
by Bronwyn Hall

In addition to the OxMetrics™ interface, a number of enhancements have been made to this release of TSP, which we describe here. The major and minor enhancements to various procedures are listed here:

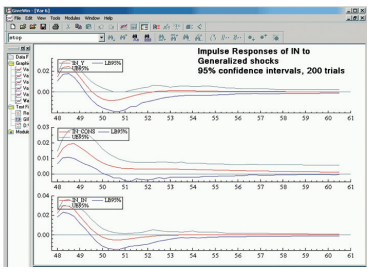
- VAR - Generalized Impulse Response and improved plotting
- LSQ, ML, and PROBIT – Panel-robust (clustered) standard errors
- ANALYZ for functions of series, improved output and options
- LP – new linear programming procedure
- SORT – speed enhancements
- LAD and LMS - enhanced iteration, looking for multiple solutions
- LIML – added the log likelihood (used for testing)
- FORM – ability to create unnormalized equations
- New stepsize option for nonlinear procedures, improving iteration behavior.
- GRAPH – circle plots (where importance of each point is shown) added

There are also a number of general enhancements: greatly improved Excel spreadsheet reading with more versions and multiple sheets, reading of Stata.dta files up to Version 10, ability to label matrices rows and columns when they are printed, more informative output from SHOW SERIES, and more efficient long programs with loops.

Sample screens for VAR regression of income on consumption in TSP/OxMetrics™



OxMetrics screen with VAR input and output



Example of Generalized Impulse Response Function

Further information about TSP is available at www.tspintl.com. The new version of TSP/OxMetrics™ 5.1 can be ordered from Timberlake Consultants.

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6. Timberlake Consultants Technical Support

Timberlake Consultants offers technical support for the OxMetrics software. We are pleased to announce a new addition to the technical support team, namely George Bagdatoglou. George holds a PhD in Economics and has 10 years experience in econometrics in academic research and industry. He is expected to address both software-specific (i.e. Stata, EViews, OxMetrics, etc) and general econometric questions (i.e. "what is cointegration analysis", "why one should apply Instrumental Variables estimation", "what is the general-to-specific approach", etc). Timberlake Consultants welcome you to submit your questions at: support@timberlake.co.uk

7. Timberlake Consultants - Consultancy and Training

Timberlake Consultants Limited has a strong team of consultants to provide training (public attendance or onsite) and consultancy projects requiring the OxMetrics software. The main language used in the courses is English. However, we can also provide some of the courses in other languages, **e.g. French, Dutch, Italian, German, Spanish, Portuguese, Polish and Japanese.**

We organise, regularly, public attendance courses in London (UK) and the East and West cost of the USA. Details on dates are found on **http://www.timberlake.co.uk**. We also offer tailored on site training courses. The most popular courses are described below:

Unobserved Components Time Series Analysis using OxMetrics and X12ARIMA (3-day course). The course aims to provide participants with background on Structural Time Series Models and the Kalman filter and demonstrate, using real-life business and industrial data, how to interpret and report the results using the STAMP™ and SsfPack™ software. The course is not restricted to STAMP users. Developers of other packages (e.g. EViews, S-Plus) have followed the work done by the developers of STAMP and SsfPack when implementing this type of models.

Financial and Econometric Modelling Using OxMetrics (3-day course). The course aims to provide delegates with background on econometric modelling methods and demonstrate, using financial data, how to interpret and report the results. Several modules of OxMetrics are used during this course.

Programming with Ox (2-day course). Object-oriented programming has turned out to be very useful also for econometric and statistical applications. Many Ox packages are successfully built on top of the pre-programmed classes for model estimation and simulation. During the first day, the relevant aspects of object-oriented programming, leading up to the ability to develop new classes. The second day focuses on extending Ox using dynamic link libraries, and developing user-friendly applications with Ox.

Modelling and Forecasting Volatility with GARCH models - from Theory to Practice (3-day course). This course aims to provide delegates with background on and when to model Volatility, using financial data. The software G@RCH - will be used through the course to demonstrate the practical issues of Volatility modeling and to interpret GARCH models.

8. Timberlake Consultancy Bookshop - New books

The Methodology and Practice of Econometrics: A Festschrift in Honour of David F. Hendry (edited by Jennifer L. Castle and Neil Shephard)

The Methodology and Practice of Econometrics collects a series of essays to celebrate the work of David Hendry: one of the most influential of all modern econometricians.
Hendry's writing has covered many areas of modern econometrics, which brings together insights from economic theory, past empirical evidence, the power of modern computing, and rigorous statistical theory to try to build useful empirically appealing models. This book is a collection of original research in time-series econometrics, both theoretical and applied, and reflects Hendry's interests in econometric methodology. Many internationally renowned econometricians who have collaborated with Hendry or have been influenced by his research have contributed to this volume, which provides a reflection on the recent advances in econometrics and considers the future progress for the methodology of econometrics. The volume is broadly divided into five sections, including model selection, correlations, forecasting, methodology, and empirical applications, although the boundaries are certainly opaque. Central themes of the book include dynamic modelling and the properties of time series data, model selection and model evaluation, forecasting, policy analysis, exogeneity and causality, and encompassing. The contributions cover the full breadth of time series econometrics but all with the overarching theme of congruent econometric modelling using the coherent and comprehensive methodology that Hendry has pioneered. The volume assimilates original scholarly work at the frontier of academic research, encapsulating the current thinking in modern day econometrics and reflecting the intellectual impact that Hendry has had, and will continue to have, on the profession.

David Hendry was awarded a knighthood for `services to social science' in Her Majesty the Queen's 2009 Birthday Honours.

David Hendry is well known as one of the pioneers of an approach to econometric modelling associated with the London School of Economics, and his name is now almost synonymous with the general-to-specific *(Gets)* methodology, which has emerged as a leading approach in empirical econometrics. *Gets* postulates that empirical analysis should start with a general model that not only reflects the background economic theory and utilises the best available data, but also accounts for all the potential explanatory variables, possible structural breaks and non-linearities, as well as dynamic adjustments. In turn, iterative selection procedures should be used to reduce the initial very general formulation to a more parsimonious representation, developed with rigorous evaluation. ``The three golden rules of econometrics are test, test and test'' has been a consistent theme.
Hendry has numerous publications in leading economics and econometrics journals, and has published several books in applied econometrics, including *Dynamic Econometrics*, and *Econometrics: Alchemy or Science*. Together with Jurgen Doornik they have developed advanced versions of PcGive to improve and facilitate practical econometric modelling, incorporating Autometrics, an automatic model selection procedure.
Currently, Hendry is Professor of Economics at the University of Oxford, and a Fellow of Nuffield College. His current research focuses on empirical modelling, forecasting and automatic model selection. These methods have also been widely applied outside of economics in such diverse areas as epidemiology, political science, and climatology, as well as by many Central Banks, regulatory institutions and policy making agencies.

8. Timberlake Consultancy Bookshop - New books
(continued)

An Introduction to State Space Time Series Analysis
by Jacques J.F. Commandeur and Siem Jan Koopman

Providing a practical introduction to state space methods as applied to unobserved components time series models, also known as structural time series models, this book introduces time series analysis using state space methodology to readers who are neither familiar with time series analysis, nor with state space methods. The only background required in order to understand the material presented in the is a basic knowledge of classical linear regression models, of book which brief review is provided to refresh the reader's knowledge. Also, a few sections assume familiarity with matrix algebra, however, these sections may be skipped without losing the flow of the exposition. The book offers a step by step approach to the analysis of the salient features in time series such as the trend, seasonal, and irregular components. Practical problems such as forecasting and missing values are treated in some detail. This useful book will appeal to practitioners and researchers who use time series on a daily basis in areas such as the social sciences, quantitative history, biology and medicine. It also serves as an accompanying textbook for a basic time series course in econometrics and statistics, typically at an advanced undergraduate level or graduate level.

9. Conferences

Visit our stand at

- **European Economic Association Annual Meeting** (EEA), **August 23-27, 2009**, Barcelona, Spain
- **Polish Econometric Society Meeting**, **September 8-10, 2009**, Torun, Poland
- **Latin American & Caribbean Meetings Econometric Society (LAMES)**, **October 1-3, 2009**, Buenos Aires, Argentina
- **International Conference on Computational and Financial Econometrics (CFE)**, **October 29-31, 2009**, Limassol, Cyprus
- **Factor Models in Economics and Finance**, **December 4-5**, 2009, London, UK
- **American Economic Association (AEA) Annual Meeting**, **January 3-5, 2010**, Atlanta, GA, USA
- **History of Econometrics** (Hope conference, Duke University Press), **April 23-25, 2010**, Duke University, USA
- **Joint Statistical Meetings** (JSM), **July 31 -August 6, 2010**, Vancouver, BC, Canada

10. 7th OxMetrics User Conference

7th OxMetrics User Conference
14 – 15 September 2009
Cass Business School

The conference will provide a forum for the presentation and exchange of research results and practical experiences within the fields of computational and financial econometrics, empirical economics, time-series and cross-section statistics and applied mathematics. The conference programme will feature keynote presentations, technical paper sessions, workshops, tutorials and panel discussions. Some of the OxMetrics' developers (Jurgen A. Doornik, Andrew Harvey, David F. Hendry, Siem J. Koopman and Sébastien Laurent) will be present as keynote speakers. Please see below for the list of papers. There will also be a **round table discussion with OxMetrics™ developers** for participants to put their comments to the development team and suggest improvements.
The conference is open to all those interested in econometrics, not just to OxMetrics™ users, from academic and non-academic organisations.

List of Papers

- DCM 2.0: An Ox Package for Estimating Demand Systems of Discrete Choice in Economics and Marketing (by M. Eklof and **M. Weeks**)
- A Robust Version of the KPSS Test Based on Ranks (by **M. Pelagatti** and P. Sen)
- Forecasting, Model Averaging and Model Selection (by **J. Reade**)
- Dynamic Factor Analysis by Maximum Likelihood (by B. Jungbacker, **S. Koopman** and M. Wel)
- A Combined Approach of Experts and Autometrics to Forecast Daily Electricity Consumption: An Application to Spanish Data (by J. Cancelo, A. Espasa and **J. Doornik**)
- Predicting Realized Volatility for Electricity Prices Using Unobservable Component Models (by E. Haugom, S. Westgaard and **G. Lien**)
- A Note on Jumps and Price Discovery in the US Treasury Market (by **A. Dumitri**)
- Quality Improvement Estimates through Export Unit Values (by **C. Pappalardo**)
- True vs. Spurious Long Memory (by A. Leccadito, O. Rachedi and **G. Urga**)
- Cointegration versus Spurious Regression and Heterogeneity in Large Panels (by **L. Trapani**)
- A Low-Dimension, Portmanteau Test for Non-linearity (by J. Castle and **D. Hendry**, forthcoming, Journal of Econometrics)
- Local kernel Density Estimation from Time Series Data (by A. Harvey and **V. Oryshchenko**)
- Robust Estimation of CCC and DCC GARCH models (by K. Boudt, J. Danielsson and **S. Laurent**)
- Testing the Invariance of Expectations Models of Inflation (by J. Castle, J. Doornik, **D. Hendry** and R. Nymoen)
- Model Selection when there are Multiple Breaks (by **J. Castle**, J. Doornik and D. Hendry)
- Dynamic Econometric Models and Errors in Variables (by **A. Harvey**)

Please visit www.timberlake.co.uk for the full programme (available at the end of July 2009)