Dynamic Models for Volatility and Heavy Tails

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This set of lectures will describe a class of nonlinear time series models known as dynamic conditional score (DCS) models. The models are designed to extract a dynamic signal from noisy observations. The signal may be the level of a series or it may be a measure of scale. Changing scale is of considerable importance in financial time series where volatility clustering is an established stylized fact. Generalized autoregressive conditional heteroscedasticity (GARCH) models are widely used to extract the current variance of a series. However, using variance (or rather standard deviation) as a measure of scale may not be appropriate for non-Gaussian (conditional) distributions. This is of some importance, since another established feature of financial returns is that they are characterized by heavy tails.

The dynamic equations in GARCH models are filters. Just as the filters for linear Gaussian level models are linear combinations of past observations, so GARCH filters, because of their Gaussian origins, are usually linear combinations of past squared observations. The models described here replace the observations or their squares by the score of the conditional distribution. When modeling scale, an exponential link function is employed, as in exponential GARCH (EGARCH), thereby ensuring that the filtered scale remains positive. The unifying feature of the models in the proposed class is that the asymptotic distribution of the maximum likelihood estimators is established by a single theorem which delivers an explicit analytic expression for the asymptotic covariance matrix of the estimators. The conditions under which the asymptotics go through are relatively straightforward to verify. There is no such general theory for GARCH models.

Other properties of the proposed models may be found. These include analytic expressions for moments, autocorrelation functions and multi-step forecasts. The properties, particularly for the volatility models, which employ an exponential link function, are more general than is usually the case. For example, expressions for unconditional moments, autocorrelations and the conditional moments of multi-step predictive distributions can be found for absolute values of the observations raised to any power.

The generality of the approach is further illustrated by consideration of dynamic models for non-negative variables. Such models have been used for modeling durations, range and realized volatility in finance. Again the use of an exponential link function combined with a dynamic equation driven by the conditional score gives a range of analytic results similar to those obtained with the new class of EGARCH models.

The course is organized as follows.

1) Introduction. Statistical distributions and maximum likelihood. Dynamic location models.

2) Beta-t-EGARCH models. Location/scale models for non-negative variables.

3) Multivariate models. Future directions.

* The lectures are based on a forthcoming Econometric Society monograph, to be published by Cambridge University Press.

See

http://www.cambridge.org/gb/knowledge/isbn/item7091594/?site_locale=en_GB

For Table of contents and Chapter 1, see

http://www.econ.cam.ac.uk/faculty/harvey/Pages-from-AHbook.pdf

* It will be assumed that those attending have a basic knowledge of time series analysis and/or financial econometrics.*

Background reading:

Harvey, A. C., *Time Series Models,* 2nd Edition, Harvester Wheatsheaf, 1993.

Mills, T. and R.N. Markellos, *The Econometric Modelling of Financial Time Series,* 3rd ed. Cambridge University Press, 2008

Taylor, S. *Asset Price Dynamics, Volatility, and Prediction.* Princeton University Press, 2005.

Also

Andersen, T.G., Bollerslev, T., Christoffersen, P.F. and F.X. Diebold. Volatility and correlation forecasting. *Handbook of Economic Forecasting*, edited by G Elliot, C Granger and A Timmermann, 777-878. North Holland, 2006.

Andersen, T.G., Davis, R.A., Kreiß, J-P. and T. Mikosch (2009). *Handbook of Financial Time Series.* Springer, 2009.

Durbin, J. and S.J. Koopman, *Time Series Analysis by State Space Methods, 2nd ed.* Oxford University Press, Oxford, 2012.

Harvey, A. C., *Forecasting, Structural Time Series Models and the Kalman Filter*, Cambridge University Press, 1989

Harvey, A.C., Forecasting with Unobserved Components Time Series Models*, Handbook of Economic Forecasting,* North Holland, 2006.

Koopman, S. J. Harvey, A. C., Doornik, J. A. and N. Shephard (2009). *STAMP 8.2 Structural Time Series Analysis Modeller and Predictor.* London: Timberlake Consultants Ltd.

Working papers

Andres, P. and A.C. Harvey (2012). The dynamic location/scale model. Cambridge Working paper in Economics, CWPE 1240

Harvey, A. C. and G. Sucarrat (2012). EGARCH Models with Fat Tails, Skewness and Leverage. Cambridge Working paper in Economics, CWPE 1236.

http://www.econ.cam.ac.uk/research/econpapers.html?ep=pha279

Computer programs

The menu-driven programs listed below are available or in the process of being developed at the time of writing. All run in Oxmetrics and are available from Timberlake consultants; see www.timberlake.co.uk/software/?id=64.

i) STAMP estimates linear Gaussian structural time series models; see Koopman *et al* (2009).

See http://www.stamp-software.com

ii) G@RCH estimates a wide range of GARCH models, including Beta-t-EGARCH; see Laurent (2009).

iii) DySco - Dynamic generalized gamma and beta estimation; see Andres and Harvey (2012).

In addition an R-program for Beta-t-EGARCH, including skew-t, is available on the website in Sucarrat (2012).

Sucarrat, G. (2012). betategarch: Estimation and simulation of the first-order Beta-t-EGARCH model. R package version 1.2. http://cran.r-project.org/web/packages/betategarch/