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Mergers and Acquisitions Waves in the U.K.:  
A Markov-Switching Approach

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## **Mergers and Acquisitions Waves in the U.K.: a Markov-Switching Approach\***

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### **Abstract**

This paper further investigated wave behaviours for mergers and acquisitions-M&A in the U.K. during the 1969Q1/2004Q1 period by means of Markov-Switching models. Previous analysis had focused on traditional models that incorporate the potentially limiting assumption of constant transition probabilities across regimes. The consideration of more general models with time-varying transition probabilities across regimes along the lines of Diebold et al (1994) provide a useful route for assessing to which extent M&A waves are driven by economic variables usually considered in the related literature. The empirical implementation considered lagged conditioning variables referring to real output growth, real growth in money supply and real stock market returns. The evidence indicated that one should reject the constant transition probability model in favour of the time-varying transition probability model and therefore the usual aggregate variables considered in the empirical literature on M&A appear indeed to play some role in determining the wave behaviour of M&A in the U.K., though the effects are asymmetric across the different regimes.

JEL Classification: C32, L12

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## 1. Introduction

The wave pattern of mergers has puzzled investigators for a long time [see e.g. Moody (1904), Bain (1944), Stigler (1950), Nelson (1959) and Scherer and Ross (1990)]. There have been specific efforts in attempting to explain particular historical episodes of merger waves. Given the absence of a unified theoretical framework, one has observed more general exploratory empirical investigations that aimed at characterising the data generation process underlying the mergers and acquisitions–M&A series. The corresponding contributions mainly consisted of descriptive assessments of M&A activity either by means of linear time series models as in Melicher et al. (1983), Shugart and Tollison (1984) and Clark et al. (1988) or yet by considering very simple limited tests for detecting wave patterns [eg. Golbe and White (1987, 1993)].

More recently, non-linear models have been implemented to capture abrupt shifts in M&A. In fact, Markov-switching models were considered by Town (1992) for aggregate M&A activity in the U.S. and the U.K. and by Resende (1999) at the sectoral level for the U.K.. Some stylised facts appear to be slowly emerging. First, Markov-switching models seem to provide a better portrayal of M&A than simpler formulations involving, for example the random walk model. Second, there is evidence of a high degree of persistence of the unobserved states for M&A. It is interesting to stress that the trajectory of the time-series literature on M&A displayed a similar evolution as the empirical literature on exchange rate as indicated by Meese and Rogoff (1983) and Engel and Hamilton (1990).

In the present paper, we intend to fill a gap in the literature by stretching further the parallelism mentioned above. In that sense, Markov-switching models with time-varying transition probabilities are considered in the context of M&A. In fact, Weinbach (1993) undertook that extension in the context of exchange rates but was unable to reject the model assuming constant transition probabilities against the more general model with time-varying transition probabilities. Previous studies indicated that a Markov switching specification appears to provide an appropriate representation for M&A. The research issue is now to evaluate to which extent M&A waves are driven by the economic variables commonly referred in the empirical literature.

The paper is organized as follows. The second section provides a brief discussion of Markov switching models. The third section discusses the data used in the study and presents the empirical results. The fourth and final section brings some final comments.

## **2- Markov Switching Models: Basic Aspects**

Markov switching models have become a popular framework for capturing non-linear behaviours associated with abrupt changes in a time series since the influential contribution by Hamilton (1989).<sup>1</sup> In the present paper we extend the works of Town (1992) and Resende (1999) on M&A. Earlier studies along the lines of Hamilton (1990) and Engel and Hamilton (1990) made the potentially limiting assumption of constant transition probabilities across regimes. The extension to the time-varying transition probabilities case has produced a small empirical literature in

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<sup>1</sup> Useful introductions to Markov switching models appear in Hamilton (1994, 1999) and Kim and Nelson (1999).

other contexts. Examples include Filardo (1991) and Simpson et al (2001) for business cycles, Weinbach (1993) for exchange rates and Schaller and Van Norden (1997) for stock market returns.<sup>2</sup> The methodological details on the time-varying transition probabilities case is provided by Diebold, Lee and Weinbach (1994) which can be summarised as follows:

Let  $\{y_t\}_{t=1}^T$  the sample path of a time series depending on unobserved states  $\{s_t\}_{t=1}^T$  such that:

$$(y_t | s_t, a_i) \sim^{iid} N(m_i, s_i^2) \quad (1)$$

where  $\alpha_i = (\mu_i, \sigma_i^2)'$  for  $i = 0, 1$  in our two-states case. Specifically one assumes the following conditional density:

$$f(y_t | s_t = i, a_i) = \frac{1}{\sqrt{2\pi} s_i} \exp\left(-\frac{(y_t - m_i)^2}{2s_i^2}\right) \quad (2)$$

The parameters governing the densities can be stacked in terms of a  $(4 \times 1)$  vector  $\alpha = (\alpha_0, \alpha_1)'$ . The transition probabilities are assumed to be time varying evolving as logistic functions of  $x_{t-1}' \beta_i$ , where  $x_{t-1}$  denotes a  $(k \times 1)$  conditioning vector comprising economic variables believed to affect the transition probabilities. The parameters governing the transition probabilities can be conveniently stacked into a  $(2k \times 1)$  vector  $\beta = (\beta_0, \beta_1)'$ . These probabilities are given by the following expressions under a logistic specification:

$$p_t^{00} = p(s_t = 0 | s_{t-1} = 0, x_{t-1}, b_0) = \frac{\exp(x_{t-1}' b_0)}{1 + \exp(x_{t-1}' b_0)} \quad p_t^{01} = (1 - p_t^{00}) = p(s_t = 1 | s_{t-1} = 0, x_{t-1}, b_0) = 1 - \frac{\exp(x_{t-1}' b_0)}{1 + \exp(x_{t-1}' b_0)} \quad (3)$$

$$p_t^{10} = (1 - p_t^{11}) = p(s_t = 0 | s_{t-1} = 1, x_{t-1}, b_1) = 1 - \frac{\exp(x_{t-1}' b_1)}{1 + \exp(x_{t-1}' b_1)} \quad p_t^{11} = p(s_t = 1 | s_{t-1} = 1, x_{t-1}, b_1) = \frac{\exp(x_{t-1}' b_1)}{1 + \exp(x_{t-1}' b_1)}$$

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<sup>2</sup> The approach considered by Diebold et al (1994) does not introduce autoregressive dynamics and therefore can be thought to some extent as an extension of Hamilton (1990) to the time varying transition probabilities case.

where  $x_{t-1} = (1, x_{1,t-1}, \dots, x_{(k-1),t-1})'$  and  $\beta_i = (\beta_{i0}, \beta_{i1}, \dots, \beta_{i,k-1})'$ . Finally one can consider a  $(2k+5 \times 1)$  vector of all model parameters given by  $\theta = (\alpha, \beta, \rho)$ ; where  $\rho \equiv p(s_1 = 1)$  is the unconditional probability of being in state 1 at period 1.

It is important to note that the transition probabilities specified in (3) collapse to the constant transition probabilities case when there are no economic variables to condition on. In this sense we will be able to compare the two classes of models by means of likelihood ratio tests. In fact, we make use of the EM algorithm to generate maximum likelihood estimates [see eg. Laird (1993)]<sup>3</sup> In broad lines the EM algorithm can be summarised as follows:

(1) Choose an initial value for the parameter vector, say  $\theta^{(0)}$  ;

(2) Obtain  $\forall t$ :  $p(s_t = 1 | y_T, x_T, \theta^{(0)})$

$$p(s_t = 0 | y_T, x_T, \theta^{(0)})$$

$$p(s_t = 1, s_{t-1} = 1 | y_T, x_T, \theta^{(0)})$$

$$p(s_t = 0, s_{t-1} = 1 | y_T, x_T, \theta^{(0)})$$

$$p(s_t = 1, s_{t-1} = 0 | y_T, x_T, \theta^{(0)})$$

$$p(s_t = 0, s_{t-1} = 0 | y_T, x_T, \theta^{(0)})$$

These elements allow to construct the expected log-likelihood for  $f(y_T, s_T | x_T, \theta^{(0)})$  using the p's as weights to the densities values corresponding to the different states' combinations. In fact, the terms in italic indicate that we are making use of the whole sample in defining these so-called smoothed probabilities. This is the expectation (E) step of the algorithm.

(3) Set  $\theta^{(1)} = \arg \max_{\theta} E \log f(y_T, s_T | x_T, \theta^{(0)})$ . This is the maximization (M) step of the algorithm.

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<sup>3</sup> In fact, the procedure for implementing the EM algorithm will be quite similar with the one from Hamilton (1990) except for the time varying transition probabilities that evolve in accordance with a logistic specification . The reader is referred to Diebold, Lee and Weinbach (1994) for a step by step exposition on the necessary recursive calculations. The Matlab code for the implementation of the EM algorithm was kindly provided by G. Weinbach.

(4) Iterate until convergence. We will adopt here the criterion  $\|\theta^{(j)} - \theta^{(j-1)}\| < 10e-8$  for two successive iterations.

Having described in general lines the estimation procedure, it is worth mentioning we will be able to calculate standard errors by approximating those by the average outer product of score vectors as an estimate of the information matrix. In the next section, the empirical implementation of such approach for M&A is discussed.

### **3. Empirical Analysis**

#### **3.1- Data Description**

The present paper addresses the U.K. case with aggregate quarterly data. Mergers and acquisitions-M&A data was available for the 1969-1/2004-1 period. This data was obtained from the Office of National Statistics of the U.K. ([www.statistics.gov.uk](http://www.statistics.gov.uk)) and referred to the number of acquired domestic firms in the U.K. The remaining data for the U.K. had the following sources:

- i) Gross domestic product in Billions of pounds [International Financial Statistics- International Monetary Fund (IFS-IMF)];
- ii) Consumer price index [IFS-IMF];
- iii) Long Term yield for government bonds [IFS-IMF];
- iv) M4 [[www.statistics.gov.uk](http://www.statistics.gov.uk)];
- v) Stock market index for the U.K.: FTSE-all shares index [[www.globalfindata.com](http://www.globalfindata.com), upon figures published in the Financial Times]

Since we will be dealing with rates of changes for the different variables, one does not need to be concerned the any particular base date for the series.

Figure 1 displays the time evolution of M&A indicating the presence of abrupt shifts.



INSERT FIGURE 1 AROUND HERE

### 3.2- Empirical Implementation

In this section, a Markov-Switching model with time-varying transition probabilities is considered. The motivation is to verify whether economic variables considered in the empirical literature play a role in explaining the wave pattern of M&A in the U.K. Given the data mentioned in the previous section, the following variables were constructed:

#### a) real output growth

Economic growth may provide a positive scenario for the occurrence of M&A. In a more direct fashion when the economy is experiencing a boom the scope for business opportunities is broader and firm growth through acquisition may become a fast and important route to penetrate in a market. Other possibility pertains the work of Gort (1969), whose “economic disturbance theory of mergers” indicates that faster growth would be associated with a higher level of uncertainty in the market and therefore a match between willing sellers and buyers would be more likely. In summary, one would expect a positive association between output growth and M&A. The empirical evidence appears to support the referred positive effect in some studies. Melicher et al. (1983) found a weak leading behaviour of changes in industrial production relative to mergers in the U.S.. Crook (1995) in an investigation for the U.K. found a positive relationship between mergers and economic growth whereas Crook (1996) detected a positive association between M&A and the level of manufacturing production in the U.S.

#### .b) real growth in money supply

Liquidity may play a role in affecting M&A decisions to the extent that it can reduce the opportunity cost of cash relative to alternative funding sources [see e.g. Fishman (1989)]. The basic underlying argument concerns the likelihood of potential competition in the bidding process under uncertainty that would tend to be weaker following a cash offer. That lower probability of the potential buyer is challenged in a scenario of higher liquidity motivates a positive link between M&A and growth in money supply. In a related vein, the evidence obtained by Clarke and Ioannidis (1994) indicates a dominant role for funding availability in the case of non-bank financial institutions in the UK.<sup>4</sup>

c) real stock market returns

In a simplistic interpretation high stock market returns would signal positive business prospects should that trend prevail in a longer run. More interestingly, however, one should focus on perceived synergies between the merging candidates that occur in specific cases and might have aggregate implications. One such framework is given by Shleifer and Vishny (2003) that is based on stock market misvaluations of the combining firms. In that model managers rationally respond to less than rational markets and more intense mergers activity would tend to occur in high valuation markets so that a positive association between mergers and stock market returns. The empirical evidence mostly appears to favour that positive association. Melicher et al. (1983) found a leading behaviour of changes in stock market prices relative to mergers in the U.S.. Geroski (1984) studied the referred relationship for the U.S. and the U.K. but was unable to find any significant effect.

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<sup>4</sup> Interest rate could in principle exert a negative effect on mergers by a similar argument that motivated the relevance of money supply growth. The evidence as indicated by the study of Benzing (1993) for the U.S. failed to capture any such influence.

Clarke and Ioannidis (1996), on the other hand, found that stock prices lead mergers in the U.K..

Taken together, the empirical evidence is not totally convincing and in some cases causality issues had emerged. The intuitive arguments just outlined should be considered in terms of an explicitly non-linear model as considered next.

In order to reinforce the notation used in the text, note that  $b_{i0}$  denotes the constant term in state  $i$  whereas  $b_{i1}$  denotes the coefficient of the conditioning variable in state  $i$ . The model assumes two possible regimes:  $i = 1$  (intense M&A activity) or  $i = 0$  ("normal" M&A activity). Finally,  $\mathbf{r} \equiv P(s_1 = 1 | y_T, x_T, \mathbf{q})$  represent the probability of regime 1 prevailing in the first period. In the time-varying case,  $\rho$  and the coefficients of the conditioning variable will represent extra parameters to be estimated.<sup>5</sup> The time-varying case can be readily compared with the constant probability case by means of likelihood ratio tests as the EM algorithm generate maximum likelihood estimates when it converges.

The empirical estimates for the constant transition probability case are presented in table 1.

INSERT TABLE 1 AROUND HERE

The results indicate two markedly distinct regimes as seen indicated by the means and variances under the two regimes. Moreover, the staying probabilities reveal a substantial degree of persistence on the unobserved regime. In other words, if the economy is under a particular regime there is a high probability of staying in that regime. The evidence confirms at the aggregate level previous

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<sup>5</sup> In the constant transition probability case, one can obtain  $\mathbf{r} = \frac{(1 - p^{00})}{(1 - p^{11}) + (1 - p^{00})}$ . See for example, Hamilton (1994), chapter 22.

evidence by Resende (1999) according to which “long swings” would prevail in M&A in a similar vein to results encountered for exchange rates [see Engel and Hamilton (1990)]. It is important to emphasise that persistence appears to be an important feature of M&A as shown by different studies for the U.S. and the U.K. under different approaches [see e.g. Resende (1996, 1999) and Barkoulas et al (2001)]

The natural extension of this model is to consider a variant with time-varying transition probabilities so as to assess whether M&A waves are driven by output growth, money supply and stock market returns. The empirical results for that more general model appear next in table 2.

INSERT TABLE 2 AROUND HERE

The inspection of the parameter estimates indicates highly significant coefficients, but the effects of the (lagged) conditioning variables seem to be asymmetric. The expected positive impact of those variables only take place at the high M&A regime whereas counterintuitive negative signs prevail under the low M&A state. On the other hand it is important to note that irrespective to the considered conditioning variable, the coefficients for means and variances in the two states are very similar and yet very close to the estimates obtained from the constant transition probabilities model. In order to further evaluate this more general formulation it is possible to undertake likelihood ratio tests as shown in table 3.

INSERT TABLE 3 AROUND HERE

The results favour the rejection of the constant transition probability and the evidence therefore provides some support to M&A waves that are driven by the economic variables just mentioned. The asymmetry result is potentially interesting and deserves additional investigations.

#### **4. Final Comments**

The paper investigates M&A waves in the U.K by means of a 2-state Markov-switching model that naturally accommodates abrupt discrete shifts in the series. The evidence for the constant transition probability model corroborated previous analogous studies indicating the presence of markedly distinct regimes and a substantial degree of persistence. The paper took a step further in the literature by considering a time-varying transition probability version of the model. This extension allowed to verify if M&A waves are driven by economic factors usually considered in the empirical literature. In fact, conditioning variables referring to real output growth, real growth in money supply and real stock market returns were introduced in the model. The evidence, when one considers this explicitly non-linear framework, confirmed the role for the aforementioned variables in determining M&A waves, but the expected appear under the low M&A regime..

The evidence presented in the paper indicates the necessity of a deeper theoretical understanding of the economic factors underlying M&A waves. At this stage, one apparently robust feature seems relevant, namely that of persistence. New theoretical models should be able to capture that feature. In any case, clearly additional research on the topic is warranted.

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FIGURE 1  
Mergers and Acquisitions in the U.K.: 1969Q1-2004Q1

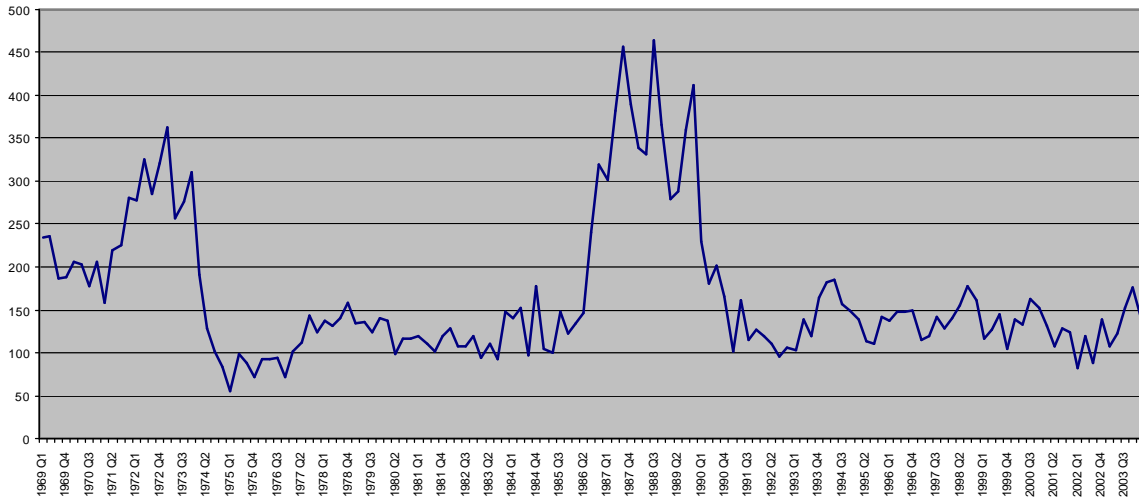


Table 1

## Constant Transition Probability Model Parameter Estimates

<b>Parameter</b>	<b>Estimates</b>	<b>p-values</b>
$\mu_1$	280.058	0.000
$\mu_0$	125.911	0.000
$\sigma_1^2$	6304.390	0.000
$\sigma_0^2$	673.599	0.000
$\beta_{10}$	2.883	0.000
$\beta_{00}$	4.544	0.000
$\rho$	0.166	-
$P^{11}$	0.947	-
$P^{00}$	0.989	-

Table 2

## Time-Varying Model Estimates

Parameter	<b>(Lagged) Conditioning Economic Variable</b>		
	real stock market return	real output growth	real growth in money supply
$\mu_1$	277.811 (0.000)	278.297 (0.000)	278.978 (0.000)
$\mu_0$	125.462 (0.000)	125.738 (0.000)	125.764 (0.000)
$\sigma_1^2$	6393.091 (0.000)	6450.117 (0.000)	6385.414 (0.000)
$\sigma_0^2$	652.945 (0.000)	662.274 (0.000)	662.414 (0.000)
$\beta_{10}$	4.279 (0.000)	3.029 (0.000)	2.342 (0.000)
$\beta_{00}$	5.113 (0.000)	4.718 (0.000)	6.827 (0.000)
$\beta_{11}$	14.474 (0.000)	66.588 (0.000)	44.507 (0.002)
$\beta_{01}$	-8.236 (0.000)	-17.092 (0.000)	-103.307 (0.001)
$\rho$	1.000 (0.000)	1.000 (0.000)	1.000 (0.366)

Table 3

Likelihood ratio tests: unrestricted time-varying transition probability vs. constant transition probability model

<b>Unrestricted model: conditioning variables</b>	<b>Test Statistic</b>	<b>p-value</b>
Real stock market returns	$\chi^2 (2) = 20.748$	0.000
Real output growth	$\chi^2 (2) = 16.282$	0.000
Real growth of money supply	$\chi^2 (2) = 18.502$	0.000