

Regime Shifts in Malaysian Exchange Rates

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ABSTRACT There has been great interest in studying the non-linearity and regime shifts in financial time series. This is due to the realisation that the nonlinear feature in the data cannot be captured by a linear time series model. Therefore, a number of nonlinear model have been introduced to overcome this problem. In this paper, we adopt the 2-regime multivariate Markov switching vector autoregressive (MS-VAR) model with regime shifts in both the mean and the variance to extract common regime shifts behaviour of Malaysian currency exchange rates against four other countries namely the British pound sterling, the Australian dollar, the Singapore dollar and the Japanese yen between 1990 and 2005. It is found that the MS-VAR model with two regimes managed to detect common shifts in all the exchange rates series and this shows evidence of co-movement among all the exchange rates series. Furthermore, we found that all the exchange rates series are affected by the 1997 financial crisis. In addition, the MS-VAR model fitted the data better than the linear vector autoregressive model (VAR).

ABSTRAK Sejak kebelakangan ini, kajian tentang ketidaklinearan dan pertukaran rejim pada siri masa kewangan telah mendapat perhatian. Ini disebabkan wujudnya kesedaran bahawa model siri masa linear tidak dapat menerangkan kelakuan tak linear pada data. Oleh yang demikian, bagi mengatasi masalah ini pelbagai model tak linear telah dibangunkan. Kertas kajian ini telah menggunakan model multivariat vektor autoregresi perubahan Markov (MS-VAR) yang membenarkan pertukaran berlaku antara dua rejim pada min dan varians untuk melihat sama ada wujud kelakuan pertukaran rejim yang sama pada tukaran matawang Malaysia terhadap empat matawang asing yang lain iaitu paun sterling British, dolar Australia, yen Jepun dan dolar Singapura. Didapati model MS-VAR berjaya menunjukkan kehadiran kelakuan pertukaran rejim yang sama pada semua tukaran matawang dan ini menggambarkan kewujudan pergerakan bersama antara siri-siri masa tersebut. Selain itu, krisis kewangan pada tahun 1997 dikenal pasti memberi kesan kepada semua tukaran matawang. Sebagai tambahan, model MS-VAR juga didapati mempunyai darjah kesuaian yang lebih baik daripada model linear vektor autoregresi (VAR).

(Regime shifts, Markov switching vector autoregressive model)

INTRODUCTION

Economic and financial crises occurring around the world have either a major or slight effect on some countries. Usually, the crisis can be seen to affect some key economic indicators such as the stock market price, currency exchange rate, gross domestic product (GDP) and interest rates. Some examples of economic and financial crises are the tremendous increase in crude oil prices during 1974 that led to economic recession in some countries, the stock market plunge in 1987 where

many markets around the world experienced a major decline in the stock prices and the 1997 currency crisis in East Asian countries where speculative attacks on their currencies led to massive currency devaluation. When crisis occurred, the entire indicator experienced heightened volatility because the price rose and plunged precipitously. Furthermore, all these events cause a change in the properties of a series and refer to regime switching behaviour. Therefore to capture this feature, researchers are motivated to use the regime switching models.

Regime switching models are designed to capture discrete changes in the series that generate the data. In this paper, we consider one of such model, namely the Markov switching model that allows the transition between regimes to be abrupt. The Markov switching models assume the regime is an unobservable stochastic process. As a result, the model is also sometimes referred to as stochastic segmented trend models. Apart from flexibility, the Markov switching models are getting much attention because it provides information about the timing of regime shifts where they are often used to create business cycle chronologies. Previous studies that employed this model have been done by Engle [1], Kirikos [2], Caporale and Spagnolo [3] and Bergman and Hansson [4] where they found the existence of regime switching behaviour in exchange rates.

Unfortunately, all the literature mentioned above considered a univariate Markov switching autoregressive model to examine regime switching behaviour in exchange rates. In this paper we extend their work by using a multivariate Markov switching vector autoregressive (MS-VAR) model to find a common regime switching behaviour in a group of Malaysian currency exchange rate series. Our major aim in this paper is to contribute in empirical modelling of regime switching in Malaysian currency exchange rates against four different countries using MS-VAR model which allow the intercept and the variance to vary across different regimes where the process driving the regime is a Markov process. The regime shifts are captured by the filter and smoothed conditional probabilities are inferred from the data. We have two major findings. First, by using likelihood ratio tests we found strong evidence in favour of the nonlinear MS-VAR model rather than the linear VAR model. Second and more importantly, MS-VAR model managed to detect common regime switching behaviour in the four exchange rate returns which shows that there is co-movement among the four series. The remainder of this paper is organised as follows. The next section introduces the Markov switching vector autoregressive model specification. This is followed by a section on the empirical results and finally, we summarise and offer a conclusion in the final section.

MARKOV SWITCHING VECTOR AUTOREGRESSIVE MODEL

The idea of co-movement among economic and financial time series that showed similar regime shifts behaviour as discussed by Diebold and Rudebusch [5] had motivated the development of Markov switching vector autoregressive (MS-VAR) model by Krolzig [6]. The MS-VAR model framework constitutes the multivariate generalisation of the Hamilton [7] single series model. In this extended models all the time series are driven by a common and unobserved regime variable that follow an ergodic Markov process. In a succession of papers, Krolzig [8], [9], [10] studied the statistical analysis of the Markov switching vector autoregressive (MS-VAR) model and their applications to dynamic multivariate systems.

The univariate Markov switching autoregressive model was originally developed by Hamilton [7] to define changes between fast and slow growth regimes in the US economy. In the univariate model, Hamilton [11], [12] assumed that the time series, y_t is normally distributed with mean μ_i in each of k possible regimes where $i = 1, 2, \dots, k$. A Markov switching model of two regimes with an autoregressive process of order p is given as follows:

$$y_t = \mu(s_t) + \left[\sum_{i=1}^p \alpha_i (y_{t-i} - \mu(s_{t-i})) \right] + u_t \quad (1)$$

$$u_t | s_t \sim NID(0, \sigma^2) \text{ and } s_t = 1, 2.$$

The Markov switching autoregressive model framework of (1) can be readily extended to MS-VAR model with two regimes that allow the intercept and the variance to shift simultaneously across the regime. This MS-VAR model of order p is given follows:

$$Y_t = v(s_t) + A_1(s_t)Y_{t-1} + \dots + A_p(s_t)Y_{t-p} + \varepsilon_t, \quad (2)$$

where $Y_t = (Y_{1t}, \dots, Y_{nt})$ is an n -dimensional time series vector, v is the vector of intercepts, A_1, \dots, A_p are the matrices containing the autoregressive parameters and ε_t is a white noise

vector process such that $\varepsilon_t | s_t \sim NID(0, \Sigma(s_t))$. Furthermore, other specifications of MS-VAR model are discussed in the monograph by Krolzig [6].

From (1) and (2), the main difference between regime shifts in the mean and regime shifts that effect the intercept in a time series can be seen from the way a transition to the next regime happens. The intercept switch specification is used in cases where the transition to the new (conditional) mean of the other regime is assumed to follow a smooth path whereas, it is a once-and-for-all jump in the time series when a shift in the mean occurs. Thus the mean is allowed to vary with the regime. Furthermore, the intercept controls the mean of Y_t through the relationship

$$\mu(s_t) = v(s_t) \{I - A_1(s_t) - \dots - A_p(s_t)\}^{-1}.$$

In (1) and (2), s_t is a random variable that triggers the behaviour of Y_t to change from one regime to another. Therefore, the simplest time series model that can describe a discrete value random variable such as the unobserved regime variable s_t is the Markov chain. Generally, s_t follows a first order Markov process where it implies that the current regime s_t depends on the regime one period ago, s_{t-1} and denoted as

$$\begin{aligned} \Pr(s_t = j | s_{t-1} = i, s_{t-2} = k, \dots) \\ = \Pr(s_t = j | s_{t-1} = i) = p_{ij}, \end{aligned} \quad (3)$$

where p_{ij} is the transition probability from one regime to another. For m regimes, these transition probabilities can be collected in an $(m \times m)$ transition matrix denoted as

$$P = \begin{bmatrix} p_{11} & p_{12} & \dots & p_{1m} \\ p_{21} & p_{22} & \dots & p_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ p_{m1} & p_{m2} & \dots & p_{mm} \end{bmatrix}, \quad (4)$$

with $\sum_{j=1}^m p_{ij} = 1, \quad i = 1, 2, \dots, m.$ and $0 \leq p_{ij} \leq 1.$

The transition probabilities also provide us with expected duration, that is, the expected length

that the system is going to stay in a certain regime. Let D define the duration of regime j . Then, the expected duration of the regime is given by

$$E(D) = \frac{1}{1 - p_{jj}}, \quad j = 1, 2, \dots \quad (5)$$

In MS-VAR model, the inference about the value of s_t is based on what happen with the observed variable Y_t . Thus, the inference for a two-regimes case can be represented by a (2×1) vector, $\hat{\xi}_{t|t}$ whose element is $P(s_t = j | \Omega_t)$ where $j = 1, 2$, $\Omega_t = \{\Omega_{t-1}, Y_t\}$ and Ω_{t-1} contains past values of Y_t . These two probabilities will sum to unity by construction. If the value $\hat{\xi}_{t-1|t-1}$ is known at prior then it would be straightforward to form forecast of the regime for t given the information at $t-1$, $\hat{\xi}_{t|t-1}$ and for $s_t = 1, 2$ the vector is denoted as follows:

$$\hat{\xi}_{t|t-1} = \begin{bmatrix} P(s_t = 1 | \Omega_{t-1}) \\ P(s_t = 2 | \Omega_{t-1}) \end{bmatrix}. \quad (6)$$

We can specify the probability law of the observed series, Y_t conditional on s_t and Ω_{t-1} . For two regimes we collect the (2×1) vector denoted by η_t :

$$\eta_t = \begin{bmatrix} f(Y_t | s_t = 1, \Omega_{t-1}) \\ f(Y_t | s_t = 2, \Omega_{t-1}) \end{bmatrix}. \quad (7)$$

Thus, the joint probability of Y_t and s_t is given by the product

$$\begin{aligned} f(Y_t, s_t = j | \Omega_{t-1}) &= f(Y_t | s_t = j, \Omega_{t-1}) \\ P(s_t = j | Y_{t-1}) &= p_{ij}, \quad j = 1, 2. \end{aligned} \quad (8)$$

The conditional density of the t th observation, Y_t is the sum of (8) over all values of s_t . For a two regimes case:

$$\begin{aligned}
 f(Y_t | \Omega_{t-1}) &= \sum_{j=1}^2 \sum_{i=1}^2 f(Y_t | s_t, \Omega_{t-1}) P(s_t | \Omega_{t-1}) \\
 &= \eta_t' \hat{\xi}_{t|t-1}.
 \end{aligned}
 \tag{9}$$

Then, the output $\hat{\xi}_{t|t}$ can be obtained from the input $\hat{\xi}_{t-1|t-1}$ by following the steps suggested by Hamilton [12] and given below:

$$\hat{\xi}_{t|t} = \frac{\eta_t \Theta \hat{\xi}_{t|t-1}}{1' (\eta_t \Theta \hat{\xi}_{t|t-1})},
 \tag{10}$$

$$\hat{\xi}_{t+1|t} = P \hat{\xi}_{t|t}.
 \tag{11}$$

Here η_t is from (7), P is the (2×2) transition matrix of (4), $1'$ represents a (2×1) vector of 1s and the symbol Θ denotes element by element multiplication. Using an initial starting value $\hat{\xi}_{1|0}$ and assuming the vector parameter is known, (10) and (11) can be iterated for $t = 1, 2, \dots, T$ to calculate the value of $\hat{\xi}_{t|t}$ and $\hat{\xi}_{t+1|t}$ for each t in the sample. During the iteration, the vector parameter can also be calculated as a by-product of the algorithm by maximising the log likelihood function of (9).

The algorithm discussed above also provides probabilistic inferences about the unobserved regime, s_t where filtered probabilities $P(s_t = j | \Omega_t)$ are inferences about s_t conditional on information up to time t ($t = 1, 2, \dots, T$) and smoothed probabilities $P(s_t = j | \Omega_T)$ are inferences about s_t by using all the information available in the sample with $t = T - 1, T - 2, \dots, 1$. Finally, the parameters vector is estimated by the maximum likelihood using the expectation-maximisation algorithm (EM algorithm) as described by Hamilton [11], [12], [13] and Kim and Nelson [14] because the regime variable, s_t is unobserved.

APPLICATION TO MALAYSIAN EXCHANGE RATES

We begin this section by giving the description of the data. Then we model the data using MSIH-VAR model. Finally, we collect a series of the filtering and smoothed probabilities to identify common regime shifts in the four series.

Data

This study makes use of monthly exchange rates of Malaysian ringgit against four other currencies, namely, the British pound sterling (MBP), the Australian dollar (MAD), the Japanese yen (MJY) and the Singapore dollar (MSD) from January 1990 to December 2005 for a total of 192 observations. All the exchange rates series are from www.x-rates.com and analysed in returns, which is the first difference of natural logarithms multiplied by 100 to express things in percentage terms. Figure 1 shows the behaviour of the four exchange rates time series over the study period. From it we can see that for most of the time, all the series are stable except for the period around 1997 where higher negative returns occur.

MODEL ESTIMATION

We begin by selecting the best specification for the MS-VAR model. From the information criteria, namely, the Akaike (AIC), the Hannan-Quinn (HQ) and the Schwarz (SC) information criteria we found that the MS-VAR model of order one or MS-VAR(1) is the best specification to model the four exchange rates returns series. Then we continue to estimate the two regimes MS-VAR(1) models and the results are presented in Table 1.¹ Estimations are carried out using the MSVAR module for Ox (Krolzig, [8]).

¹ As discussed by Taylor [15], the financial time series can be characterised by two common behaviours, that is, either the prices move up or down. Therefore, in this paper we use a two regimes model to capture period where the exchange rates increase or decrease.

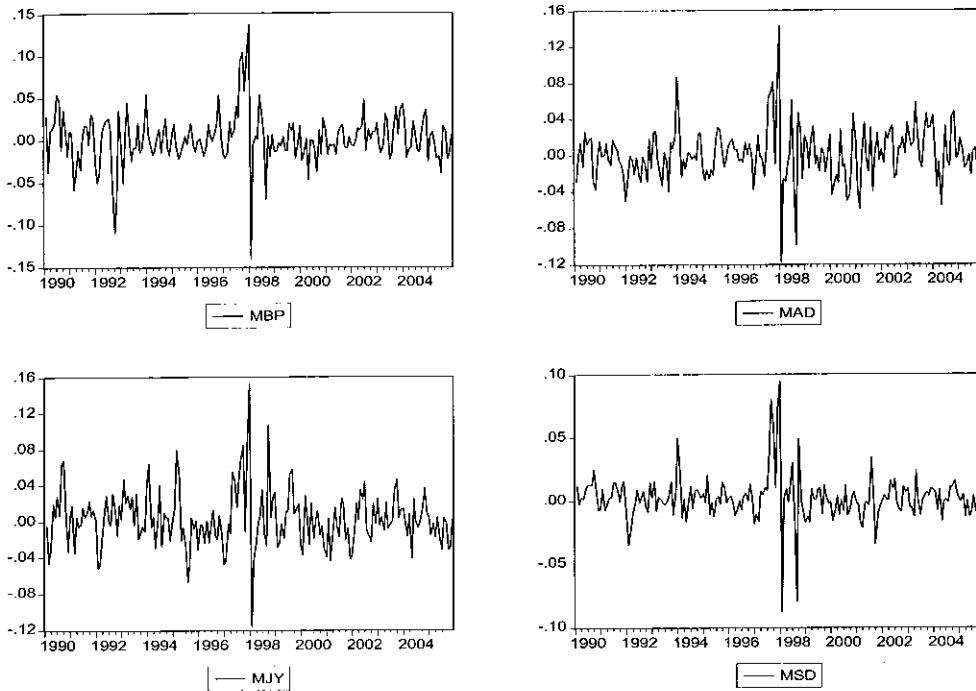


Figure 1. The return of exchange rates series.

From Table 1 it is clear from the low values of the AIC, HQ and SC criteria that the MS-VAR(1) model better describe the data than the linear VAR(1) model. This is further justified by the likelihood ratio test (LR test) which tests the null hypothesis of linear model (VAR) against an alternative of regime switching model (MS-VAR model) where it is found that the null hypothesis can be rejected.² Furthermore, additional evidence in favour of the MS-VAR(1) is provided by plots of the actual series and one step prediction series for each exchange rates series given in Figure 2 where the fit of the model seems to be good. Therefore, we conclude that the performance of nonlinear time series models is better than that of linear time series models in describing the data under study.

The estimate parameters of the MS-VAR(1)

²The LR test statistic is computed as $LR_{MS-VAR} = 2|\log Lik_{MS-VAR(1)} - \log Lik_{VAR(1)}|$ and critical value is based on Davies [16] *p*-value as suggested by Garcia and Perron [17].

model are shown in Table 1. It seems that the variance of regime 2, $\sigma^2(s_t = 2)$, is higher than the variance of regime 1, $\sigma^2(s_t = 1)$. This result shows that regime 2 ($s_t = 2$) is more volatile than regime 1 ($s_t = 1$). Therefore, we can characterise regime 1 as the tranquil period where the exchange rate returns are in normal phase, whereas regime 2 is associated with the turbulent period where returns are in upward phase. Furthermore, the intercept values during the turbulent period $v(s_t = 2)$ are higher than the intercept values during the tranquil period $v(s_t = 1)$. This result indicates that the return of exchange rates increase during the turbulent period and fall or experience a small increase during the tranquil period.³ From Table 1 we also found that the expected duration of being in

³ The positive signs of the intercept either in regime 1 or regime 2 refer to an increase of return of exchange rates and the negative signs refer to decrease in return of exchange rates.

regime 2, $P(s_t = 2 | s_{t-1} = 2) = p_{22}$, is very small, that is, 5.5 months as compared to being in regime 1, $P(s_t = 1 | s_{t-1} = 1) = p_{11}$, 39.4 months. This means that the exchange rates will be in the

turbulent period in a short time before reverting back to a normal period which refers to the tranquil period.

Table 1. ML estimation result for the MS-VAR(1), 1990(2)-2005(12).

	MBP_t	MAD_t	MJY_t	MSD_t
<i>Regime dependent intercepts</i>				
ϕ_1	0.084248 (0.5494)	-0.009461 (-0.0569)	-0.027796 (-0.1492)	0.034386 (0.4417)
ϕ_2	0.591317 (0.4340)	1.233960 (0.9939)	1.951099 (1.6646)	1.383204 (1.5741)
<i>Coefficients</i>				
MBP_{t-1}	0.198584 (2.4046)	0.060765 (0.7840)	0.100646 (1.1328)	0.068900 (1.6276)
MAD_{t-1}	0.220908 (0.4340)	0.328890 (4.4865)	-0.038275 (-0.4602)	0.062751 (1.7305)
MJY_{t-1}	0.060013 (0.8821)	-0.066267 (-0.9467)	0.278662 (3.4974)	0.004090 (0.1185)
MSD_{t-1}	-0.199003 (-1.1160)	-0.105758 (-0.6184)	-0.128615 (-0.6639)	0.019136 (0.2097)
σ_1	1.927717	2.115674	2.383266	0.973290
σ_2	6.566067	5.900154	5.529039	4.229828
<i>Fitting</i>		<i>MSMH(2)-VAR(1)</i>		<i>linear VAR(1)</i>
<i>Log Lik</i>		-1509.3634		-1601.6777
<i>AIC</i>		16.3722		17.1756
<i>HQ</i>		16.6907		17.3832
<i>SC</i>		17.1584		17.6882
<i>LR_{MSMH-VAR}</i>		184.6285 (.0000)		
p_{ij}	$s_{t-1} = 1$	$s_{t-1} = 2$	<i>Duration</i>	
$s_t = 1$	0.9747	0.0253	39.49	
$s_t = 2$	0.1813	0.8187	5.52	

Please refer to (2) for full specification of the equation. Figures in the () and [] brackets are the *t*-values and the Davies *p*-value, *Log Lik* is the log-likelihood.

As mentioned in the last section, during the estimation process, the filter and the smoothed probabilities are collected for each point of time. Figure 3 gives a graphical display of the filter and smoothed probability plots of regimes 1 and 2 produced by MS-VAR(1) model. Generally, the filter and smoothed probability plots would lead to very similar conclusion. In most cases, much attention is given to the regime which represents the turbulent period. This is because this regime

triggers the system to alternate between two different regimes. In our case this refers to regime 2. From Figure 3, the smoothed probability plots of regime 2 or turbulent regime display that downswings are abrupt and much shorter while upswings are more gradual and highly persistent. Furthermore, there are three periods of being in turbulent regime where the probabilities are near to unity: 1992:9-1993:2, 1994:1-1994:2 and 1997:8-1998:10.

It is interesting to see that the first period of turbulence between September 1992 and February 1993 is inline with the exchange rate crisis in the European Monetary System (EMS) in 1992/93. It appears that the financial crisis that struck many European countries had some effect on the Malaysian exchange rate market.⁴ In addition, the second period of turbulence only lasted for two months between January 1994 until February 1994 and it may be an early sign of the turbulent period in 1997. Finally, the duration of the two periods of turbulence mentioned earlier was very short whereas the duration of the last period of turbulence appears to be longer. This period of turbulence began in August 1997 until October 1998 and lasted for 15 months. During this period of turbulence, Malaysia and other ASEAN countries were affected by the 1997 financial crisis because of speculative attack on their local currencies. In a survey done by Lee [18], the Malaysian ringgit began to depreciate against the US dollar in the middle of July 1997 where the value of the Malaysian ringgit depreciated from RM 2.7-2.8 to a dollar to as low as RM 4.88 to a dollar in January 1998. In a subsequent study, a chronology of the 1997 financial crisis built by Kellberg et al. [19] indicated that the Malaysian government had applied capital controls by fixing the Malaysian ringgit exchange rate against the US dollar in September 1998 to curb the crisis. As a result, the MS-VAR(1) models show that the Malaysian exchange rate market recovered from the 1997 financial crisis in October 1998, just after the capital controls were put in place. Thus, it was a wise decision to peg the exchange rate against the US dollar.⁵

CONCLUSION

In this paper, we adopt a two regimes multivariate Markov switching vector autoregressive (MS-VAR) model with regime shifts in both the intercept and the variance (MS-VAR(1)) to extract common regime shifts behaviour in monthly returns exchange rates series of Malaysia ringgit against four other currencies from 1990 until 2005. Our finding can

be summarised as follows. Firstly, we can reject linearity in four exchange rates series which imply that there is regime switching structure in all the series. Secondly, we found that the four exchange rates series are well fitted by the MS-VAR(1) model and a common regime shifts behaviour can be extracted. This is shown by the filter and smoothed probability plots of regimes 1 and 2. Furthermore, regime 1 represents the tranquil period and regime 2 refers to the turbulent period of the four exchange rates series. The turbulent period occurred in a very short period whereas the tranquil period lasted longer. Finally, for future research it is worth to capture a common regime switching behaviour among the ASEAN countries currencies.

⁴ A complete survey about the financial crisis can be found in Buiters et al. [20]

⁵ As the Malaysian ringgit against the US dollar has been fixed since 1998, we cannot use the series in our modeling because the analysis is done in returns.

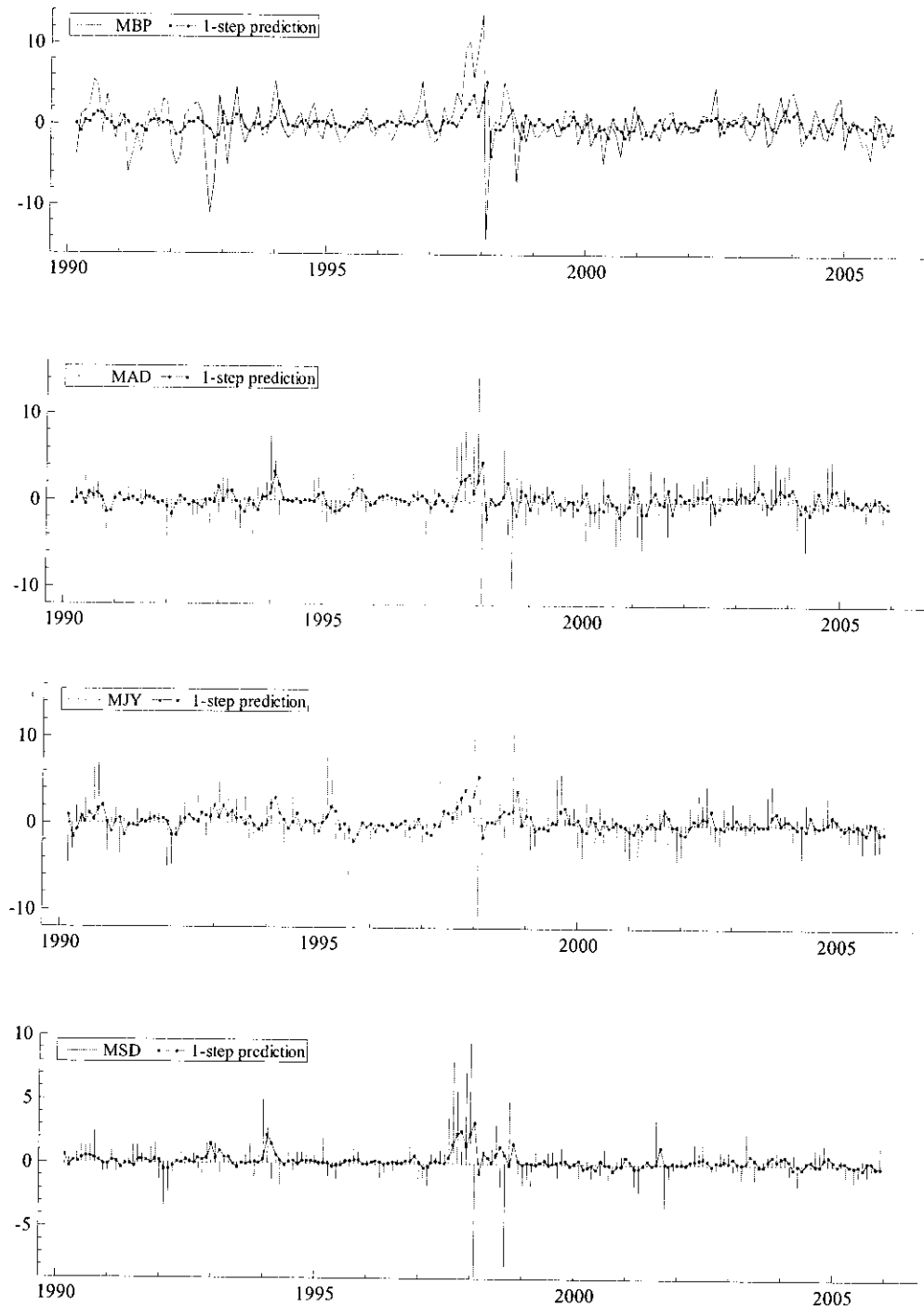


Figure 2. Fit of the MSIH(2)-VAR(1), 1990(2)-2005(12)

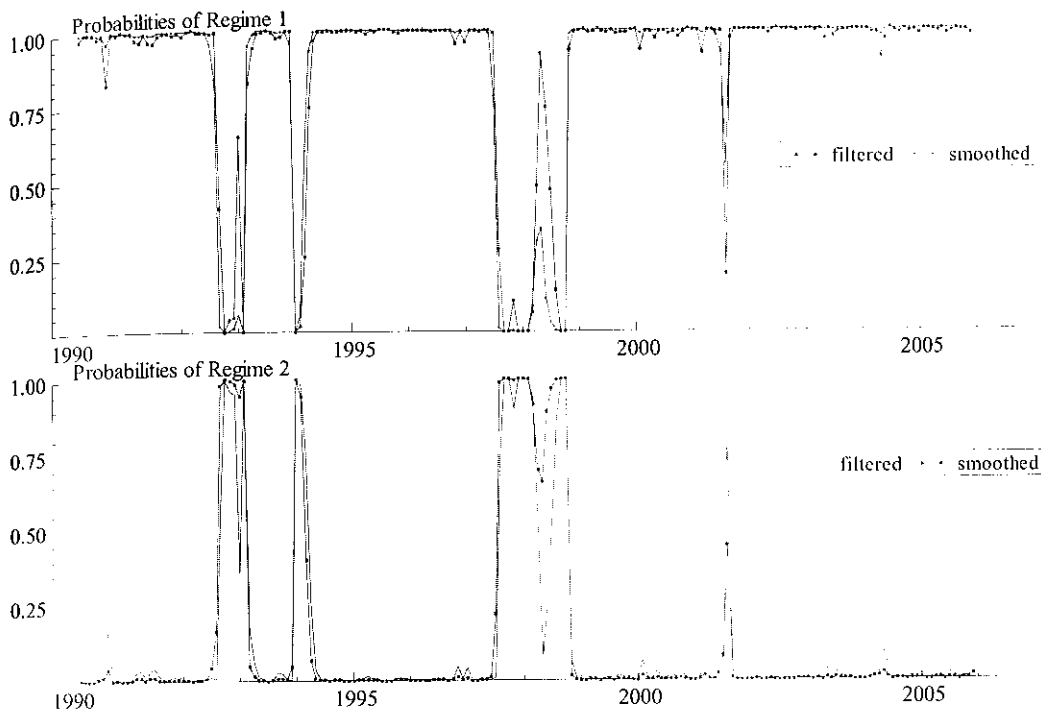


Figure 3. Regime Probabilities of the MSIH(2)-VAR(1), 1990(2)-2005(12)

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