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Research Article

Falling and explosive, dormant, and rising markets via multiple-regime financial time series models

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Abstract

A multiple-regime threshold nonlinear financial time series model, with a fat-tailed error distribution, is discussed and Bayesian estimation and inference are considered. Furthermore, approximate Bayesian posterior model comparison among competing models with different numbers of regimes is considered which is effectively a test for the number of required regimes. An adaptive Markov chain Monte Carlo (MCMC) sampling scheme is designed, while importance sampling is employed to estimate Bayesian residuals for model diagnostic testing. Our modeling framework provides a parsimonious representation of well-known stylized features of financial time series and facilitates statistical inference in the presence of high or explosive persistence and dynamic conditional volatility. We focus on the three-regime case where the main feature of the model is to capturing of mean and volatility asymmetries in financial markets, while allowing an explosive volatility regime. A simulation study highlights the properties of our MCMC estimators and the accuracy and favourable performance as a model selection tool, compared with a deviance criterion, of the posterior model probability approximation method. An empirical study of eight international oil and gas markets provides strong support for the three-regime model over its competitors, in most markets, in terms of model posterior probability and in showing three distinct regime behaviours: falling/explosive, dormant and rising markets.

REFERENCES

1 Engle RF. Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica* 1982; **50**: 987–1008.

Web of Science® Google Scholar

2 Bollerslev T. Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics* 1986; **31**: 307–327.

Web of Science® | Google Scholar

3 Nelson DB. Conditional heteroscedasticity in asset returns: a new approach. *Econometrica* 1991; **59**: 347–370.

Web of Science® | Google Scholar

4 Glosten LR, Jagannathan R, Runkle DE. On the relation between the expected value and the volatility of the nominal excess return on stocks. *Journal of Finance* 1993; **48**: 1779–1801.

Web of Science® | Google Scholar

5 Clements MP, Franses PH, Swanson NR. Forecasting economic and financial time-series with non-linear models. *International Journal of Forecasting* 2004; **20**: 169–183.

Web of Science® | Google Scholar

6 Li WK, Lam K. Modelling asymmetry in stock returns by a threshold ARCH model. *The Statistician* 1995; **44**: 333–341.

Web of Science® | Google Scholar

7 Tong H. On a threshold model. In *Pattern Recognition and Signal Processing*, CH Chen (ed.). Sijhoff and Noordhoff: Amsterdam, 1978.

Google Scholar

8 Li CW, Li WK. On a double-threshold autoregressive heteroscedastic time series model. *Journal of Applied Econometrics* 1996; **11**: 253–274.

Web of Science® | Google Scholar

9 Brooks C. A double-threshold GARCH model for the French Franc/Deutschmark exchange rate. *Journal of Forecasting* 2001; **20**: 135–143.

Web of Science® | Google Scholar

10 Chen CWS, Chiang TC, So MKP. Asymmetrical reaction to US stock-return news: evidence from major stock markets based on a double-threshold model. *Journal of Economics and Business* 2003; **55**: 487–502.

Web of Science® | Google Scholar

Web of Science® | Google Scholar

11 Brooks C, Garrett I. Can we explain the dynamics of the UK FTSE 100 stock and stock index futures markets. *Applied Financial Economics* 2002; **12**: 25–31.

Google Scholar

12 Boeroa G, Marrocu E. The performance of SETAR models: a regime conditional evaluation of point, interval and density forecasts. *International Journal of Forecasting* 2004; **20**: 305–320.

Web of Science® | Google Scholar

13 Tong H. In *Threshold Models in Non-linear Time Series Analysis*, K Krickegerg (ed.). Lecture Notes in Statistics, vol. 21. Springer: New York, 1983.

Google Scholar

14 Giordani P, Kohn R, van Dijk D. A unified approach to nonlinearity, structural change, and outliers. *Journal of Econometrics* 2007; **137**: 112–133.

Web of Science® | Google Scholar

15 Bauwens L, Lubrano M, Richard JF. *Bayesian Inference in Dynamic Econometric Models*. Oxford University Press: Oxford, 1999.

Google Scholar

16 Bauwens L, Lubrano M. Bayesian inference on GARCH models using the Gibbs sampler. *The Econometrics Journal* 1998; **1**: 23–46.

Google Scholar

17 Vrontos D, Dellaportas P, Politis DN. Full Bayesian inference for GARCH and EGARCH models. *Journal of Business and Economics Statistics* 2000; **18**: 187–198.

Web of Science® | Google Scholar

18 Medeiros MC, Veiga A. Modeling multiple regimes in financial volatility with a flexible coefficient GARCH model. *Textos Para Discussão No. 486*, Department of Economics, PUC-Rio, Brazil, 2005.

Google Scholar

19 Gospodinov N. Testing for threshold nonlinearity in short-term interest rates. *Journal of Financial Econometrics* 2005; **38**: 344–371.

Google Scholar

20 Chen CWS, Gerlach RH, So MKP. Comparison of nonnested asymmetric heteroscedastic models. *Nonlinear Modelling and Financial Econometrics* 2006; **51**: 2164–2178. Computational Statistics and Data Analysis, a special issue.

Google Scholar

21 Green PJ. Reversible jump MCMC computation and Bayesian model determination. *Biometrika* 1995; **82**: 711–732.

Web of Science® | Google Scholar

22 Gerlach R, Tuyl F. MCMC methods for comparing stochastic volatility and GARCH models. *International Journal of Forecasting* 2006; **22**: 91–107.

Web of Science® | Google Scholar

23 Gerlach R, Carter CK, Kohn R. Diagnostics for time series analysis. *Journal of Time Series Analysis* 1999; **20**: 309–330.

Google Scholar

24 Chib S. Marginal likelihood from the Gibbs output. *Journal of the American Statistical Association* 1995; **90**: 1313–1321.

Web of Science® | Google Scholar

25 Chib S, Jeliazkov I. Marginal likelihood from the Metropolis–Hastings output. *Journal of the American Statistical Association* 2001; **96**: 270–281.

Web of Science® | Google Scholar

26 Kass RE, Raftery AE. Bayes factors. *Journal of the American Statistical Association* 1995; **90**: 773–795.

Web of Science® | Google Scholar

27 Berg A, Meyer R, Yu J. Deviance information criterion for comparing stochastic volatility models. *Journal of Business and Economic Statistics* 2004; **22**: 107–120.

Web of Science® | Google Scholar

28 Carlin BP, Chib S. Bayesian model choice via Markov chain Monte Carlo. *Journal of the Royal Statistical Society, Series B* 1995; **57**: 473–484.

Web of Science® | Google Scholar

29 Godsill SJ. On the relationship between Markov chain Monte Carlo methods for model uncertainty. *Journal of Computational and Graphical and Graphical Statistics* 2001; **10**: 1–19.

Google Scholar

30 Congdon P. Bayesian model choice based on Monte Carlo estimates of posterior model probabilities. *Computational Statistics and Data Analysis* 2006; **50**: 346–357.

Web of Science® | Google Scholar

31 Robert C, Marin JM. On some difficulties with a posterior probability approximation technique. *Bayesian Analysis Journal* 2008; **2**: 427–448. DOI: 10.1214/08-BA316.

Web of Science® | Google Scholar

32 So MKP, Lam K, Li WK. A stochastic volatility model with Markov switching. *Journal of Business and Economic Statistics* 1998; **16**: 244–253.

Web of Science® | Google Scholar

33 Wong CS, Li WK. On a mixture autoregressive conditional heteroscedastic model. *Journal of the American Statistical Association* 2001; **96**: 982–995.

Web of Science® | Google Scholar

34 Metropolis N, Rosenbluth AW, Rosenbluth MN, Teller E. Equations of state calculations by fast computing machines. *Journal of Chemical Physics* 1953; **21**: 1087–1091.

CAS | PubMed | Web of Science® | Google Scholar

35 Hastings WK. Monte-Carlo sampling methods using Markov chains and their applications. *Biometrika* 1970; **57**: 97–109.

Web of Science® | Google Scholar

36 Chib S, Greenberg E. Explaining the Metropolis–Hastings algorithm. *The American Statistician* 1995; **49**: 327–335.

Web of Science® | Google Scholar

37 Chen CWS, So MKP. On a threshold heteroskedastic model. *International Journal of Forecasting* 2006; **22**: 73–89.

Web of Science® | Google Scholar

38 Gelman A, Roberts G, Gilks W. Efficient Metropolis jumping rules. In *Bayesian Statistics 5*, JM Bernardo, JO Berger, AP Dawid, AFM Smith (eds). Oxford University Press: London, 1996.

Google Scholar

39 Spiegelhalter D, Best NG, Carlin BP, Van der Linde A. Bayesian measures of model complexity and fit (with discussion). *Journal of the Royal Statistical Society, Series B* 2002; **64**: 583–616.

Google Scholar

40 Congdon P. Model weights for model choice and averaging. *Statistical Methodology* 2007; **4**: 143–157.

Google Scholar

41 Smith JQ. Diagnostic checks of non-standard time series. *Journal of Forecasting* 1985; **4**: 283–291.

Web of Science® | Google Scholar

42 Geweke JF. Bayesian comparison of econometric models. Working Paper 532, Research Department, Federal Reserve Bank of Minneapolis, University of Minnesota, 1994.

Google Scholar

43 Engle RF, Ng VK. Measuring and testing the impact of news on volatility. *Journal of Financial Economics* 1993; **48**: 1749–1778.

Web of Science® | Google Scholar

44 Pagan AR, Schwert GW. Alternative models for conditional stock volatility. *Journal of Econometrics* 1990; **45**: 267–290.

Web of Science® | Google Scholar

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