

# 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. Copyright © 2009 John Wiley & Sons, Ltd.

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