A Markov Switching Model for UK Acquisition Levels

Sian Owen*

School of Banking and Finance, University of New South Wales

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Abstract

This paper examines the time series properties of UK acquisition numbers in the period 1969 to 2003 using a three-regime Markov Switching Model. The majority of the data is characterised by a relatively stable series, and this regime has by far the longest duration. It is necessary, however, to also include regimes that represent both the beginning and end of the waves to accurately model the data. The expected duration of the regime that marks the end of a wave is longer than that characterising the start, revealing that the start of a merger wave is marked by more extreme changes in behaviour. This somewhat surprising result is then confirmed with further analysis of the characteristics of the regimes marking the beginning and end of the waves.

Keywords: Merger waves, Markov switching model

JEL Classification: C32, E32, G34

*Direct correspondence to the author at the School of Banking and Finance, UNSW, Sydney, NSW 2052, Australia. E-mail: Sian.Owen@unsw.edu.au

Introduction

Levels of acquisition activity are known to fluctuate between periods of relative stability and periods of excessive activity, often called merger waves. During these waves, the number of mergers and acquisitions rises very quickly to a level that seems disproportionately high when compared to the corresponding state of the economy. These waves usually occur when the economy is booming but any increases in the economic cycle are not sufficiently large to account for the growth in the number of mergers and acquisitions.

Most of the previous research in this area has concentrated on finding a link between acquisition activity and the behaviour of the economy. The results suggest that there is a link between the availability of funding and levels of takeover activity. However, finding a model that works across several time periods, or in different countries, has proved impossible thus far, leading to the development of a newer branch of exploration concentrating on the time-series properties of the series itself. This paper falls into the latter group and extends existing research by using a Markov Switching Model, allowing the series to follow three regimes with different mean values enabling the series to be modelled using multiple time series representations. The three regimes used here represent the series (1) when it falls at the end of a merger wave, (2) in the stable periods, and (3) when it rises at the beginning of a merger wave. Examining each of these different types of behaviour provides a considerably more informative picture of the behaviour of the series over time than has been previously available.

Merger Waves and the Existing Literature

Previous research on acquisition activity is divided broadly into two types, as mentioned above. Firstly there are papers that have studied takeover levels using macro-economic factors and, secondly, there are the papers that have use time-series econometrics to analyse the series itself.

One of the earliest papers to use macro-economic factors was Gort (1969). Here the author found that acquisitions took place because economic conditions changed in some way that sparked differences in opinion about firm values. The different opinions then generated acquisition activity. Gort's hypothesis implies that there are substantial informational asymmetries between individuals with respect to the value of the target firm, and also that the target is thought to be undervalued as a result of the changes in the economic conditions.

In the years following Gort's paper, many other articles have also attempted to link the level of activity in the corporate control market to specific macro-economic factors. In 1975 Steiner modelled takeover activity using a variety of economic variables and concluded that numbers of acquisitions were positively related to stock prices and GNP, suggesting that improving economic circumstances are responsible for increases in acquisition activity. A similar result can also be found in Melicher, Ledolter and D'Antonio (1983) which linked changes in the expected level of economic growth and the capital market conditions to acquisition levels. Specifically, these authors found that increases in the stock market coupled with decreases in interest rates were followed by increases in acquisition activity. They concluded that the level of takeover activity was driven by the financing options available to the bidders and, when funding is easier to get, takeover activity increases. Polonchek and Sushka (1987) took a slightly different approach and viewed mergers and acquisitions as capital budgeting decisions but still used information about the economic conditions in their model. Using this perspective, they found that company specific factors such as the cost of capital and the expected returns on investment were important, as were factors representing the strength of the economy. In the following year, Golbe and White (1988) used regression models to analyse the link between the number of takeovers in America and the economic situation in the proceeding periods. Their results also suggested that GNP is positively related to acquisition activity whilst real interest rates are negatively linked to takeovers. The overall size of the economy is sometimes important as, logically, larger economies will experience more takeovers than smaller ones.

Golbe and White also used time-series techniques to demonstrate that takeover numbers follow a wave pattern. Unfortunately, combining these cross-sectional features with some basic time-series elements, as in Owen (1998), does not substantially improve the overall performance of the model. This combined approach can identify the points at which the waves began and end, but it fails to adequately model the amplitude. Overall, the existing research using cross-sectional methods fails to produce models that can be used successfully out of sample.

The second type of article concerning the level of acquisition activity has concentrated on time-series methodologies and ignored the possible links between acquisition levels and economic conditions. Here the results are considerably more varied than in the first group of papers. Some authors have found that acquisition activity is random and therefore unpredictable whilst others contend that the series can be modelled. Shugart and Tollison (1984) claimed that numbers of acquisitions are best described by a first order autoregressive process and, as a result, merger waves do not exist. This was refuted by Golbe and White (1993) who analysed the residuals of a regression of takeover activity against time and found evidence of clusters of positive and negative terms, supporting the existence of cyclical behaviour.

Chowdhury (1993) used unit roots tests to show that the changes in the series of merger numbers are random, although he did not extend this analysis to investigating levels. Town (1992) used a two-regime Markov Switching model to allow for the differences in mean values, which was considerably more accurate than the benchmark ARIMA models reported in the paper. The same data set was used the following year by Golbe and White (1993) who successfully fitted a sine wave to the series. More recently, Barkoulas, Baum and Chakraborty (2001) used a long-memory process to represent the aggregate level of takeover activity in the United States. This model allows waves to occur without any consistency between the duration of the waves or in the time intervals between waves occurring.

Methodology and Empirical Results

Simple econometric techniques, such as cross-sectional regression models, have failed to generate a consistent model for merger waves. The next logical methodological step is the estimation of linear time series models, such as autoregressive or moving average processes. This technique simply involves transforming the data into a stationary series and then identifying a time-series model for the data using a set of criteria to ensure that the model is a good fit. Once the model has been identified, it is relatively simple to analyse the data or to attempt to predict the future values of the series. Models of this type have many advantages because they are relatively simple to implement but, obviously, cannot be used to replicate the behaviour of a non-linear series.

The failure of past models for acquisition activity to adequately replicate the behaviour of the data suggests that it may be non-linear and should be modelled accordingly. Many series do exhibit non-linear behaviour over time and there are several methods of analysis that are capable of dealing with this characteristic. Of particular interest here are those models devised to deal with data that displays very different behaviour over time. This leads to the use of a non-linear time-series model in this paper, specifically a regime shifting model.

Models of regime shifts are often used to represent non-linear data by splitting the series into a finite number of regimes, each of which is characterised by a linear equation. The structure of the process remains unchanged across regimes but the parameters differ in each case. Movement between the regimes is determined by a regime variable.

More formally, we define a stationary series Δy_t as being conditional on a regime variable, $s_t \in \{1,2,...M\}$, in the manner typified by equation 1.

$$p(\Delta y_t \mid Y_{t-1}, X_t, s_t) = \begin{cases} f(\Delta y_t \mid Y_{t-1}, X_t, \theta_1) & if\ s_t = 1 \\ f(\Delta y_t \mid Y_{t-1}, X_t, \theta_2) & if\ s_t = 2 \\ \cdots & \\ f(\Delta y_t \mid Y_{t-1}, X_t, \theta_M) & if\ s_t = M \end{cases} \tag{1}$$

where $p(\Delta y_t \mid Y_{t-1}, X_t, s_t)$ is the probability density function of the vector of endogenous variables $\Delta y_t = (\Delta y_{1t}, \Delta y_{2t}, ..., \Delta y_{Kt})'$ which, in turn, is conditional on the past behaviour of the process, $Y_{t-1} = \{\Delta y_{t-i}\}_{i=1}^{\infty}$, some exogenous variables $X_t = \{x_{t-i}\}_{i=1}^{\infty}$ and the regime variable s_t. The term θ_m represents the parameter vector when the series is in regime m, where $m = 1, ..., M$.

For a full description of the process Δy_t, it is also necessary to specify the stochastic process, s_t, that defines the regime, as in equation 2.

$$\Pr(s_t \mid Y_{t-1}, S_{t-1}, X_t; \rho) \tag{2}$$

where S_{t-1} represents the history of the state variable and ρ is a vector of parameters of the regime generating process.

In many cases the regime variable cannot be observed and the historical behaviour of the series must be inferred from the actual behaviour of the process. The appeal of this approach is that the historical behaviour of the series, Δy_t, does not determine the regime in any way - that is left entirely to the regime variable, s_t. However, there are also instances in which the switching variable cannot be observed, especially when there are multiple regime changes and this can be problematical. To circumvent this issue, a Markov chain is often used for the switch. This is a simple system that represents the probability of changing state in the future.

Using a first-order Markov chain specification, the regime variable is assumed to take only integer values $\{1,2,...,M\}$ and the probability of s_t taking any value is dependent only on its previous value. Thus, the Markov chain represents the probability that the system will be in a particular state in the next time increment, conditional on the current state of the system, as in equation 3.

$$\Pr(s_t \mid Y_{t-1}, S_{t-1}, X_t; \rho) = \Pr(s_t \mid s_{t-1}; \rho) \tag{3}$$

This relationship is linked to the transition probabilities $p_{ij} = \Pr(s_{t+1} = j \mid s_t = i)$ which are often represented as a transition matrix of the form given in equation 4.

$$\mathrm{P} = \begin{bmatrix} p_{11} & p_{12} & p_{13} & \cdots & p_{1j} & \cdots & p_{1M} \\ p_{21} & p_{22} & p_{23} & \cdots & p_{2j} & \cdots & p_{2M} \\ p_{31} & p_{32} & p_{33} & \cdots & p_{3j} & \cdots & p_{3M} \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ p_{i1} & p_{i2} & p_{i3} & \cdots & p_{ij} & \cdots & p_{iM} \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ p_{M1} & p_{M2} & p_{M3} & \cdots & p_{Mj} & \cdots & p_{MM} \end{bmatrix}. \tag{4}$$

This multi-regime framework allows the series to display different characteristics at different times and to move between these regimes from period to period. Modelling time series data in this way allows for some potentially very informative results to be generated in cases when the data seems to display several different types of behaviour over time.

In this paper, the data represents the total number of mergers and acquisitions in the UK between the beginning of 1969 and the beginning of 2003, reported on a quarterly basis. The data is from the UK Office of National Statistics (ONS) and is limited to completed deals only. Even the most superficial examination of the series of acquisition numbers is sufficient to reveal that this is clearly not a series that behaves in a conventional manner, as Figure 1 demonstrates. The most striking features of the data series are the two periods of excessive activity (merger waves) that occur within the sample period. The majority of the series is characterised by the stable periods, typified by relatively small changes between observations. In addition to this stable regime, there are also periods of explosive growth and dramatic falls that denote the beginning and end of the merger waves and these also need to be taken into consideration.

[Insert Figure 1 here]

The data is I(1) and strongly autoregressive with the first and fourth lags being particularly important.[1] Figure 2 represents the data after making it stationary.

[Insert Figure 2 here]

Using the Markov Switching model over three regimes, this data will be modelled as an autoregressive process of order 4 which is typified by equation 5.

$$\Delta y_t = v_m + \theta_{m1}\Delta y_{t-1} + \theta_{m2}\Delta y_{t-2} + \theta_{m3}\Delta y_{t-3} + \theta_{m4}\Delta y_{t-4} + \varepsilon_t, \qquad \varepsilon_t \sim IID\left(0, \sigma_m^2\right) \tag{5}$$

[1] Given that the data used here is quarterly, this result is not unexpected.

The transition matrix will be of the form given in equation 6.

$$P = \begin{bmatrix} p_{11} & p_{12} & p_{13} \\ p_{21} & p_{22} & p_{23} \\ p_{31} & p_{32} & p_{33} \end{bmatrix} \text{ where } p_{i3} = 1 - \left(p_{i1} + p_{i2}\right) \text{ for } i = 1,2,3 \qquad (6)$$

The results reported here are all generated using Ox version 3.2 (Doornik, 2002) and MSVAR version 1.31e (Krolzig, 2003). The results support the hypothesis that there are three distinct regimes in the series. A likelihood ratio (LR) test rejects the possibility of fitting a linear model to the series and this result remains true when the test is adjusted in the manner advocated by Davies (1977, 1987). The test proposed by Davies is a modified form of the LR test which gives a corrected upper bound for the probability value[2]. The model diagnostics are illustrated in Figure 3 and they suggest that the model is generally well-specified. There is a slight problem with serial correlation in the standardised residuals but this problem does not extend to the predictive errors, which all lie comfortably within the standard error bands. The density and QQ plots both suggest that the model is well-specified, as they are very close to normal distributions for both the standardised residuals and the predictive errors.

[Insert Figure 3 Here]

The estimated coefficients for this model are given in Table 1.

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[2] For a clear and concise description of the test devised by Davies, the reader is directed to Garcia and Perron (1996).

[Insert Table 1 Here]

The mean values are clearly different, supporting the hypothesis that the series follows three distinct regimes over the sample period and the coefficients on the four lags are all statistically significant. The transition matrix for these regimes is given as equation 7 and the regime probabilities are illustrated in Figure 4.

$$\mathrm{P} = \begin{bmatrix} p_{11} & p_{12} & p_{13} \\ p_{21} & p_{22} & p_{23} \\ p_{31} & p_{32} & p_{33} \end{bmatrix} = \begin{bmatrix} 0.5704 & 0.4296 & 1.378e-11 \\ 0.02719 & 0.8203 & 0.1524 \\ 0.01964 & 0.5736 & 0.4067 \end{bmatrix} \tag{7}$$

[Insert Figure 4 Here]

In these results, Regime 1 represents the periods in which the series is dropping sharply at the end of a merger wave, Regime 2 represents the more stable periods in between the increases and decreases and, finally, Regime 3 represents the periods in which the series is rising rapidly as a merger wave develops.

When the series is in Regime 1 it is most likely to remain in that regime (57%), although the probability of the series flattening out and moving to Regime 2 is almost as likely (43%). There is virtually no chance of the series changing directly from Regime 1 to Regime 3.

The dominant regime is clearly Regime 2, which could be described as the normal behaviour of the series; the period in which the merger waves do not exist. The probability that the series will remain in Regime 2, given that it is currently there, is high (82%). If the series deviates from Regime 2, it is more likely to move to Regime 3 (15%), than Regime 1 (2.7%), but neither of these changes has a particularly high probability. Finally, when the series is rising (Regime 3), it is most likely to return to the stable behaviour typified by Regime 2 (57%) and this is the only instance in which the data is more likely to change regime rather than remain where it currently is. If the data does not return to Regime 2, it is most probable that it will continue in Regime 3. The probability of a change to Regime 1 is most unlikely (1.9%).

In addition to the transition probabilities, the expected duration for each of these regimes can also be calculated and appears in Table 2.

[Insert Table 2 here]

The durations confirm the information supplied by the transition probabilities. The expected duration of Regime 2 is considerably longer than the durations of either of the other two regimes, and the majority of the data demonstrates this more stable behaviour. When considering Regimes 1 and 3, it is clear that the drops tend to last longer than increases, as indicated by the longer expected duration for Regime 1.

There have been suggestions that merger waves are akin to bubbles as they are both phenomena in which the data rises above the fundamental value of the series. As with a bursting bubble, the merger wave ultimately ends and the series returns to the more normal level of activity. With a rational bubble, the time that the series takes to return to its fundamental value is usually considerably shorter than the time spent rising at the start. Here, the opposite is true and the creation of the merger wave is more dramatic than the end. This is somewhat unexpected and merits some further analysis, so more tests are carried out here to investigate the behaviour of the data in these periods.

Following work on business cycle asymmetry by Clements and Krolzig (2003), tests are conducted to determine whether the increases and decreases in the series of merger waves are symmetric or not. The first test is for “sharpness”, or asymmetry, in the peaks and troughs of the data. This test evaluates whether the peaks and troughs are similar in nature, or if one is more rounded and the other sharper. The null hypothesis in this test is that there is no difference in the turning points and this is tested by determining whether the transition probabilities to and from the outer regimes are the same. For the three regime model estimated here, accepting the null hypothesis jointly requires $p_{13} = p_{31}$, $p_{12} = p_{32}$ and $p_{21} = p_{23}$. Given the nature of the merger and acquisition data, it is unlikely that the null hypothesis will be rejected in this test.

The second test is for “deepness” which determines whether the amplitude of the troughs is substantially different to the amplitude of the peaks and, as before, the null hypothesis is that there is no difference. This is a form of Wald test and is based on an evaluation of the skewness of the data. Once again, given the fact that merger waves appear to represent a temporary deviation in the series away from its normal value, it is reasonable to expect that this null hypothesis will also be accepted.

Finally, there is the test for “steepness” which investigates the possibility that the movement of the series in one direction is significantly steeper than in the other direction. This is the most pertinent of these tests in relation to the merger and acquisition data. The null hypothesis is that there is no difference in the steepness but, following the analysis of the regime durations, it is expected that this hypothesis will be rejected for this data.

The results for these three tests reported in Table 3 and match our expectations. There is no evidence of differences in the sharpness or deepness of the periods in which the merger waves start and fall but there is evidence of significant differences in the steepness with which the waves begin and end. The null hypothesis of no difference in steepness is rejected at the 5% level, which supports the earlier supposition that merger waves begin more rapidly than they end.

[Insert Table 3 Here]

Conclusion

The three regime model used here represents an improvement on the existing models for merger waves as it accurately replicates the different behaviour exhibited by the series over time. The results suggest that there are three distinctly different types of behaviour in the series of takeover numbers and these all need to be modelled in order to fully understand the activity in the series.

The results reported here confirm the observed behaviour of the series, in which it can be seen that the majority of the time the series is relatively stable (Regime 2) but there are periods in which the series either rises sharply or falls dramatically. Whenever one of these other periods occurs, the data is more likely to flatten out, if only for a short time, before changing direction. Thus, the dominance of Regime 2 is not a surprising result, nor is the fact that this regime has the longest expected duration. More surprising, however, is the longer duration associated with Regime 1 as compared to Regime 3, suggesting that the start of a merger wave is often marked by an explosive increase in takeover activity which is considerably steeper than the drop marking the end of the wave. This offers an explanation for the failure of previous attempts to model merger waves as bubbles, and offers some interesting potential areas for future research.

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Table 1. Estimated Parameters for the Three Regimes

Regime Dependent Mean Values	
v_1	-0.1413
	(-7.2535 ***)
v_2	-0.0148
	(-4.8979 ***)
v_3	0.0875
	(6.1415 ***)
Autoregressive Coefficients, θ_{im}	
Δy_{t-1}	-1.0948
	(-10.1884 ***)
Δy_{t-2}	-1.0442
	(-7.5404 ***)
Δy_{t-3}	-0.6956
	(-5.2978 ***)
Δy_{t-4}	-0.1632
	(-1.8372 *)

***, **, * denotes significance at 1%, 5% and 10% respectively (two tailed tests)

Table 2. Durations for the Three Regimes

	Number of Observations	Ergodic Probability	Duration
Regime 1	7.3	0.0563	2.33
Regime 2	96.8	0.7508	5.57
Regime 3	25.0	0.1928	1.69

Table 3. Test Statistics for the Tests of Asymmetry

Test	Calculated Value
Sharpness test	3.8916
Deepness test	0.0705
Steepness test	6.1044 **

***, **, * denotes significance at 1%, 5% and 10% respectively (two tailed tests)

Figure 1. Levels of UK Acquisition Activity 1969 to 2002

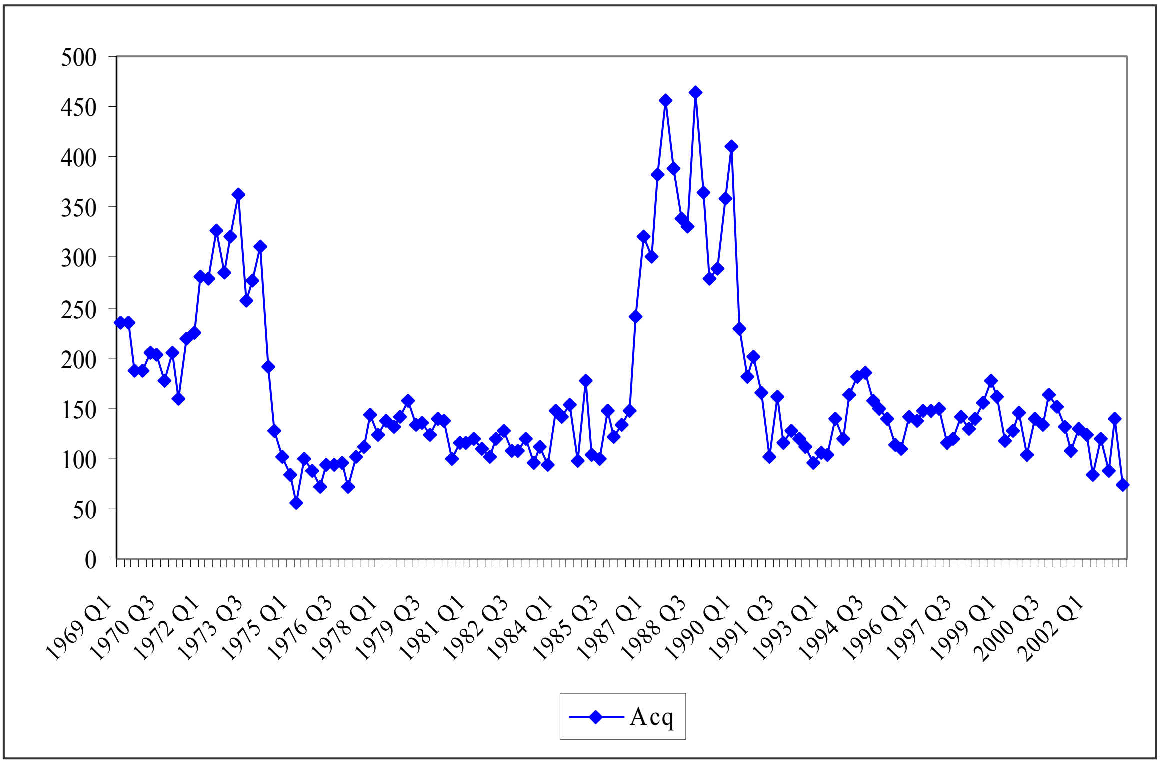

Figure 2. Differenced Data for UK Acquisition Activity 1969 to 2002

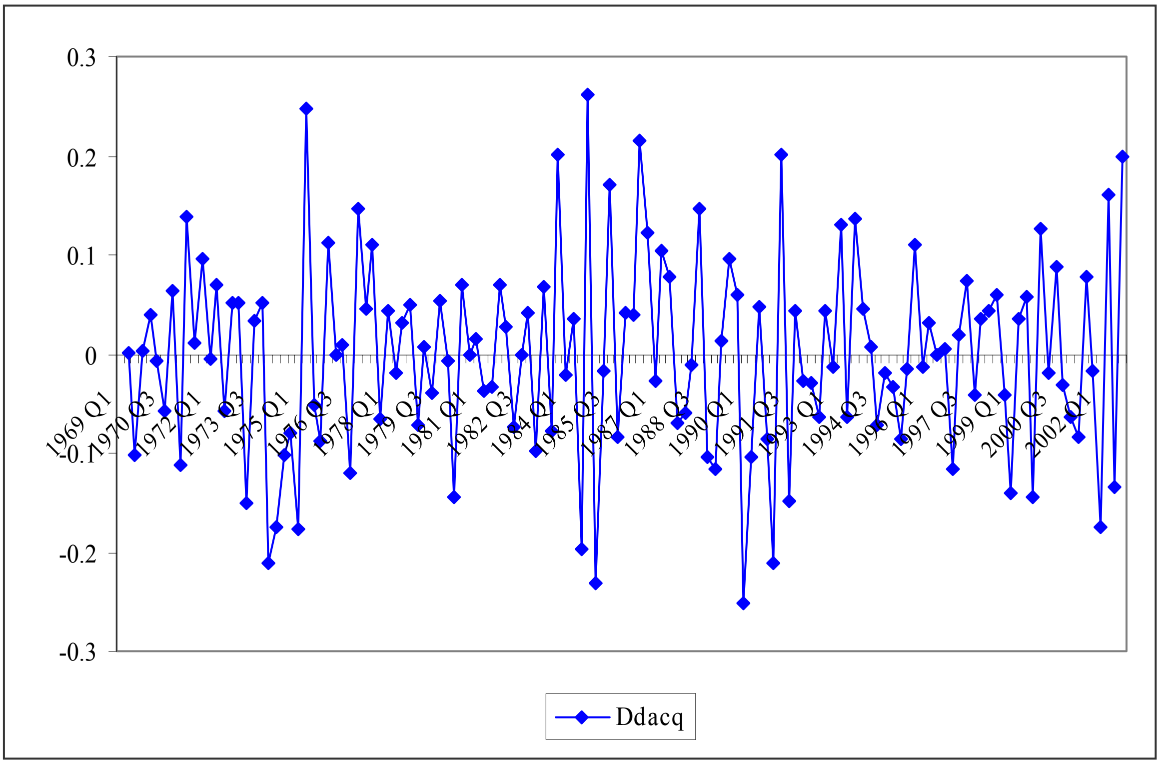

Figure 3. Model Diagnostics

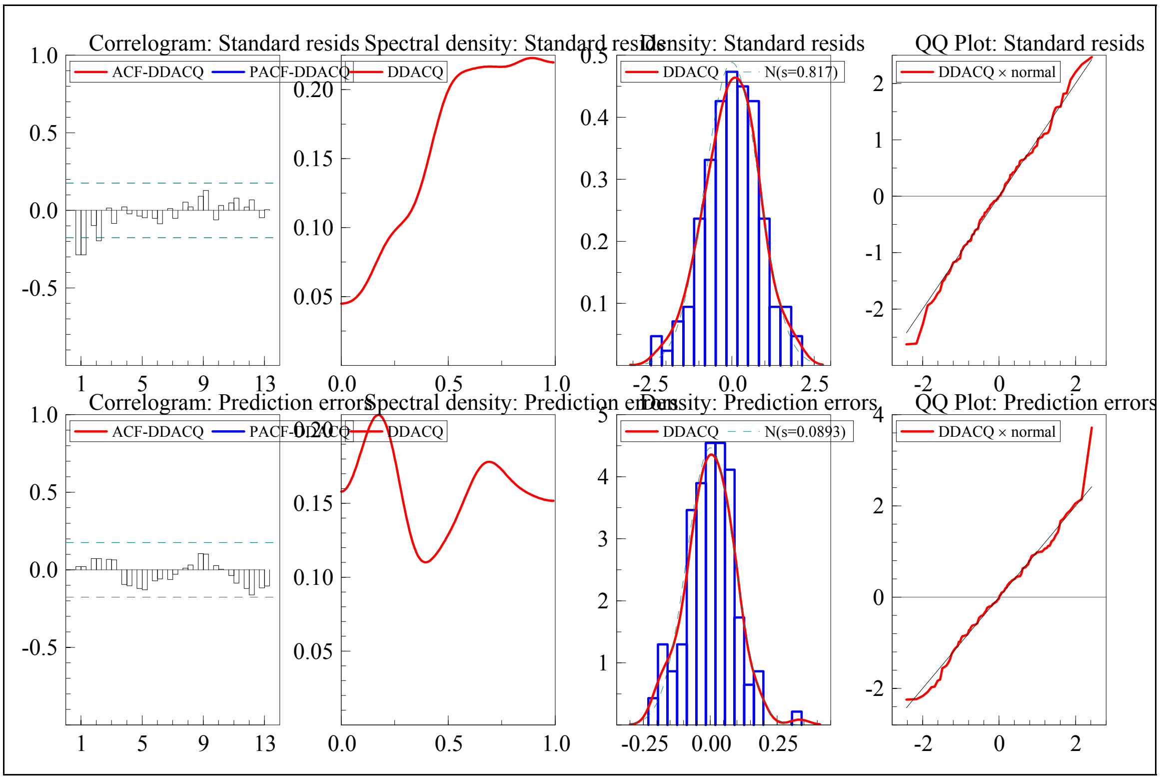

Figure 4. Regime Probabilities