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**Liang, Rubing and Xia, Qiang and Pan, Jiazhu and Liu, Jinshan (2015)
Testing a linear ARMA Model against threshold-ARMA models : A
Bayesian approach. Communications in Statistics - Simulation and
Computation. ISSN 0361-0918 ,
<http://dx.doi.org/10.1080/03610918.2014.1002616>**

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Testing a Linear ARMA Model against Threshold-ARMA Models: a Bayesian Approach

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Abstract. We introduce a Bayesian approach to test linear autoregressive moving-average (ARMA) models against threshold autoregressive moving-average (TARMA) models. Firstly, the marginal posterior densities of all parameters, including the threshold and delay, of a TARMA model are obtained by using Gibbs sampler with Metropolis-Hastings algorithm. Secondly, reversible-jump Markov chain Monte Carlo (RJMCMC) method is adopted to calculate the posterior probabilities for ARMA and TARMA models: Posterior evidence in favor of TARMA models indicates threshold nonlinearity. Finally, based on RJMCMC scheme and Akaike information criterion (AIC) or Bayesian information criterion (BIC), the procedure for modeling TARMA models is exploited. Simulation experiments and a real data example show that our method works well for distinguishing a ARMA from a TARMA model and for building TARMA models.

Mathematics Subject Classification (2010) : 62F10, 62F15

Key words: Bayesian inference; ARMA models; Gibbs sampler; Metropolis-Hastings algorithm; RJMCMC methods; AIC; BIC; TARMA models.

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1 Introduction

Threshold autoregressive (TAR) models have become a standard and popular class of nonlinear time series models to describe the asymmetric phenomena in many branches of science and social science. Since Tong (1978) and Tong and Lim (1980), a huge amount of literature on theoretical properties and statistical inference of TAR models has appeared, see Tong (1990) and Tsay (2005) among others. But complicated analytical works and numerical multiple integration is involved in statistical inference of TAR models by the likelihood approaches. To overcome the computing problem and to avoid analytical difficulty, some authors have applied Bayesian method to carry out parameter estimation for TAR models. McCulloch and Tsay (1993a, 1993b) proposed a Bayesian procedure for detecting threshold values in a TAR model via posterior probability plots. Chen and Lee (1995) applied the Gibbs sampler of Geman and Geman (1984), and the Metropolis-Hastings (M-H) algorithm of Metropolis et al. (1953) and Hastings (1970), for inference of TAR models. So and Chen (2003) developed an efficient way to select the best subset from threshold autoregressive models.

Some authors have realized that threshold moving average (TMA) models have their own advantages and are as important as TAR models in practice, see Ismail and Charif (2003) and Ling and Tong (2005) among others. Ismail and Charif (2003) introduced a Bayesian analysis for TMA models, and Ling and Tong (2005) proposed a likelihood ratio test for linear MA model against TMA models. Recently, Xia et al. (2010) gave Bayesian test for nonlinear of a TMA model.

However, in order to get a parsimonious model for asymmetrical high order dependence, some authors found that threshold autoregressive moving average (TARMA) should be used. For likelihood approach to statistical inference of TARMA models, analytical works and computation are even more complicated than those for TAR and TMA models. So Bayesian method has been used to do statistical analysis of TARMA models, see for instance Sáfadi and Morettin (2000), Chen,

Liu and Gerlach (2011), and Xia et al. (2012). Chen et al. (2011) developed an efficient way to select a subset from a general family of TARMA models, but they did not give any discussion about the threshold nonlinear test. Meanwhile, fundamental theory about TARMA models, such as identifying the threshold and delay values, estimating the parameters, and testing the threshold nonlinearity, needs to be developed further.

The aim of this paper is to propose a Bayesian test for the threshold nonlinearity of TARMA models. Firstly, Bayesian estimation of the threshold value and other parameters of TARMA models is investigated. Chen and Lee (1995) and Sáfadi and Morettin (2000) adopted the MCMC technique and used the arranged autoregression approach to estimate the threshold and delay values as well as the coefficients simultaneously. Basing on their work, we combine Gibbs sampler and Metropolis-Hastings algorithm to give a Bayesian analysis of two-regime TARMA models. We do not need to employ the arranged autoregression. Secondly, to avoid analytical difficulty and complicated computation, Xia et al. (2010) applied the RJMCMC method (Green, 1995) for testing TMA models, but they only constructed kernels by not including the variance parameter. We know that the variance parameter, especially different variance in each regime, is a very important characteristic for the TARMA models to be identified. Thus, we add the variance parameter into the kernels by using the reversible-jump MCMC method for testing TARMA models. It is demonstrated that the reversible-jump method is easy to implement and fits well within our framework of Bayesian procedure. Finally, since the order of each regime is also important to TARMA models, we will try to combine the reversible-jump MCMC method and AIC or BIC to determine whether the threshold nonlinearity is significant.

The context of this paper is arranged as follows. The TARMA models and the methodology of Bayesian inference are presented in Section 2. Section 3 gives details of a Bayesian model selection procedure by RJMCMC method. Section 4 exploits the procedure for modeling TARMA models briefly. Simulation results and a real data example are presented in Section 5. Section 6 is

our conclusion.

Throughout the paper, we denote the transpose of a matrix A by A' .

2 Threshold ARMA and Its Bayesian Inference

2.1 TARMA Model

A time series $\{Y_t, t = 1, 2, \dots\}$ is said to follow a TARMA(2; p_1, q_1, p_2, q_2, d) model with two regimes if it satisfies the following equation

$$Y_t = \begin{cases} \phi_0^{(1)} + \sum_{j=1}^{p_1} \phi_j^{(1)} Y_{t-j} + \sum_{k=1}^{q_1} \theta_k^{(1)} \xi_{t-k}^{(1)} + \xi_t^{(1)}, & Y_{t-d} > r \\ \phi_0^{(2)} + \sum_{j=1}^{p_2} \phi_j^{(2)} Y_{t-j} + \sum_{k=1}^{q_2} \theta_k^{(2)} \xi_{t-k}^{(2)} + \xi_t^{(2)}, & Y_{t-d} \leq r \end{cases} \quad (2.1.1)$$

where $\{\xi_t^{(i)}\}$ is assumed to be a sequence of independent and identically distributed (i.i.d.) random variables with common distribution $N(0, \sigma_i^2)$, p_1, q_1, p_2, q_2, d are positive integers. Here d is called the delay (or threshold lag) parameter of the model, and $r \in R$ is called the threshold parameter.

2.2 Bayesian Inference

Suppose we have a sample $\mathbf{Y} = \{Y_1, Y_2, \dots, Y_n\}$. Let $p = \max\{p_1, p_2\}$ and $q = \max\{q_1, q_2\}$. Then we assume the threshold variable Y_{t-d} takes values in $\{Y_{h-d}, \dots, Y_{n-d}\}$, where $h = \max\{d + 1, p + 1, q + 1\}$.

Given the first $h - 1$ observations and $\xi_1^{(i)} = \dots = \xi_{h-1}^{(i)} = 0$, the conditional likelihood function of TARMA(2; p_1, q_1, p_2, q_2, d) model can be easily obtained as follows

$$\begin{aligned} & L(\Phi_1, \Phi_2, \sigma_1^2, \sigma_2^2, r, d \mid \mathbf{Y}) \\ & \propto \sigma_1^{s_1} \sigma_2^{s_2} \exp \left\{ \left[-\frac{1}{2\sigma_1^2} \sum_{t=h}^n \left(Y_t - \phi_0^{(1)} - \phi_1^{(1)} Y_{t-1} - \dots - \phi_{p_1}^{(1)} Y_{t-p_1} \right. \right. \right. \\ & \quad \left. \left. \left. - \theta_1^{(1)} \xi_{t-1}^{(1)} - \dots - \theta_{q_1}^{(1)} \xi_{t-q_1}^{(1)} \right)^2 I(Y_{t-d} > r) \right. \right. \\ & \quad \left. \left. - \frac{1}{2\sigma_2^2} \sum_{t=h}^n \left(Y_t - \phi_0^{(2)} - \phi_1^{(2)} Y_{t-1} - \dots - \phi_{p_2}^{(2)} Y_{t-p_2} \right. \right. \right. \\ & \quad \left. \left. \left. - \theta_1^{(2)} \xi_{t-1}^{(2)} - \dots - \theta_{q_2}^{(2)} \xi_{t-q_2}^{(2)} \right)^2 I(Y_{t-d} \leq r) \right] \right\} \end{aligned} \quad (2.2.1)$$

where I is the indicator function, and $s_1 = \sum_{t=h}^n I(Y_{t-d} > r)$, $s_2 = \sum_{t=h}^n I(Y_{t-d} \leq r)$. Denote

$$\begin{aligned} Y &= (Y_h, Y_{h+1}, \dots, Y_n)', \quad \Xi_1 = (\xi_h^{(1)}, \xi_{h+1}^{(1)}, \dots, \xi_n^{(1)})', \quad \Xi_2 = (\xi_h^{(2)}, \xi_{h+1}^{(2)}, \dots, \xi_n^{(2)})', \\ \Phi_1 &= (\phi_0^{(1)}, \phi_1^{(1)}, \dots, \phi_{p_1}^{(1)}, \theta_1^{(1)}, \dots, \theta_{q_1}^{(1)})', \quad \Phi_2 = (\phi_0^{(2)}, \phi_1^{(2)}, \dots, \phi_{p_2}^{(2)}, \theta_1^{(2)}, \dots, \theta_{q_2}^{(2)})', \\ I_1 &= \text{diag}(I(Y_{h-d} > r), I(Y_{h+1-d} > r), \dots, I(Y_{n-d} > r)), \\ I_2 &= \text{diag}(I(Y_{h-d} \leq r), I(Y_{h+1-d} \leq r), \dots, I(Y_{n-d} \leq r)), \end{aligned}$$

$$X_1 = \begin{bmatrix} 1 & Y_{h-1} & \dots & Y_{h-p_1} & \xi_{h-1}^{(1)} & \dots & \xi_{h-q_1}^{(1)} \\ 1 & Y_h & \dots & Y_{h+1-p_1} & \xi_h^{(1)} & \dots & \xi_{h+1-q_1}^{(1)} \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ 1 & Y_{n-1} & \dots & Y_{n-p_1} & \xi_{n-1}^{(1)} & \dots & \xi_{n-q_1}^{(1)} \end{bmatrix},$$

and

$$X_2 = \begin{bmatrix} 1 & Y_{h-1} & \dots & Y_{h-p_2} & \xi_{h-1}^{(2)} & \dots & \xi_{h-q_2}^{(2)} \\ 1 & Y_h & \dots & Y_{h+1-p_2} & \xi_h^{(2)} & \dots & \xi_{h+1-q_2}^{(2)} \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ 1 & Y_{n-1} & \dots & Y_{n-p_2} & \xi_{n-1}^{(2)} & \dots & \xi_{n-q_2}^{(2)} \end{bmatrix}.$$

Then

$$\Xi_1 = I_1(Y - X_1\Phi_1), \quad \Xi_2 = I_2(Y - X_2\Phi_2),$$

and we can rewrite (2.2.1) as

$$L(\Phi_1, \Phi_2, \sigma_1^2, \sigma_2^2, r, d \mid \mathbf{Y}) \propto |\Sigma_1|^{-\frac{1}{2}} |\Sigma_2|^{-\frac{1}{2}} \cdot \exp \left[-\frac{1}{2} (\Xi_1' \Sigma_1^{-1} \Xi_1 + \Xi_2' \Sigma_2^{-1} \Xi_2) \right] \quad (2.2.2)$$

where $\Sigma_1 = \text{diag}(\sigma_1^2, \dots, \sigma_1^2)$ and $\Sigma_2 = \text{diag}(\sigma_2^2, \dots, \sigma_2^2)$ are all $(n - h + 1) \times (n - h + 1)$ diagonal matrix, respectively. Taking $\{\xi_t^{(i)} = 0, t < h\}$, we can compute $\{\xi_t^{(i)}, t \geq h\}$ recursively as follows

$$\xi_t^{(1)} = Y_t - X_{1t}' \Phi_1 \quad \text{if } Y_{t-d} > r; \quad \xi_t^{(2)} = Y_t - X_{2t}' \Phi_2 \quad \text{otherwise,} \quad (2.2.3)$$

where $X_{1t} = (1, Y_{t-1}, \dots, Y_{t-p_1}, \xi_{t-1}^{(1)}, \dots, \xi_{t-q_1}^{(1)})'$, $X_{2t} = (1, Y_{t-1}, \dots, Y_{t-p_2}, \xi_{t-1}^{(2)}, \dots, \xi_{t-q_2}^{(2)})'$.

To carry out the Bayesian inference about the parameters $\Phi_1, \Phi_2, \sigma_1^2, \sigma_2^2, r, d$ in the TARMA(2; p_1, q_1, p_2, q_2, d) model, we need to obtain the marginal distribution by the joint posterior distribution $P(\Phi_1, \Phi_2, \sigma_1^2, \sigma_2^2, r, d | \mathbf{Y})$, which is difficult to be finished and can be replaced by using conditional posterior distributions in a MCMC process. Therefore, we need to choose priors to derive the conditional posterior distribution for the unknown parameters.

Referring to Chen and Lee (1995), Xia et al. (2010), and Chen et al. (2011) we assume that Φ_i follows $N(\Phi_{0i}, V_i^{-1})$, where V_i denotes the precision, $i = 1, 2$, and Φ_1 is independent of Φ_2 . Let σ_i^2 follow the inverse gamma distribution $IG(\alpha_i, \beta_i)$, where the hyper-parameters are known. For r , similar to Geweke and Terui (1993), we adopt that it follows a uniform distribution on an interval (a, b) . Assume that d follows a discrete uniform distribution on a set of integers $\{1, 2, \dots, d_0\}$, where d_0 is a prescribed positive integer.

Using Bayesian techniques, we derive the conditional posterior distributions of $\Phi_1, \Phi_2, \sigma_1^2, \sigma_2^2, r, d$ based on the above priors as follows.

- (1) The conditional posterior probability function of Φ_i is

$$p(\Phi_i | \mathbf{Y}, \sigma_1^2, \sigma_2^2, r, d) \propto \exp \left\{ -\frac{1}{2} \left[\Xi_i' \Sigma_i^{-1} \Xi_i + (\Phi_i - \Phi_{0i})' V_i (\Phi_i - \Phi_{0i}) \right] \right\} \quad (2.2.4)$$

for $i = 1, 2$.

- (2) The conditional posterior distribution of σ_i^2 is

$$p(\sigma_i^2 | \mathbf{Y}, \Phi_1, \Phi_2, r, d) \sim IG\left(\alpha_i + \frac{s_i}{2}, \beta_i + \frac{S_i^2}{2}\right), \quad (2.2.5)$$

where $S_i^2 = \Xi_i' \Xi_i$ for $i = 1, 2$.

- (3) The conditional posterior probability function of r is

$$p(r | \mathbf{Y}, \Phi_1, \Phi_2, \sigma_1^2, \sigma_2^2, d) \propto \exp \left[-\frac{1}{2} \left(\frac{S_1^2}{\sigma_1^2} + \frac{S_2^2}{\sigma_2^2} \right) \right] \cdot I(a < r < b). \quad (2.2.6)$$

Note that S_i^2 is a function of r .

- (4) The conditional posterior probability function of d is a multinomial distribution with probability

$$p(d | \mathbf{Y}, \Phi_1, \Phi_2, \sigma_1^2, \sigma_2^2, r) = \frac{L(\Phi_1, \Phi_2, \sigma_1^2, \sigma_2^2, r, d | \mathbf{Y})}{\sum_{d=1}^{d_0} L(\Phi_1, \Phi_2, \sigma_1^2, \sigma_2^2, r, d | \mathbf{Y})} \quad (2.2.7)$$

where $d = 1, 2, \dots, d_0$.

2.3 Sampling Scheme

From the previous section, we see that the conditional densities for σ_i^2 and d can be identified. Then, the Gibbs sampler can be used. But there are not closed form for the conditional distributions of r and Φ_i ($i = 1, 2$). The random walk Metropolis-Hastings (M-H) algorithm will be applied to draw Φ_i , $i = 1, 2$, and r . Details of the Gibbs sampler and Metropolis-Hastings algorithm can be found in Casella and George (1992) and Chib and Greenberg (1995), respectively. Denote the target density in (2.2.3) by $f_1(\cdot)$. The algorithm for drawing Φ_i is described below.

Step 1: At iteration j , generate a point Φ_i from the random walk kernel

$$\Phi_i = \Phi_i^{[j-1]} + \xi_{\Phi_i}, \quad \xi_{\Phi_i} \sim N(0, \Sigma_{\Phi_i}^*)$$

where $\Phi_i^{[j-1]}$ is the $(j-1)$ th iterate for Φ_i .

Step 2: Accept Φ_i as $\Phi_i^{[j]}$ with probability $p = \min\{1, f_1(\Phi_i)/f_1(\Phi_i^{[j-1]})\} > u$, $u \sim U(0, 1)$. Otherwise, set $\Phi_i^{[j]} = \Phi_i^{[j-1]}$.

We usually select $\Sigma_{\Phi_i}^*$ to be a diagonal matrix, whose elements are tuned by monitoring the acceptance rate between 0.25 and 0.75.

Remark 1. Chen et al. (2011) employed the modified GM (George and McCulloch, 1993) method for M-H steps of Φ_i , we use the similar idea to draw Φ_i .

Denote the target density in (2.2.5) by $f_2(\cdot)$. The algorithm for drawing r is described as follows.

- At iteration j , generate a point r from the random walk kernel

$$r = r^{[j-1]} + \xi_r, \quad \xi_r \sim N(0, \sigma_r^{*2})$$

where $r^{[j-1]}$ is the $(j - 1)$ th iterate of r .

- Accept r as $r^{[j]}$ with probability $p = \min\{1, f_2(r)/f_2(r^{[j-1]})\} > u, u \sim U(0, 1)$.

Otherwise, set $r^{[j]} = r^{[j-1]}$.

In summary, we use the following iterative sampling scheme to construct the desired posterior sample:

- (1) Draw Φ_i using the random walk Metropolis-Hastings algorithm from the conditional posterior distribution in (2.2.3), $i = 1, 2$;
- (2) Draw σ_i^2 from the inverse Gamma distribution in (2.2.4), $i = 1, 2$;
- (3) Draw r using the random walk Metropolis-Hastings algorithm the conditional posterior distribution in (2.2.5);
- (4) Draw d from a multinomial distribution with probabilities proportional to the likelihood function in (2.2.6).

This completes one iteration. Of course, we can change the order in sampling the variables. So and Chen (2003) have illustrated that fast convergence is attained irrespective of the order. In addition, these desired posterior samples will be used in RJMCMC scheme to test the significance of threshold nonlinearity by comparing a ARMA model and its counterpart of a TARMA model, and the details are introduced in the following section.

Remark 2. Chen et al. (2011) pointed out that it remains difficult to find necessary and sufficient conditions of stationarity and invertibility for the general TARMA model. Therefore, we

simply ignore the stationary assumptions and proceed to use the normal-gamma family as a conjugate prior distribution, such as in Chen (1999), So and Chen (2003) and So et al. (2006) for AR, TAR and ARX-GARCH models, respectively.

3 Selecting Model by RJMCMC

The main goal of our study is to test for the threshold nonlinearity of TARMA models. The testing problem will be transferred to a Bayesian model-selection problem. To do this, we need to calculate the posterior probabilities $P(M_k|\mathbf{Y})$, $k = 1, 2$, where M_1 and M_2 represent ARMA and TARMA models respectively. The RJMCMC method in Green (1995), which is a very useful mechanism to allow jumps between spaces with different dimensions while maintaining the detailed balance condition ensuring convergence of the Markov chain, can be adopted here. This method was used to choose between pairs of GARCH models by Vrontos et al. (2000), So et al. (2005), Chen et al. (2008).

We consider the jump from M_1 with parameter $\Phi^{(1)}$ to M_2 with parameter $\Phi^{(2)}$. Here $\Phi^{(1)}$ consists of a set of ARMA parameters, and $\Phi^{(2)}$ consists of Φ_1 , Φ_2 , σ_1^2 , σ_2^2 and r in TARMA model. Generally speaking, $\Phi^{(1)}$ and $\Phi^{(2)}$ have different dimensions. To jump from M_1 to M_2 , we construct two variables $U^{(1)}$ and $U^{(2)}$ to form a bijection between $(\Phi^{(1)}, U^{(1)})$ and $(\Phi^{(2)}, U^{(2)})$, that is, an one-to-one bijective transformation which links $(\Phi^{(2)}, U^{(2)})$ with $(\Phi^{(1)}, U^{(1)})$. This transformation ensures the necessary condition that the dimensions of $(\Phi^{(1)}, U^{(1)})$ and $(\Phi^{(2)}, U^{(2)})$ are the same, i.e., $\dim(\Phi^{(1)}) + \dim(U^{(1)}) = \dim(\Phi^{(2)}) + \dim(U^{(2)})$.

To jump from M_1 to M_2 , we simulate $U^{(1)}$ from a kernel $Q_1(U^{(1)}|\Phi^{(1)})$ and determine $\Phi^{(2)}$ from $Q_2(U^{(2)}|\Phi^{(2)})$. Then, we accept the jump with probability $\min\{1, p\}$, where

$$p = \frac{L(\mathbf{Y}|M_2, \Phi^{(2)})\Pi(\Phi^{(2)}|M_2)P(M_2)J(M_1, M_2)Q_2(U^{(2)}|\Phi^{(2)})}{L(\mathbf{Y}|M_1, \Phi^{(1)})\Pi(\Phi^{(1)}|M_1)P(M_1)J(M_2, M_1)Q_1(U^{(1)}|\Phi^{(1)})} \cdot \left| \frac{\partial(\Phi^{(2)}, U^{(2)})}{\partial(\Phi^{(1)}, U^{(1)})} \right|. \quad (3.1)$$

The term $L(\mathbf{Y}|M_i, \Phi^{(i)})$ is the likelihood function of model M_i , $\Pi(\Phi^{(i)}|M_i)$ is the prior distribution, and $P(M_i)$ is the prior probability, $i = 1, 2$. Denote the probability of the jump from M_i to M_j by $J(M_i, M_j)$. The last part in (3.1) is the Jacobian of the transformation. We can implement the jump from M_2 to M_1 in the reversed way by simulating $U^{(2)}$ from a kernel $Q_2(U^{(2)}|\Phi^{(2)})$ and determining $\Phi^{(1)}$ from $Q_1(U^{(1)}|\Phi^{(1)})$ to calculate the acceptance probability $\min\{1, p^{-1}\}$.

To introduce the bijection for RJMCMC, we follow Vrontos et al. (2000), So et al. (2005), and define $U^{(1)} = \Phi^{(2)}$, $U^{(2)} = \Phi^{(1)}$, which implies a Jacobian $\left| \frac{\partial(\Phi^{(2)}, U^{(2)})}{\partial(\Phi^{(1)}, U^{(1)})} \right| = 1$. In addition, we set $J(M_i, M_j) = 1$ to allow a jump in each MCMC iteration, and $P(M_1) = P(M_2) = 0.5$ to reflect prior model ignorance. In this case, we can simplify the acceptance probability of reversible jump in (3.1) to

$$p = \frac{L(\mathbf{Y}|M_2, \Phi^{(2)})\Pi(\Phi^{(2)}|M_2)Q_2(U^{(2)})}{L(\mathbf{Y}|M_1, \Phi^{(1)})\Pi(\Phi^{(1)}|M_1)Q_1(U^{(1)})} \quad (3.2)$$

with the kernels Q_1 and Q_2 being independent of $\Phi^{(1)}$ and $\Phi^{(2)}$, respectively.

It is important to choose appropriate kernels Q_1 and Q_2 to apply the RJMCMC successfully. To do this, firstly, the Gibbs sampler combining with random walk M-H algorithm in the subsection 2.3 is implemented for M iterates, and sample means $\mu_{\Phi_i}, \mu_r, \mu_{\sigma_i^2}, \mu_d$, the sample covariance matrix Σ_{Φ_i} and sample variances $\sigma_r^2, \sigma_{\sigma_i^2}^2, \sigma_d^2$ can be obtained. And then, we will substitute μ_d for d in the TARMA model, and use $\mu_{\Phi_i}, \Sigma_{\Phi_i}, \mu_r, \sigma_r^2$ and $\mu_{\sigma_i^2}, \Sigma_{\sigma_i^2}$ to form the Gaussian kernels $N(\mu_{\Phi_i}, \Sigma_{\Phi_i}), N(\mu_r, \sigma_r^2)$ and $N(\mu_{\sigma_i^2}, \Sigma_{\sigma_i^2})I(\sigma_i^2 > 0)$. Therefore, we select the kernel $Q_1(U^{(1)})$ for drawing $\Phi^{(2)} = (\Phi'_1, \Phi'_2, r, \sigma_1^2, \sigma_2^2)'$ to be the product of the above four Gaussian kernels, i.e., $Q_1(U^{(1)}) \sim N(\mu_{\Phi_1}, \Sigma_{\Phi_1}) \cdot N(\mu_{\Phi_2}, \Sigma_{\Phi_2}) \cdot N(\mu_r, \sigma_r^2) \cdot N(\mu_{\sigma_1^2}, \Sigma_{\sigma_1^2})I(\sigma_1^2 > 0) \cdot N(\mu_{\sigma_2^2}, \Sigma_{\sigma_2^2})I(\sigma_2^2 > 0)$. For the simulation of $u^{(2)}$, which is the parameters $\Phi^{(1)} = (\tilde{\Phi}', \tilde{\sigma}^2)'$ in ARMA model, we use the same method as described in the previous section to construct $N(\mu_{\tilde{\Phi}}, \Sigma_{\tilde{\Phi}})$ and $N(\mu_{\tilde{\sigma}^2}, \Sigma_{\tilde{\sigma}^2})I(\tilde{\sigma}^2 > 0)$ from the first M iterates of $\tilde{\Phi}$ and $\tilde{\sigma}^2$. We then choose $Q_2(u^{(2)}) \sim N(\mu_{\tilde{\Phi}}, \Sigma_{\tilde{\Phi}}) N(\mu_{\tilde{\sigma}^2}, \Sigma_{\tilde{\sigma}^2})I(\tilde{\sigma}^2 > 0)$ as the kernel for drawing $\Phi^{(1)} = (\tilde{\Phi}', \tilde{\sigma}^2)'$. In summary, the jumping scheme is as follows.

- From ARMA(M_1) to TARMA (M_2):
 - (1) Draw $\Phi_i \sim N(\mu_{\Phi_i}, \Sigma_{\Phi_i}), i = 1, 2, r \sim N(\mu_r, \sigma_r^2)$ and $\sigma_i^2 \sim N(\mu_{\sigma_i^2}, \Sigma_{\sigma_i^2})I(\sigma_i^2 > 0)$ and accept the jump with probability $\min\{1, p\}$.
 - (2) If accepted, update $\Phi^{(2)}$. Otherwise, update $\Phi^{(1)}$.
- From TARMA(M_2) to ARMA (M_1):
 - (1) Draw $\tilde{\Phi} \sim N(\mu_{\tilde{\Phi}}, \Sigma_{\tilde{\Phi}}), \tilde{\sigma}^2 \sim N(\mu_{\tilde{\sigma}^2}, \Sigma_{\tilde{\sigma}^2})I(\tilde{\sigma}^2 > 0)$, and accept the jump with probability $\min\{1, p^{-1}\}$.
 - (2) If accepted, update $\Phi^{(1)}$. Otherwise, update $\Phi^{(2)}$.

4 Modeling TARMA Models

Based on the results of RJMCMC method, we propose a procedure for building a TARMA model, as long as its threshold nonlinearity is significant. We hope that the potential of TARMA models can be exploited by this procedure in simulation and application, which consists of several steps and is described as follows.

Step 1. Select the appropriate AR order p and MA order q for ARMA models by AIC or BIC.

Step 2. For given p and q , use the sampling scheme as described in Subsection 2.3 to construct the Gaussian kernels ($N(\mu_{\tilde{\phi}}, \Sigma_{\tilde{\phi}}), N(\mu_{\tilde{\sigma}^2}, \Sigma_{\tilde{\sigma}^2})I(\tilde{\sigma}^2 > 0)$) for ARMA model.

Step 3. For given p and q , use the sampling scheme as described in Subsection 2.3 to construct the Gaussian kernels ($N(\mu_{\Phi_1}, \Sigma_{\Phi_1}), N(\mu_{\Phi_2}, \Sigma_{\Phi_2}), N(\mu_r, \sigma_r^2), N(\mu_{\sigma_1^2}, \Sigma_{\sigma_1^2})I(\sigma_1^2 > 0), N(\mu_{\sigma_2^2}, \Sigma_{\sigma_2^2})I(\sigma_2^2 > 0)$) for TARMA model.

Step 4. Using the jumping scheme, choose the appropriate TARMA model. If necessary, refine the AR order, MA order and parameters of TARMA model with AIC or BIC and MCMC sampling scheme again.

Remark 3. For the specified ARMA or TARMA model, the AIC and BIC are taken as the following form

$$\text{AIC}(k) = -\ln(L) + 2k, \quad \text{BIC}(k) = -\ln(L) + \ln(n)k$$

where L is the likelihood value for the model in (2.1.1), n is the "effective number of observations" and k is the number of independent parameters of the models.

5 Simulation Experiments and a Real Data Example

In this section, we first present simulation results to show the effectiveness of our MCMC sampling scheme, model selection method and the procedure for modeling TARMA models, and then apply our method to a real data set.

5.1 Simulation Experiments

We set $M = 8000$ in all experiments, and apply the sampler scheme to draw all parameters and to form the means and the normal kernels by discarding the first 5000 iterations. We then perform 8000 iterations for posterior inference and model selection. The hyper-parameters are $\Theta_{0i} = (0, \dots, 0)'_{p+q}$, $V_i = \text{diag}(0.1, \dots, 0.1)_{p+q}$, $i = 1, 2$, and furthermore we choose $\alpha = 2.5$, $\beta = 1.6$, $d_0 = 3$, $a = p_{10}$, $b = p_{90}$, where p and q is the most AR and MA order of TARMA model respectively, p_k denotes the k th percentile of the data.

The RJMCMC scheme in testing the significance of threshold nonlinearity will be studied firstly. The null is the ARMA(1, 1) model with constant term $\phi_0 = 0$, and the alternative is the TARMA(2; 1, 1, 1, 1, 1) model with constant terms $\phi_0^{(j)} = 0$, $j = 1, 2$, $r = 0$, $\phi_1^{(2)} = \theta_1^{(2)} = 0.5$ and $\phi_1^{(1)} = \theta_1^{(1)} = -1, -0.5, 0, 0.2, 0.4, 0.5$, denoted by model 1 ~ 6 respectively. We generate 400 points of y with $y_0 = 0$, but only use the last 300 observations as data set for each realization. Table 1 lists the posterior probabilities (prob.) of identifying the true models, the posterior means, the posterior standard deviations (s.d.) for the true model efficiently.

From Table 1, it is clear that the posterior means are closed to the true values under the good performance of the RJMCMC scheme testing, although there are slightly bias for $\phi_1^{(1)}$ of model 3 and r of model 4 and 5.

To make some discussion about the power of the proposed Bayesian test and the effectiveness of our MCMC sampling scheme, we continue to study the above models with the same prior setting as the generated examples before based on 500 samples each with size 300. The rate of correct selections of TARMA models (rate) and Bayesian estimates of the above six models are shown in Table 2. From Table 2, our results in this simulation study are fine. Based on 500 samples each with size 300, the estimates of the coefficients are approximately unbiased, and the power of correct selections of TARMA models increases when the alternative departs from the linear ARMA model.

For the check of convergence of our algorithm, we will use the visual inspection of CUMSUM statistics (Yu and Mykland, 1994) defined by

$$CS_t = \left(\frac{1}{t} \sum_{j=1}^t \theta^{(j)} - \mu_\theta \right) / \sigma_\theta$$

where μ_θ and σ_θ are the empirical mean and standard deviation of the 500 draws. Figure 1 shows that our algorithm is almost convergent for the model 2 in some sense. Meanwhile, the histogram of all parameters are nearly symmetric form the Figure 2.

To illustrate the usefulness of our procedure for building a TARMA model a bit further, we conduct an preliminary investigation about the following two TARMA models. Here, we also generate 400 points of y with $y_0 = 0$ and discard the first 100 observations as data set for each realization, and then carry out MCMC iterations for them.

- Model 7: $TARMA(2; 1, 1, 1, 1, 1)$

$$Y_t = \begin{cases} \xi_t + 0.6\xi_{t-1} + 0.4Y_{t-1}, & Y_{t-1} > 0.5 \\ \xi_t - 0.5\xi_{t-1} - 0.3Y_{t-1}, & Y_{t-1} \leq 0.5 \\ \xi_t \sim N(0, 1). \end{cases} \quad (5.1)$$

- Model 8: $TARMA(2; 2, 1, 3, 1, 2)$

$$Y_t = \begin{cases} \xi_t - 0.4\xi_{t-1} + 0.8Y_{t-1} - 0.6Y_{t-2}, & Y_{t-2} > -0.1 \\ \xi_t + 0.4\xi_{t-1} + 0.2Y_{t-1} + 0.5Y_{t-3}, & Y_{t-2} \leq -0.1 \\ \xi_t \sim N(0, 1). \end{cases} \quad (5.2)$$

For the data simulated from model 7, we choose $(p, q) = (2, 2)$ for ARMA model by AIC or BIC, and then we investigate the four cases of RJMCMC scheme testing by decreasing the order (p, q) and obtain the corresponding results recorded in Table 3. Although the true order (p, q) of model 7 is $(1, 1)$, the RJMCMC scheme testing is still efficient and the posterior means are almost closed to the true values in other cases of appropriate AR and MA order. In particular, the posterior means of some parameters are quite closed to 0, which is the true values of model 7. Furthermore, AIC and BIC values indicate that $(p, q) = (1, 1)$ is the best choice, which just suggests that our procedure for building a TARMA model may be useful. In addition, the posterior means of all parameters, the trace plot and the histogram of r (Figure 1) show that the final modeling results would pass in crowd.

For model 8, this is an special example, we hope our MCMC algorithm to be useful to it by identifying as $TARMA(2; 2, 1, 3, 1, 2)$ model with $\phi_2^{(2)} = 0$. Firstly, we select the order $(p, q) =$

(3, 2) for ARMA model by AIC or BIC. To examine the efficiency of the RJMCMC scheme, we also attempt to change the order as low as possible. Table 4 lists the results for six cases, which illustrate that the RJMCMC scheme can obtain good performance on the nonlinear case. If the order (p, q) of the fitted model is lower than the true model, the values of AIC and BIC will be larger. Under these circumstances, we should refine the order (p, q) to gain the final results by AIC and BIC again. If the order (p, q) of the fitted model is larger than or equal to the true model, the posterior means of parameters are quite closed to the true values as well. The final model may be TARMA(2; 2, 1, 3, 1, 2), which can keep close consistent to model 8, although $\phi_1^{(2)}$ and $\phi_3^{(1)}$ has slightly bias, the other estimates are close to the true parameters, especially the $\phi_2^{(2)}$ is close to 0. Meanwhile, the trace plot and the histogram of r (Figure 2) also give fine results.

The visual inspection of CUMSUM statistics are also used to check the convergence of our algorithm to r of model 7 and 8, depicted in Figure 5, which indicates that our MCMC algorithm has been almost convergent in some sense.

The above simulation analysis shows that our MCMC sampling methods can perform well in providing posterior samplers for statistical inference for TARMA models. Therefore, it should be useful in practice.

Remark 4. The maximum of AR and MA order is prescribed to 3 in all above simulations. In addition, the order p and q can be also chosen starting from the low order.

5.2 Some Real Data Examples

To make a supplement for our MCMC sampling method, we consider a data set in an application: the exchange rate of Japanese Yen v.s. USA dollar. Similar to Chen and Lee (1995) and Xia et al. (2010), the hyper-parameters used are $\Phi_{0i} = (0, 0)'$ for $i = 1, 2$, $V = \text{diag}(0.1, 0.1)$, $\alpha = 2.5$, $\beta = 1.6$, and $a = p_5$ and $b = p_{95}$, which are defined as in subsection 5.1. Set $M = 10000$ to run MCMC iterations. Burning the first 5000 times, the posterior means and variances can be got to form the normal kernels which are applied to RJMCMC iterations for 10000 times.

The monthly data from Jan. 1971 to Dec. 2000 are used and there are 360 observations. This data set were analyzed recently by Ling and Tong (2005) and Xia et al. (2010). P_t denotes the exchange rate at t th month. Let $x_t = 100[\log(P_t) - \log(P_{t-1})]$ and $y_t = x_t - \sum_{i=2}^{360} x_i/359$ for $t \geq 2$.

We take the order $(p, q) = (1, 1)$ for ARMA model by AIC and BIC, i.e., employ ARMA(1, 1) and TARMA(2; 1, 1, 1, 1, d) models to fit the data $\{y_2, y_3, \dots, y_{360}\}$. The estimate of the posterior probability identifying the TARMA model is 0.7813, which suggests that the threshold nonlinearity is significant. According to our procedure for modeling TARMA model, we should refine the order (p, q) by AIC or BIC and MCMC sampler. Table 5 lists the values of AIC and BIC, which illustrate that $(p, q) = (1, 1)$ is best choice for TARMA model. For illustrative purposes, we obtain estimated model (4.1) with the standard errors in the square brackets. From model (4.1), we can see that the estimates of threshold and delay parameters are $r = 3.7197$ and $d = 3$ respectively. Figure 4 displays the trace plot for all MCMC iterations of r and the histogram of r for TARMA model. We see that the trace plot of r is stationary gradually, and after 5000 MCMC iterations it is almost stationary. The histogram of r also shows that its distribution is symmetric in some sense.

$$Y_t = \begin{cases} -0.9663Y_{t-1} + 0.6666\xi_{t-1} + \xi_t, & Y_{t-3} > 3.7197 \\ (0.1981) & (0.1481) & (0.0293) \\ 0.0494Y_{t-1} + 0.3863\xi_{t-1} + \xi_t, & Y_{t-3} \leq 3.7197 \\ (0.0144) & (0.0120) \\ \xi_t = \sqrt{6.7239}e_t, & e_t \sim N(0, 1). \\ (0.0293) \end{cases} \quad (4.1)$$

6 Conclusion

In this paper, we develop a Bayesian testing scheme for threshold nonlinearity of two-regime TARMA models. Firstly, combining Gibbs sampler and Metropolis-Hastings algorithm, we propose a Bayesian method to analysis the TARMA models. And then, with these Bayesian estiamtes, we use a RJMCMC algorithm to select model between a ARMA model and a TARMA model by constructing the Normal kernels. The main idea is to compute the posterior probabilities of competitive models, hence, our procedure can avoid some analytical difficulty and complicated computation, therefore, it is simple to implement and requires no subjective specification of threshold and delay values. This is the main advantage of our Bayesian approach. Finally, based on RJMCMC scheme and AIC or BIC, we give the procedure for modeling TARMA models. Simulation results

and a real data example show that our approach can perform good. However, this work is only limited to two-regime case without considering the heteroscedastic model. In the further research, the heteroscedasticity can be added as an extension of our work.

ACKNOWLEDGMENTS

The authors thank the editor, and the referees for their constructive suggestions and comments that led to an improvement of the manuscript. The research of Qiang Xia was supported in part by National Social Science Foundation of China (No:12CTJ019), Ministry of Education in China Project of Humanities and Social Sciences (Project No.11YJCZH195), and the National Natural Science Foundation of China (grant 61375006). The research of Jinshan Liu was supported by National Natural Science Foundation of China (grant 11171117).

References

- [1] Akaike, H. (1974). A new look at statistical model identification. *IEEE Transactions on Automatic Control*, **19**, 716-722.
- [2] Casella, G. and George, E. I. (1992). Explaining the Gibbs sampler. *The American Statistician*, **46**, 167-174.
- [3] Chen, C. W. S. (1999). Subset selection of autoregressive time series models. *Journal of Forecasting*, **18**, 505-516.
- [4] Chen, C. W. S. and Lee, J. C. (1995). Bayesian inference of threshold autoregressive models. *Journal of Time Series Analysis*, **16**, 483-492.
- [5] Chen, C. W. S., Gerlach, R., and So, M. K. P. (2008). Bayesian model selection for heteroskedastic models. *Advances in Econometrics*, **25**, 567-594.
- [6] Chen, C. W. S., Liu, F. C., and Gerlach, R. (2011). Bayesian subset selection for threshold autoregressive moving-average models. *Computational Statistics*, **26**, 1-30.
- [7] Chib, S. and Greenberg, E. (1995). Understanding the Metropolis-Hastings algorithm. *The American Statistician*, **49**, 327-335.
- [8] Geman, S. and Geman, D. (1984). Stochastic relaxation, Gibbs distribution and the Bayesian restoration of images. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, **6**, 721-741.
- [9] George E. I. and McCulloch R. E. (1993). Variable selection via Gibbs sampling. *Journal of the American Statistical Association*, **88**, 881-889.
- [10] Geweke, J. and Terui, N. (1993). Bayesian threshold autoregressive models for nonlinear time series. *Journal of Time Series Analysis*, **14**, 441-454.
- [11] Green, P.J. (1995). Reversible jump MCMC computation and Bayesian model determination. *Biometrika*, **82**, 711-732.
- [12] Hastings, W. K. (1970). Monte-Carlo sampling methods using Markov chains and their applications. *Biometrika*, **57**, 97-109.

- [13] Ling, S. and Tong, H. (2005). Testing a linear moving-average model against threshold moving-average models. *Ann. Statist.*, **33**, 2529-2552.
- [14] Ismail, M. A. and Charif, H. A. (2003). Bayesian Inference for threshold moving average models. *METRON*, **1**, 119-132.
- [15] Mcculloch, R. E. and Tsay, R. S. (1993a). Bayesian analysis of threshold autoregressive processes with a random number of regimes. *Computing Science and Statistics. Proceedings of the 25th Symposium on the Interface*, Fairfax Station, VA: Interface Foundation of North America, 253-262.
- [16] Mcculloch, R. E. and Tsay, R. S. (1993b). Bayesian inference and prediction for mean and variance shifts in autoregressive time series. *Journal of the American Statistical Association*, **88**, 968-978.
- [17] Metropolis, N., Rosenbluth, A. W, Rosenbluth, M. N., and Teller, E. (1953). Equations of state calculations by fast computing machines. *Journal of Chemical Physics*, **21**, 1087-1091.
- [18] So, M. K. P. and Chen, C. W. S. (2003). Subset threshold autoregression. *Journal of Forecasting*, **22**, 49-66.
- [19] So, M. K. P., Chen, C. W. S., and Chen, M. T. (2005). A Bayesian threshold nonlinearity test in financial time series, *Journal of Forecasting*, **24**, 61-75.
- [20] So, M. K. P., Chen, C. W. S., and Liu, F. C. (2006) Best subset selection of autoregressive models with exogenous variables and generalized autoregressive conditional heteroscedasticity errors. *J Roy Stat Soc Ser C*, **55**, 201-224.
- [21] Sáfadi, T. and Morettin, P. A. (2000). Bayesian Analysis of threshold autoregressive moving average models. *Sankyã*, **62**, 353-371.
- [22] Tong, H. (1978). On a Threshold Model, in C.H. Chen (eds). *Pattern Recognition and Signal Processing*, Amsterdam: Sijthoff and Noordhoff, 101-141.
- [23] Tong, H. and Lim, K. S. (1980). Threshold autoregressions, limit cycles, and data. *Journal of the Royal Statistical Society B*, **42**, 245-292.

- [24] Tong, H. (1990). *Non-Linear Time Series: A Dynamical System Approach*. Oxford University Press, Oxford.
- [25] Tsay, R. S. (2005). *Analysis of Financial Time Series*. 2nd Edition, John Wiley & Sons.
- [26] Vrontos, I. D., Dellaportas, P., and Politis, D. N. (2000). Full Bayesian inference for GARCH and EGARCH models. *Journal of Business & Economic Statistics*, **18**, 187-198.
- [27] Xia Q., Liu J.S., Pan J.Z., and Liang R.B. (2012). Bayesian Analysis of two-regime Threshold Autoregressive-Moving Average Models with Exogenous Inputs. *Communications in Statistics - Theory and Methods*, **41**, 1089-1104.
- [28] Xia Q., Pan J. Z., Zhang Z. Q., and Liu J. S. (2010). A Bayesian nonlinearity test for threshold moving average models. *Journal of Time Series Analysis*, **31**, 329-336.
- [29] Yu, B. and P. Mykland (1994). Looking at Markov samplers through CUMSUM path plots: a simple diagnostic idea. Technical Report 413. Department of Statistics, University of California at Berkeley.

Table 1. Simulation results for six cases of TARMA(2;1,1,1,1,1)

true model	prob.		$\phi_1^{(1)}$	$\theta_1^{(1)}$	$\phi_1^{(2)}$	$\theta_1^{(2)}$	σ^2	r	d
1		true means	-1	-1	0.5	0.5	1	0	1
	1.0000	means	-1.0048	-0.9096	0.4147	0.4916	1.0213	0.0144	1
	-	s. d.	0.0413	0.0186	0.0031	0.0055	5e-05	5e-07	-
2		true means	-0.5	-0.5	0.5	0.5	1	0	1
	1.0000	means	-0.2906	-0.7830	0.4654	0.5269	0.8642	0.0064	1
	-	s. d.	0.0385	0.0141	0.0040	0.0065	3e-05	2e-08	-
3		true means	0	0	0.5	0.5	1	0	1
	1.0000	means	0.0512	-0.1548	0.4236	0.5974	1.1196	-0.1009	1
	-	s. d.	0.0482	0.0380	0.0061	0.0064	7e-05	0.0010	-
4		true means	0.2	0.2	0.5	0.5	1	0	1
	0.9690	means	0.2278	0.2784	0.4394	0.6021	0.8718	0.2396	1
	-	s. d.	0.0168	0.0145	0.0088	0.0105	3e-05	0.0113	-
5		true means	0.4	0.4	0.5	0.5	1	0	1
	0.0273	means	0.2622	0.5342	0.5094	0.4109	0.9783	0.5057	1
	-	s. d.	0.0162	0.0214	0.0077	0.0183	4e-05	0.5886	-
6		true means	0.5	0.5	0.5	0.5	1	0	1
	0.0017	means	0.4422	0.5517	-	-	0.8993	-	-
	-	s. d.	0.0042	0.0036	-	-	0.0056	-	-

Table 2. The rate of correct selections of TARMA models and Bayesian estimates based on 500 samples

model	rate		$\phi_1^{(1)}$	$\theta_1^{(1)}$	$\phi_1^{(2)}$	$\theta_1^{(2)}$	σ^2	r	d
1		true means	-1	-1	0.5	0.5	1	0	1
	0.9843	means	-0.9051	-0.9839	0.5262	0.4171	1.0896	0.0610	1
	-	s. d.	0.5133	0.1772	0.0954	0.2680	0.2857	0.3054	-
2		true means	-0.5	-0.5	0.5	0.5	1	0	1
	1.0000	means	-0.4595	-0.5259	0.5185	0.4121	1.0404	0.0745	1
	-	s. d.	0.2205	0.2377	0.0923	0.1995	0.1558	0.1886	-
3		true means	0	0	0.5	0.5	1	0	1
	1.0000	means	-0.0187	0.0206	0.4993	0.4856	0.9996	0.0662	1
	-	s. d.	0.2283	0.2063	0.0796	0.0964	0.0844	0.2107	-
4		true means	0.2	0.2	0.5	0.5	1	0	1
	0.8020	means	0.2127	0.1905	0.4952	0.4864	0.9944	0.0231	1
	-	s. d.	0.1670	0.1867	0.0891	0.0964	0.0831	0.4282	-
5		true means	0.4	0.4	0.5	0.5	1	0	1
	0.0375	means	0.4149	0.4078	0.4858	0.4781	0.9937	0.0740	1
	-	s. d.	0.1245	0.1573	0.1112	0.1571	0.0799	0.8099	-
6		true means	0.5	0.5	0.5	0.5	1	0	1
	0.0140	means	0.4981	0.4935	-	-	0.9945	-	-
	-	s. d.	0.0632	0.0650	-	-	0.0810	-	-

Table 3. Simulation results for four cases of model 7

(p, q)	prob.		$\phi_1^{(1)}$	$\phi_2^{(1)}$	$\theta_1^{(1)}$	$\theta_2^{(1)}$	σ^2	r	d	AIC (BIC)
			$\phi_1^{(2)}$	$\phi_2^{(2)}$	$\theta_1^{(2)}$	$\theta_2^{(2)}$				
(2,2)	0.9997	means	0.5730	-0.0569	0.3274	0.0008	0.9715	0.2368	1	7.755
	-	s. d.	0.0061	0.0075	0.0141	0.0112	5e-05	0.0037	-	(48.2)
	-	means	-0.5403	-0.1272	-0.5688	0.2935	-	-	-	
	-	s. d.	0.1084	0.0331	0.0569	0.0340	-	-	-	
(2,1)	0.9998	means	0.5526	-0.0495	0.3829	-	0.9676	0.3952	1	8.027
	-	s. d.	0.0092	0.0042	0.0186	-	4e-05	0.0031	-	(41.3)
	-	means	-0.4159	0.0203	-0.4369	-	-	-	-	
	-	s. d.	0.0695	0.0152	0.0366	-	-	-	-	
(1,2)	0.9998	means	0.5443	-	0.3544	-0.0589	0.9683	0.3439	1	7.159
	-	s. d.	0.0055	-	0.0152	0.0053	4e-05	0.0033	-	(40.4)
	-	means	-0.5292	-	-0.4058	0.1713	-	-	-	
	-	s. d.	0.0961	-	0.0377	0.0233	-	-	-	
(1,1)	1.000	means	0.5142	-	0.4241	-	0.9641	0.3820	1	3.05
	-	s. d.	0.0053	-	0.0121	-	4e-05	0.0042	-	(28.9)
	-	means	-0.4952	-	-0.3829	-	-	-	-	
	-	s. d.	0.0713	-	0.0280	-	-	-	-	

Table 4. Simulation results for six cases of model 8

(p, q)	prob.		$\phi_1^{(1)}$	$\phi_2^{(1)}$	$\phi_3^{(1)}$	$\theta_1^{(1)}$	$\theta_2^{(1)}$	σ^2	d	AIC
			$\phi_1^{(2)}$	$\phi_2^{(2)}$	$\phi_3^{(2)}$	$\theta_1^{(2)}$	$\theta_2^{(2)}$	r		(BIC)
(3,2)	0.9991	means	0.6391	-0.3908	-0.1999	-0.3779	-0.0001	1.1853	2	68.56
	-	s. d.	0.0298	0.0147	0.0073	0.0447	0.0163	9e-05	-	(116.6)
	-	means	0.0205	-0.0128	0.4925	0.4578	0.0615	-0.0919	-	-
	-	s. d.	0.0120	0.0143	0.0075	0.0137	0.0152	2e-08	-	-
(3,1)	0.997	means	0.6911	-0.4165	-0.1893	-0.4447	-	1.1817	2	64.30
	-	s. d.	0.0359	0.0074	0.0069	0.0567	-	9e-05	-	(104.9)
	-	means	0.0778	-0.0059	0.4816	0.4009	-	-0.0933	-	-
	-	s. d.	0.0135	0.0088	0.0049	0.0149	-	2e-08	-	-
(2,2)	0.9523	means	0.7347	-0.7028	-	-0.3233	0.2505	1.3165	2	99.84
	-	s. d.	0.0544	0.0203	-	0.0895	0.0211	0.0001	-	(140.5)
	-	means	0.0212	0.4325	-	0.4418	-0.3367	-0.0738	-	-
	-	s. d.	0.0268	0.0105	-	0.0288	0.0191	5e-06	-	-
(2,1)	0.975	means	0.1212	-0.5330	-	0.2676	-	1.3549	3	101.13
	-	s. d.	0.0358	0.0161	-	0.0551	-	0.0002	-	(134.4)
	-	means	0.1592	0.1739	-	0.2598	-	0.2196	-	-
	-	s. d.	0.0642	0.0085	-	0.0907	-	0.0005	-	-
(1,2)	0.9184	means	0.0642	-	-	0.3635	-0.3743	1.3884	3	112.83
	-	s. d.	0.0511	-	-	0.0741	0.0239	0.0002	-	(146.1)
	-	means	0.4561	-	-	-0.0694	0.0209	0.1751	-	-
	-	s. d.	0.0792	-	-	0.0996	0.0138	0.0008	-	-
(1,1)	0.9691	means	-0.3990	-	-	0.9050	-	1.4133	3	114.16
	-	s. d.	0.0205	-	-	0.0162	-	0.0002	-	(140.0)
	-	means	0.5685	-	-	-0.1851	-	-0.0448	-	-
	-	s. d.	0.0222	-	-	0.0360	-	0.0021	-	-

Table 5. Values of AIC (BIC) for different order (p, q) of TARMA model

$p \setminus q$	1	2	3
1	683.91(714.04)	692.98(730.86)	692.0(737.62)
2	685.10(723.0)	694.92(740.57)	693.08(746.46)
3	688.46(734.09)	685.86(739.23)	690.45(751.58)

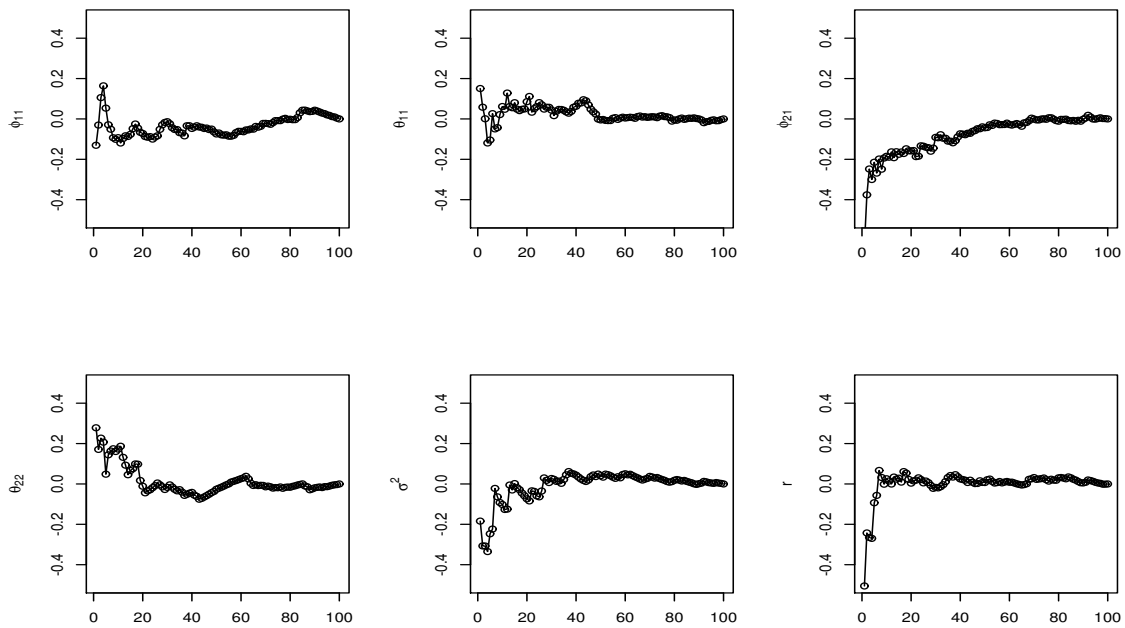


Figure 1. The CUMSUM plots of posterior mean estimates for the model 2

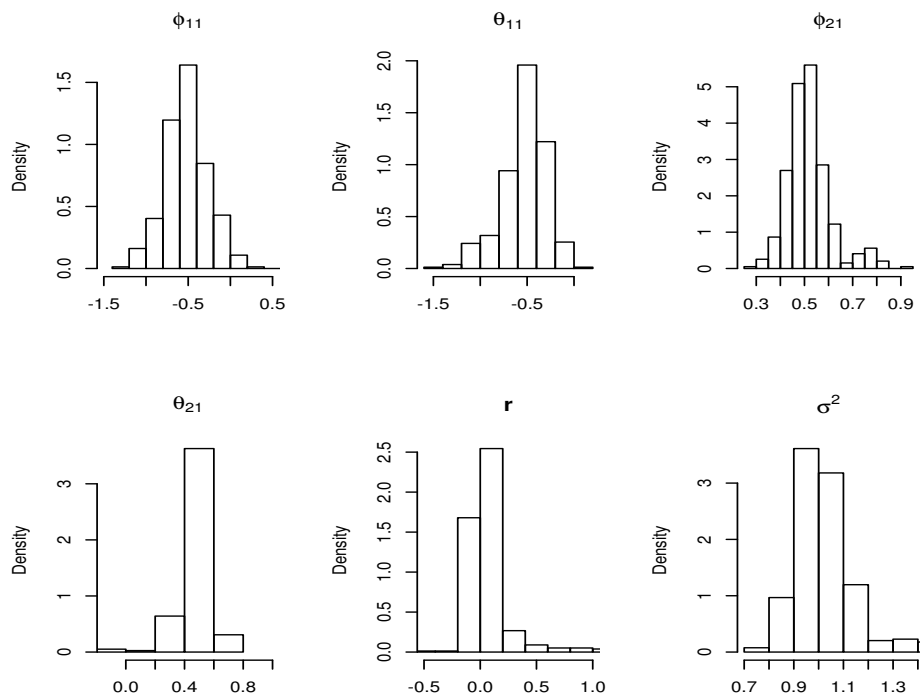


Figure 2. The histogram of all parameters for model 2

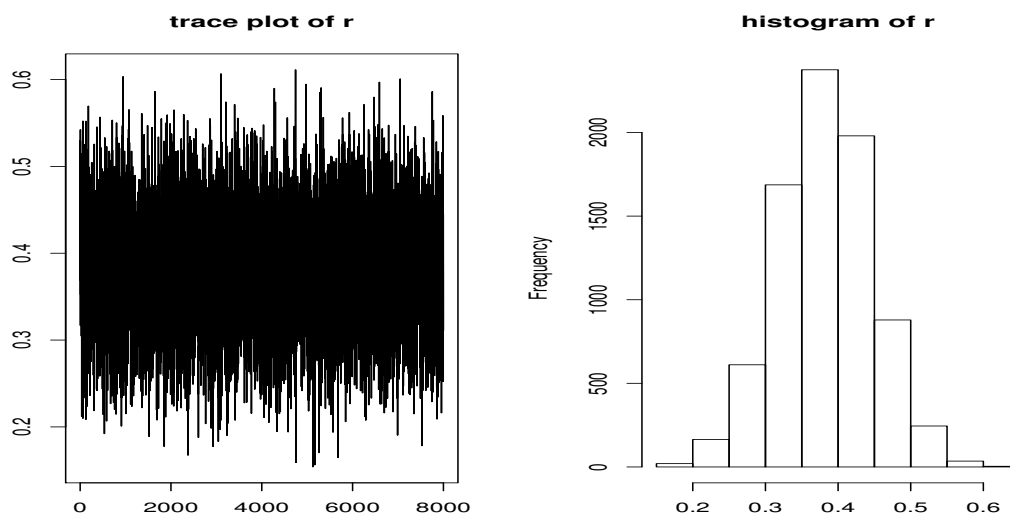


Figure 3. The trace plot and the histogram of r for model 7

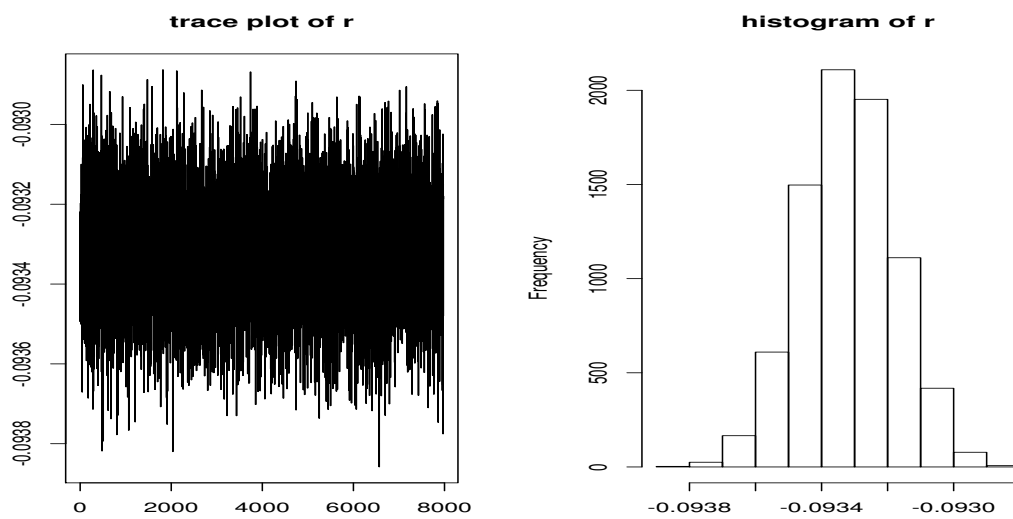


Figure 4. The trace plot and the histogram of r for model 8

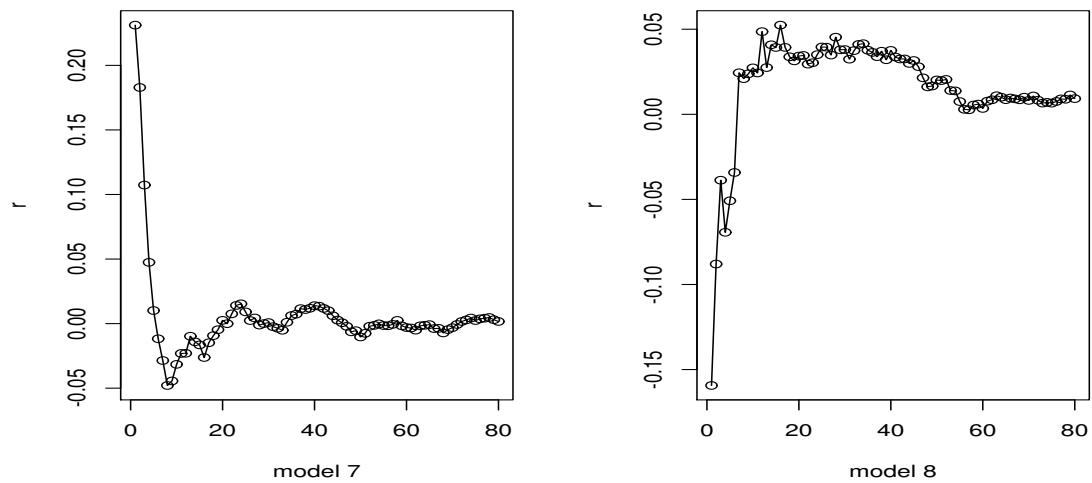


Figure 5. The CUMSUM plots of posterior mean estimates of r for model 7 and 8

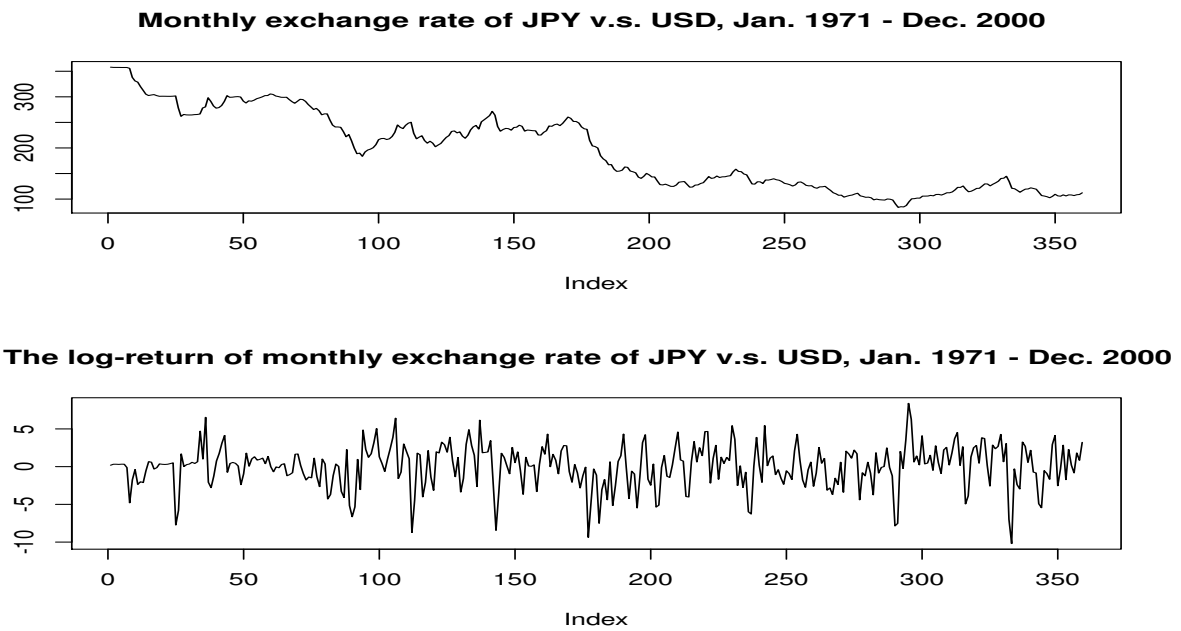


Figure 6. Time series plots for the exchange rate of Japanese Yen v.s. USA dollar

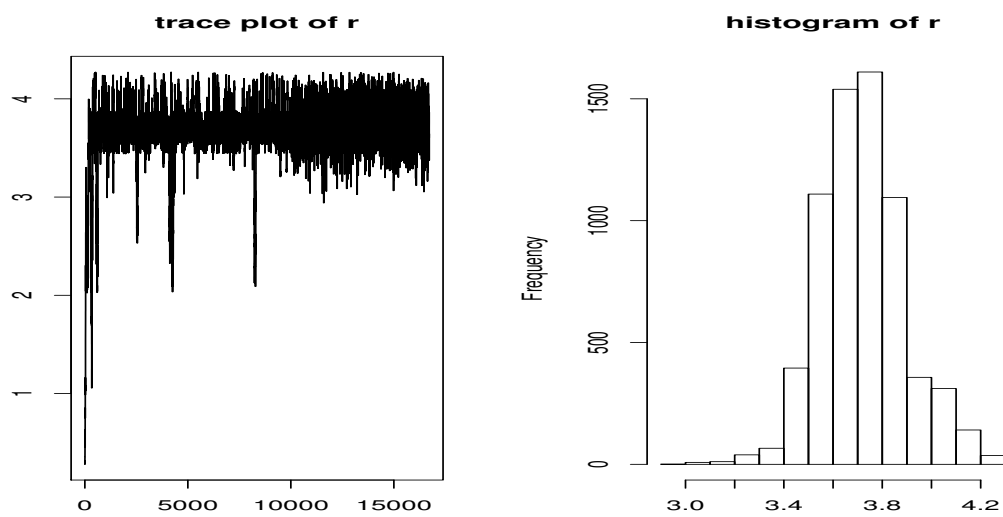


Figure 7. The trace plot and the histogram of r for the real data example