International Scholars Journals

International Journal of Accounting, Auditing and Taxation ISSN: 2756-3634 Vol. 8 (1), pp. 001-008, January, 2021. Available online at www.internationalscholarsjournals.org © International Scholars Journals

Full Length Research Paper

A study of structural breaks in Malaysian stock market

Mohd Tahir Ismail[1], Samsul Ariffin Abdul Karim[2] and S. Alwadi[1]*

[1]School of Mathematical Sciences, Universiti Sains Malaysia, 11800 Minden, Penang, Malaysia.
[2]Department of Fundamental and Applied Sciences, University of Technology Petronas, Bandar Seri Iskandar, 31750 Tronoh, Perak Darul Ridzuan, Malaysia.

Accepted 15 October, 2020

In recent years the study of regime shifts or structural breaks behaviour in time series has gained much attention. This is due to realization that many economic time series undergo episodes in which the behaviour of the series change quite dramatically as a result of financial crises or abrupt changes in the government policy. The paper use two difference approaches to capture the possibility of structural breaks in KLCI index of Bursa Malaysia between 1977 and 2008. The first approach is by using the Markov switching model where the movement between regimes or regime shifts are unrelated to the past observations of the process and enables probabilistic statements to be made about the likelihood of the series being in a particular regime in any time period. While the second approach is via the wavelets method where a time series is transform using a particular wavelet basis functions. The transform series is well localized in both the time (position) and the frequency (scale) domain. Hence, the study can detect precisely a sudden change in the data. Finally, the study compares the results from the two approaches and discusses the advantage and disadvantage of each approach. Several numerical results will be presented.

Key words: Structural breaks, financial time series, Markov switching model, wavelets transform**.**

INTRODUCTION

In recent years economists and financial researchers have focus their studies on regime shifts or structural change, long memory and volatility clustering in financial time series. These three features are the main concerns to them because they are the usual observed behaviors that occur in financial time series. Furthermore, by monitoring these main features frequently, the reasearchers hope to understand more about a series and the probable development in the future. A comprehensive overview on the recent development of modelling structural breaks, the analysis of long memory and stock market volatility can be found in Banarjee and Urga (2005).

Structural breaks are the main highlight that will be discuss in this study. Structural break has been a major concern especially for economists. Various theories of economic assume that economic relationship changes over time. Such a change has been explained in descriptive way without being use a statistical test. With the introduction of regression analysis as the principle tool of economic data processing in the 1950s and 1960s, attempts were made to describe changes of economic relationship in regression framework. A detail discussion of structural break in economic and financial data can be found in Hackl (1989).

This paper will examine the existence of regime shifts or structural breaks in Kuala Lumpur Composite Index (KLCI) from Bursa Malaysia. The KLCI index is the leading stock market indicator in Bursa Malaysia and its movements are closely monitored by the institutional and retail investors. As of 1998, the number of constituent stocks that made up the KLCI index has been capped at 100. The KLCI index has undergo periods of crash and expansion since its

*Corresponding author. E-mail: mtahir@cs.usm.my.

lunch. Some examples of these events are the stock market plunge around the world in 1987 where KLCI index also experienced a major decline in the stock prices and the 1997 currency crises where KLCI index was also affected. Usually after the crash periods, the KLCI index will steadily increase before become stable. All of these events indicate the possibility of structural change occur in the KLCI index historical series.

As a result, it motivates us to show statistically and mathematically the presence of structural breaks in KLCI index using two difference methods. The first method is by using Markov switching autoregressive model (MS-AR) and the second method is via wavelet transform (WT). Markov switching autoregressive model are designed to capture sudden shifts in the series that generate the data. The MS-AR model assumed the regime is an unobservable stochastic process.

This means the movement between regimes or regime shifts are unrelated to the past observations of the process and enables probabilistic statements to be made about the likelihood of the series being in a particular regime in any time period. Therefore, the regime shifts is said to be happened exogenously with assigns probabilities to the occurrence of different regimes and the probabilities are called transition probabilities. The advantage of the transition probabilities is that they specified a probability which regime occurs at each point in time rather than imposing particular dates at priori.

These allow the data to tell the nature and incidence of significant shifts. While, wavelets method have a property to 'zoom in' on very short lived frequency phenomena, such as transients in signals and singularities in functions. This property provides a tool to learn localized changes in a series.

This method require a series to be represented by some wavelet functions, hence a series have to be transform to a certain wavelet functions. The transform series is well localized in both the time (position) and the frequency (scale) domain. Hence, the study can detect precisely a sudden change in the data.

METHODOLOGY

In this section the study will give a brief introduction about the Markov switching autoregressive model and the wavelet analysis.

Markov switching autoregressive models

In this section we consider a univariate autoregressive process, AR which subject to regime shifts. The study extends the conventional Hamilton's model with focus on one time regime shifts in the mean by allowing the mean and the variance to shift simultaneously across the regime. The variable under investigation is the monthly exchange rates changes. Therefore, a Markov switching autoregressive model (MS-AR) of two regimes with an AR process of order p is given as follow:

$$y_t = \alpha(s_t) + \sum_{i=1}^{p} \alpha_i \left(y_{t-i} - \alpha(s_{t-i}) \right) + u_t$$
$$u_t \sim i.i.d\,(0, \sigma^2(s_t)) \qquad (1)$$
$$s_t = j,\; s_{t-i} = i \qquad i, j \in 1, 2$$

Where s_t and s_{t-i} are the unobserved regime variables that take the values of 1 or 2 and the transition between regimes is governed by a first order Markov process as follows:

$$P(s_t = 1 \mid s_{t-1} = 1) = p_{11}$$
$$P(s_t = 1 \mid s_{t-1} = 2) = p_{12} = 1 - p_{11}$$
$$P(s_t = 2 \mid s_{t-1} = 1) = p_{21} = 1 - p_{22} \qquad (2)$$
$$P(s_t = 2 \mid s_{t-1} = 2) = p_{22}.$$

With $p_{11} + p_{12} = p_{21} + p_{22} = 1$. The Markov process is assumed to be ergodic and irreducible so that unobserved regime will not exist. Equation (2) is calls the transition probability and it specifies as a constant coefficient that is independent of time, *t* (time-invariant). This means the probability of switching between regimes do not depend on how long the process is in a given regime.

The conventional procedure for estimating the model parameters is to maximize the log-likelihood function and then use these parameters to obtain the filtering and smoothing inference for the unobserved regime variable s_t . However, this method becomes disadvantageous as the number of parameters to be estimated increases. Generally in such cases, the expectation maximization (EM) algorithm is used. This technique starts with the initial estimates of the unobserved regime variable, s_t and iteratively produces a new joint distribution that increases the probability of observed data. These two steps are referred to as expectation and maximization steps. The EM algorithm has many desirable properties as stated in Hamilton (1990), Hamilton (1993), Hamilton (1994); Kim and Nelson (1999).

Wavelets analysis

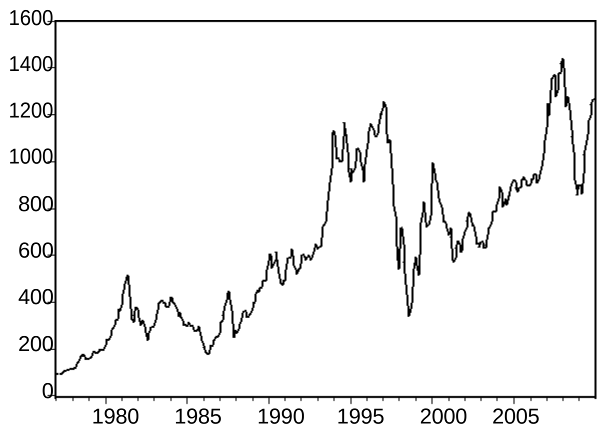
The wavelet basis function are constructed via the dilation equation invloving the scaling function using the multiresolution analysis (MRA). For the detailed description refer to Mallat (1989) and Daubechies (1992) or an easy treatment in Karim and Ismail (2008). For a signal c_0 , its fast wavelets transform (FWT) can be implemented by (Chui, 1992; Mallat, 1989 and Daubechies, 1992)

$$c_{j,k} = \sum_{m=1}^{N} h_{m-2k}\, c_{j-1,m} \qquad (3)$$

$$d_{j,k} = \sum_{m=1}^{N} g_{m-2k}\, c_{j-1,m} \qquad (4)$$

or simply written as $c_j = H^* c_{j-1}$ and $d_j = G^* c_{j-1}$.

Where *c* and *d* with the index represent of the decomposed components *c* and *d* from the original signal c_0 by wavelet transform



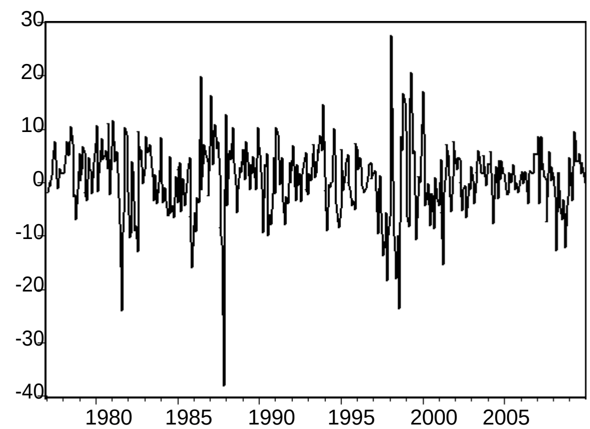


Figure 1. Monthly original and return series.

$H^* = \{h_{-k}\}_{k \in Z}$ and $G^* = \{g_{-k}\}_{k \in Z}$ are discrete filters corresponding to the wavelet function $\psi(x)$ and the scaling function $\varphi(x)$, and $j = 1,2,..., J$, where J represented the maximum level/scale of the data. N represents the length of the vector c_{j-1} (for example the length of the data set, say $N = 1024 = 2^{10}$ etc., in this case $J = 10$).

In these two equations, the wavelet transform of the signal c_0 means that the resulting signals c_1 (called discrete approximation or scale coefficient) and d_1 (called discrete detail or wavelet coefficient) are, respectively, the convolution of c_0 with the discrete filters H* and G* followed by the properly of "downsampling by factor 2". The low pass filter and high pass filter are related by the following equation (Mallat, 1989 and Daubechies, 1992)

$$g_k = (-1)^k \overline{h}_{N-k} \tag{5}$$

The original signal c_0 with length N can be reconstructed from the scale coefficients c_j and wavelet coefficients d_j, following the backward procedures of using the inverse FWT (IFWT)

$$c_{j,k} = \sum_{m=1}^{N} n_{k-2m} c_{j+1,m} + \sum_{m=1}^{N} g_{k-2m} a_{j+1,m} \tag{6}$$

or simply written as $c_j = Hc_{j+1} + Gd_{j+1}$. Where H and G are conjugate filters of the filters H* and G*. In the calculation, c_j and d_j must be followed by an "upsampling by factor 2" with zeroes added between each adjacent elements of the vectors (see Strang and Nguyen (1996) for more details on filter bank with its connection to the wavelet theory).

The decomposition and reconstruction equations presented above are useful for data compression because the wavelet transform procedure is capable of retaining a large percentage of the total energy of the signal in the scale coefficients c_j at different resolution levels.

Usually only a small number of the wavelet coefficients are needed to effectively represent the original signal with better compression rate. This is the main advantages of using wavelet transform in data compression. For determined which coefficients should be retained, the thresholding method is used. There exists two choice of thresholding method that is hard thresholding and soft thresholding. For detail refer to Hardle et al. (1998), Antoniadis (1997), Donoho, and Johnstone (1994, 1995), Karim et al. (2008), Resnikoff and Wells (1998), Van Fleet (2008). For data compression, the hard thresholding is used because the main objective is to remove the small coefficients (that is the detail coefficients).

RESULTS AND DISCUSSION

This section starts by giving a description of the data. Then the study show the presence of structural change using the 2-regime Markov switching autoregressive model and the wavelet transform. Finally, the study compares the results from the two methods.

Data

The data under investigation are monthly KLCI index from Bursa Malaysia. The estimation period for the monthly data is from January 1977 - December 2008 with 384 observations. The KLCI index series are analyzed in returns, which is the first difference of natural algorithms multiplied by 100 to express things in percentage terms. The study uses the monthly returns series because the study assumes that regime shifts can be observed more clearly across time if low frequency data is used. The study proved this by plotting the monthly returns series (Figure 1). In Figure 1 we manage to detect large negative

Table 1. Estimated MS-AR (1) model for monthly KLCI Index return series.

Parameters	KLCI
$\propto_1$	-1.4114
$\propto_2$	1.2005
a	0.3817
p_{11}	0.9457
p_{22}	0.9845
σ_1	9.9324
σ_2	4.2151
$E(D_{St=1})$	18.0
$E(D_{St=2})$	65.0

returns at 1987 and 1997. This feature suggests that regime shifts happen during these periods.

Identifying structural breaks via MS-AR model

The estimated parameters for the MS-AR (1) model using maximum likelihood estimation via EM-algorithm are presented in Table 1. As stated in Table 1, the estimated MS-AR (1) model successfully identified two difference regimes for the return of KLCI index. This shows that the movements of the return series will alternate between these two regimes. The first regime captures the behaviors of the KLCI index in a recession phase or in a bear market with high volatility (9.9%) and low (and negative) expected return (-1.4%). While the second regime, which is more persistent and associate with high-expected return (1.1%) and lower volatility (4.2%). This regime can be referring to the state where the KLCI index is in the expansion phase or in the bull market.

Moreover, the probability of staying in regime 1 and 2, p_{11} and p_{22} is 0.9459 and 0.9834 respectively with the expected duration of staying in regime 1, $E\left(D_{St}=1\right)$ is 18 months and the expected duration of staying in regime 2, $E\left(D_{St}=2\right)$ is 60 months. It appears that the expected duration of being in regime 2 is longer than regime 1 which implies that the KLCI index return series stay much longer in regime 2 than regime 1. This indicate that only an extremely event can switch the series from regime 2 to regime 1, or from a bull market to a bear market.

In addition, the estimate MS-AR(1) model also provides the smoothed probability plot which shows which regime happen at each point of time. It can be seen from Figure 2 that the smoothed probability plot of regime 1 is near unity around early 1981, end of 1985, middle of 1997 and early 2001. All of these points are inline with some events of economic crisis, which triggers the KLCI index to show structural breaks behaviour. The structural breaks in 1981 happened because of 1981-1982 recession period happened because of the restructuring in the industrial sector in major industrial countries such as the US, which also affected Malaysia as the export of raw material is slow. Then the second and third structural break in 1985 and 1997 occurred because of stock market crash around the world and the Asian financial crisis. Finally the fourth structural breaks in 2001, took place because of world recession that started in US. While regime 2 show the behavior of KLCI index after each of the crisis, which is increasing steadily before, become stable. As noted in Table 2 the duration of staying in regime 2 or expansion period is very long as compare to regime 1 which is quite short except for 1987 and 1997 crisis. This shows the KLCI index will be in the contraction period in a short time before reverting back to a normal period with refer to the expansion period. In addition from all this results, it suggests that MS-AR (1) model perform well in getting the direction of change in a series either the series is in contraction or expansion.

Identifying structural breaks via Wavelet method

The procedure for detecting structural breaks using discrete wavelet transform (DWT) starts by computing the wavelets transformation of the noisy KLCI index return data. Then the wavelet coefficients are compared with the estimated threshold. Thus, it uses the spatial positions at which the wavelet transformation across fine scale levels

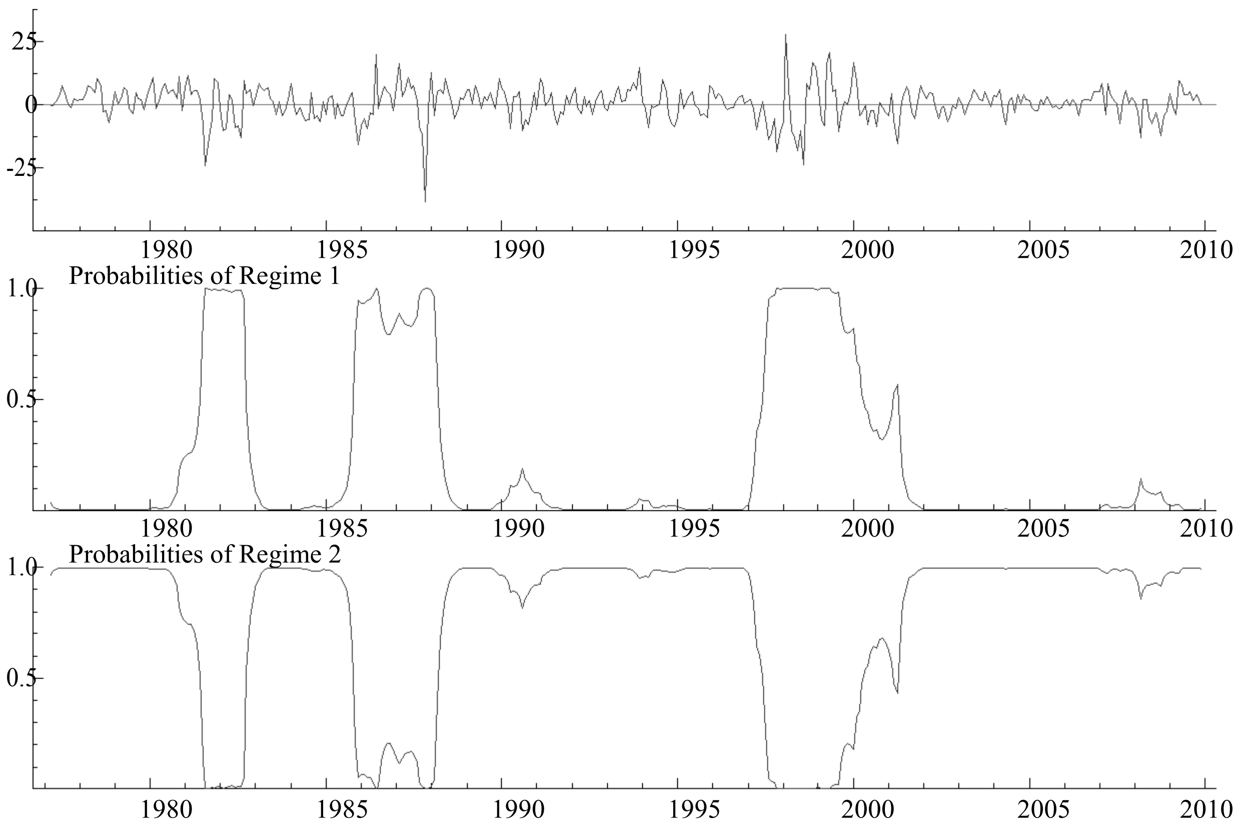


Figure 2. Original series and smoothed plot of regime 1 and regime 2.

Table 2. Duration of regime 1 and regime 2.

Regime/Index	Regime 1(Contraction period)	Regime 2(Expansion period)
KLCI	1981:7 - 1982:9 [0.9506]	1977:3 - 1981:6 [0.9547]
	1985:11 - 1988:3 [0.8931]	1982:10 - 1985:10 [0.9442]
	1997:7 - 2000:4 [0.9245]	1988:4 - 1997:6 [0.9577]
	2001:3 - 2001:4 [0.5375]	2000:5 - 2001:2 [0.6368]
		2001:5 - 2009:12 [0.9709]

exceeds the threshold to detect and locate change point or structural breaks.

For the purpose of KLCI decomposition by using DWT the study used symlet 8 (with 8 wavelet filters), for more detail refer to Daubechies (1992). The symlet 8 wavelet is relatively smooth, when the study compared with the Haar wavelet filter, and therefore, it will produce a smoothly varying MRA. Figure 3 show the symlet 8 scaling function and wavelet function. Effectively, by using DWT, enables us to study and make comparison between all scales of the decomposition. Figure 4 shows the result when the study decomposes the KLCI time series up to level 3. Even though the study can use up to maximum level of 7 to decompose the time series, the optimum level is at level 3. It can be seen that at level 3 the detail d_3 already contains the main patterns of the original time series data. There is a noticeable large negative return at 1987 (120 months) and 1997 (240 months), in particular at the third wavelet detail. One of the advantages of wavelets is from the wavelet detail (first, second and third) the study can see clearly that at the year 2007 - 2008 also notice the larger negative return, which are true in current global economic crisis. There is also noticeable break in the original time series wavelet smooth s_3 at early 1981, end of 1985, middle of 1997, early 2001 and year 2007 - 2008 (current global economic crisis). This result indicates that wavelet

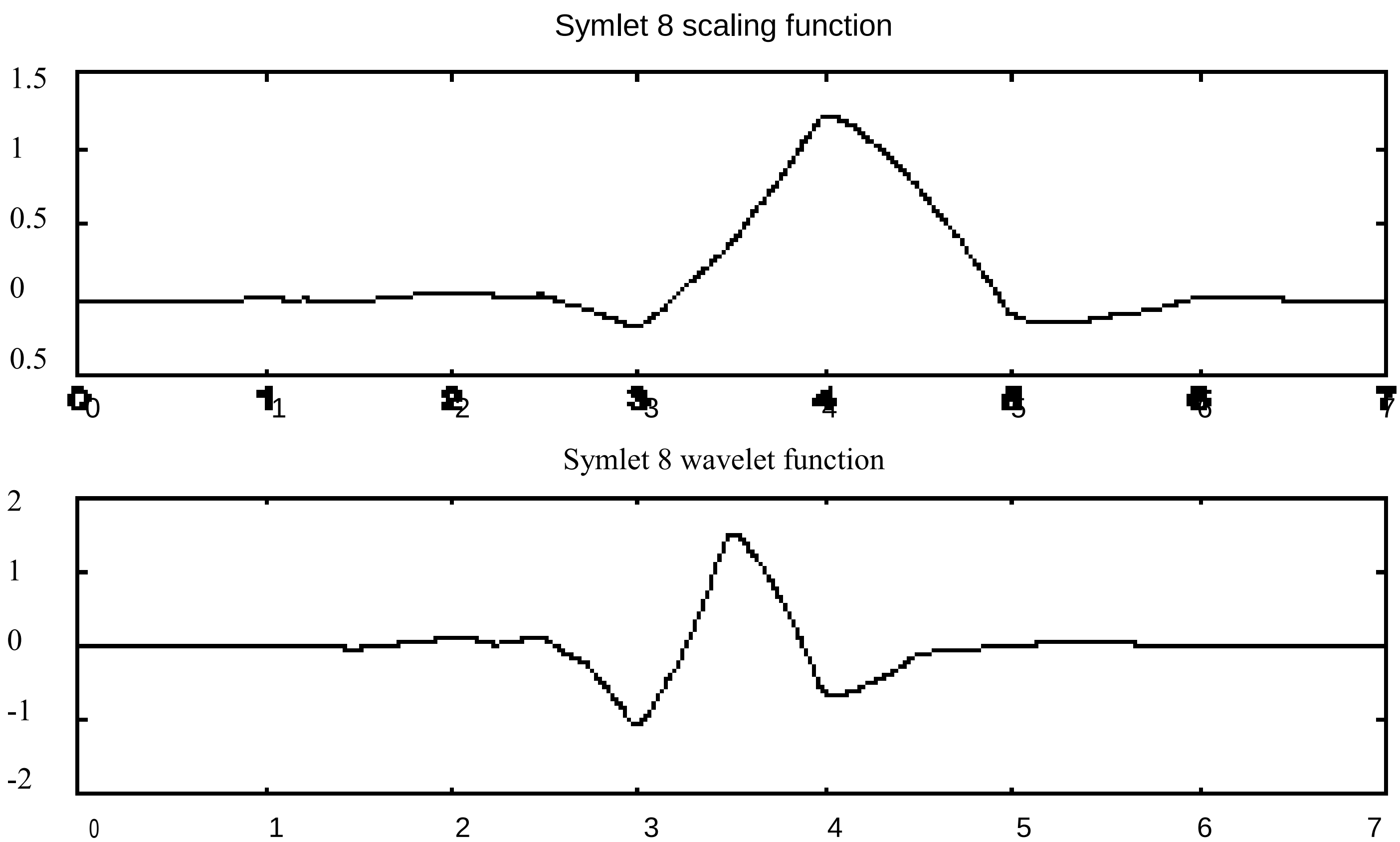


Figure 3. Symlet 8 scaling function and wavelet function.

method via DWT capable to detect the structural break by using MRA decomposition even at level 3.

Comparison between results

Basically both methods (that is Markov switching model and Wavelet) are capable of detecting structural breaks in the KLCI stock return series. Clearly by using the Markov switching model the study are noticeable that the structural breaks happen at 1981, 1985, 1997 and 2001. Table 2 shows this result. But by using DWT, we are enables to find that the structural breaks happen at the above mentioned date together at the most recent ones year 2007- 2008 (current global economic crisis).

As the study look into the detail of this 2007 until 2008 global economic crisis, the study finds that this crisis started because of economic slowdown in US. As the US is the main trade partner of Malaysia and many other countries, whatever crisis happen in US would effect the economic of Malaysia. As discussed by Serwer and Sloan (2008) the crisis began in early 2007 because of mortgages were given easily for consumer in US and international investor to invest in housing and securities in US. The greediness of people investing had lead to the collapse of US financial system with slowing the US economy. Furthermore, because of this crisis one of US main investing company the Lehman Brothers had filed for bankruptcy in September 2008.

Conclusion

This paper have discussed two most efficient method in order to study the structural break in original time series (KLCI) namely applying the Markov switching model and wavelet method. Basically they could say that both methods are good enough to obtain the date of the structural break happen together with statistical analysis. But the wavelet method via DWT has much more advantages as compare to the Markov switching model. All information which contained in the volatility series (in

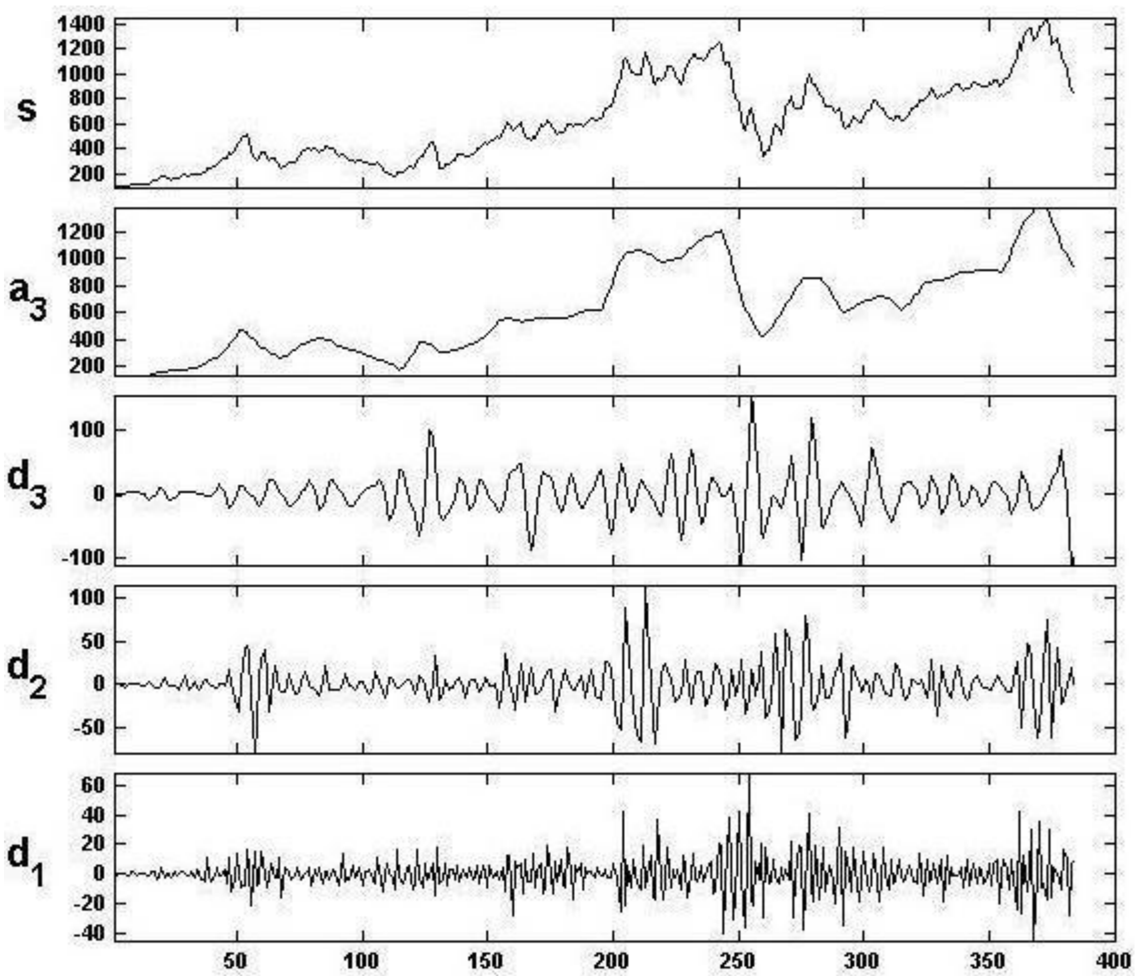


Figure 4. Original series and multiresolution analysis of the time series (KLCI) up to level 3 using symlet 8.

this paper, KLCI time series) is perfectly captured in the MRA. No anomalies have been introduced by DWT. Furthermore we are capable to find that year 2007- 2008 also has structural break where we are not able to analyst it via Markov switching model approach.

ACKNOWLEDGMENT

This research is financed by FRGS grant (203/ PMATHS/6711121) from the Ministry of Higher Education, Malaysia and Short Term grant (304/PMATHS/631005) from Universiti Sains Malaysia.

REFERENCES

Antoniadis A (1997). Wavelets in statistics: a review. J. Ital. Stat. Soc., 6(2): 97-130.

Banarjee A, Urga G (2005). Modelling structural breaks, long memory and stock market volatility: an overview. J. Econ., 129(1-2): 1-34.

Chui CK (1992). An Introduction to Wavelets. New York, Academic Press.

Daubechies I (1992). Ten Lectures on Wavelets. Vol. 61, Philadelphia, PA, CBMS-NSF Reg. Con. Ser. Appl. Math., Society for Industrial Applied Maths (SIAM).

Donoho DL, Johnstone IM (1994). Ideal spatial adaptation by wavelets shrinkage. Biometrika, 81(3): 425-455.

Donoho DL, Johnstone IM (1995). Adapting to unknown smoothness via wavelet shrinkage. J. Am. Stat. Soc., 90(432): 1200-1224.

Hackl P (1989). Statistical Analysis and Forecasting of Economic Structural Change. New York, Springer Verlag.

Hamilton JD (1990). Analysis of time series subject to changes in regime. J. Econ., 45(1-2): 39–70.

Hamilton JD (1993). Estimation, inference and forecasting of time series subject to changes in regime. Handbook of Statistics 11, ed. Maddala GS, Rao CR, Vinod HD, Amsterdam, North-Holland.

Hamilton JD (1994). Time Series Analysis. Princeton, Princeton University Press.

Hardle W, Kerkyacharian G, Picard D, Tsybakov A (1998). Wavelets, Approximation and Statistical Applications. Lecture Notes in Statistics, Volume 129. New York: Springer.
Karim SAA, Ismail MT, Karim B (2008). Denoising non-stationary time series using daubechies wavelets. Seminar Kebangsaan Matematik & Masyarakat (SKMM), UMT Terengganu 13-14 February 2008, Grand Continental Hotel, Kuala Terengganu (In CD).
Karim SAA, Ismail MT (2008). Wavelet Method in Statistics. In Proceedings of the Sixteenth National Symposium on Mathematical Sciences, 3-5 Jun at Hotel Renaissance, Kota Bharu, Malaysia: pp. 255-261.
Kim CJ, Nelson CR (1999). State-Space Models with Regime-Switching: Classical and Gibbs-Sampling Approaches with Applications.MIT, MIT Press.
Mallat S (1989). A theory of multiresolution signal decomposition: the wavelet representation. IEEE Trans. Pattern Anal. Mach. Learn., 11(9): 674-693.
Resnikoff HL, Wells RO (1998). Wavelets Analysis: A Scalable Structure of Information. New York, Springer-Verlag.
Strang G, Nguyen T (1996). Wavelets and Filter Banks. Massachusetts, Wellesly-Cambridge Press.
Serwer A, Sloan A (2008). The Price of Greed. Time, 172(12): 18-23.
Van Fleet PJ (2008). Discrete Wavelet Transformation: An Elementary Approach with Application. New Jersey, John Wiley and Sons.