Regime Switching Behavior of the Nominal Exchange Rate in Uganda

By

Eria Hisali
Makerere University, Uganda

Abstract

This paper examines regime switching behaviour of the nominal exchange rate. The nominal exchange rate process at times depicts sharp and even volatile movements, followed by calm and orderly changes. Periods of sharp and volatile changes if persistent and occurring for long periods have implications for the orderly functioning of markets and efficiency in general and usually justify central bank intervention actions. But, are the observed 'sharp and volatile' changes a systematic part of the exchange rate data generating process? To answer this question, a homogenous two-state Markov chain was employed to fit a regime switching model to data from the Uganda currency market. The maximum likelihood parameter estimates were obtained using the BFGS iteration algorithm. The results validate the hypothesis that nominal exchange rate data generating process evolves according to two distinct state spaces. One state is characterized by sharp and disruptive, but short-lived depreciations and the other is characterised by small appreciations occurring over a long time. The results highlight the need to mitigate the disruptive effects of the sharp depreciations.

1.1 Introduction

Evolution of the nominal exchange rate is usually thought to reflect developments and directions in important underlying fundamentals such as the current account and the international investments position. There is some evidence, however, that suggests that the exchange rate can be detached from its fundamental economic determinants over some episodes (see Rankin, 1998), and this can result in a multiple equilibria solution. This phenomenon can emanate from the various possibilities including human psychology and herd behaviour, political announcements and at times over reaction to news (Goodhart, 1988). A multiple equilibria solution could also emanate from the destabilizing effects of speculative traders and seasonal patterns in the evolution of short term exchange rates.

Ultimately, what will be observed in such cases will be a tendency for the nominal exchange rate to depict sharp and volatile movements of a large and at times persistent magnitude over some periods in a sample. Generally speaking, this means that a time series may follow different processes over different sub-samples. It therefore seems plausible to argue that standard single regime models may not provide the most appropriate mechanism to mimic the evolution of a time series. Instead, a complete description of the data generating process in such cases should involve understanding the different state spaces or regimes that the process may be following over different sub-samples.

This paper thus seeks to analyse the regime switching behaviour of the nominal exchange rate in Uganda. There are reasons why such a study is important. Large and rapid movements in the exchange rate have important implications for the orderly functioning of markets and market efficiency in general. This in turn has implications for central banks market activities. It is usually periods of sharp and volatile changes that central banks give as justification for intervention in foreign exchange markets. Indeed, the observed nominal exchange rates in Uganda at times depict sharp changes[1]. As a result the bank of Uganda intervenes occasionally in the foreign exchange market, supposedly to ensure stability of the exchange rate process and conditions in the money market (Mutebile, 2001). But, are the sharp and volatile changes that the bank of Uganda gives as justification for intervention a systematic part of the exchange rate data generating process? Understanding the statistical plausibility of the different exchange rate state spaces can thus shed light on the necessity of central bank market participation.

In order to analyse regime switching behaviour of the nominal exchange rate in Uganda, a two state Markov chain was employed to fit a regime switching model using daily Uganda shilling/US dollar nominal exchange rate data covering the period 3rd January 2000 to 31st December 2004.

A number of studies have sought to understand the regime switching behaviour of the exchange rate data generating process. Engel and Hamilton (1990) and Cheung and Erlandsson (2004) employ the mixture *iid* variant of the Markov chain analysis with time

[1] Graphs of the log exchange rate and log exchange rate changes indeed show some sharp spikes in both directions in the nominal exchange rate and so do the summary statistics. See section 2.2

invariant transition probabilities, based on the assumptions that the process follows a normal distribution in the different regimes. However, it has been shown that mixture *iid* models usually have a skewed unconditional distribution if the means are different, and the distributions are usually leptokurtic (Mclachlan and Peel, 2001).

Taylor (2004) employs a specification that allows for the possibility of time varying transition probabilities in his regime switching analysis of volatility of the real exchange rate. In as much as real and nominal exchange rates bear some relationship, the former is less likely to depict as much volatile behaviour as its nominal counterpart, and may thus not be the best way to capture the volatility. In addition, his specification proceeds under the assumption that the determinants of the exchange rate are completely known to the analyst. Bazdresch and Werner (2005) allow both the transition probabilities and other parameter estimates to change across the different regimes but make inference about the states on the basis of current period observation and known initial conditions for iteration.

The approach employed in this paper uses the regime switching variant of the Markov chain specification in which inference about the different possible state spaces is made on the basis of all available information. This is our point of departure from the work by Engel and Hamilton (1990) and Cheung and Erlandsson (2004). In addition, given the poor empirical performance of structural models of exchange rate determination we opted for a homogenous Markov chain specification. This way, the paper avoids the pitfalls that may arise by attempting to specify a structural model for the exchange rate as in Bazdresch and Werner (2005) and Taylor (2004). Lastly, the initial values that were used for iteration were obtained from a least squares specification instead of being assumed as in Bazdresch and Werner (2005).

The maximum likelihood parameter estimates were obtained using the BFGS iteration algorithm. Our results validate the hypothesis that nominal exchange rate data generating process in Uganda over the study sample evolves according to two distinct state spaces. The full sample probabilities lead to the same conclusion. One state is characterized by sharp and disruptive, but short-lived depreciations and the other is characterised by quite small appreciations but taking place over a long period. The ergodic probabilities suggest that in as much the appreciations are persistent, they are nonetheless so small and unable to reverse the strong depreciation episodes. The results also suggest that the Markov chain is irreducible and that both states can be accessed from each other. The overall time varying stochastic volatility is low and appears to be driven largely by the sharp depreciation episodes. The results highlight the need to mitigate the disruptive effects of the sharp depreciations.

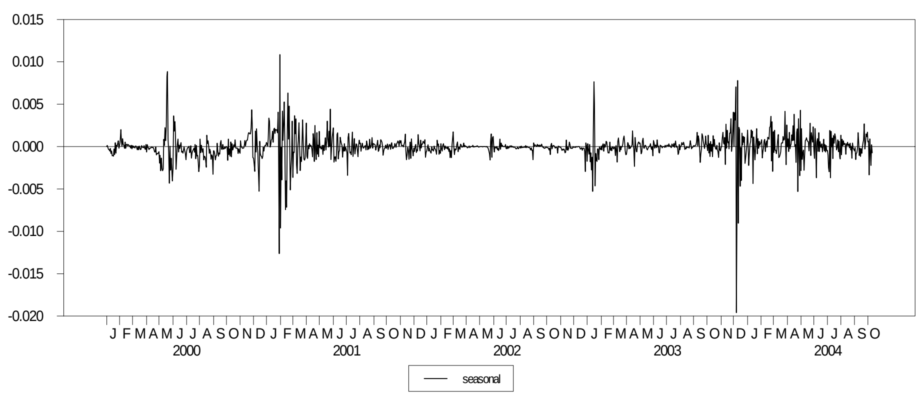
The rest of the paper is organized as follows. The exchange rate determination and trends in Uganda are presented in section 2 followed by an overview of the literature in section 3. The methodology employed is presented in section 4. The main findings of the study are presented in section 5 and the paper ends with some concluding remarks in section 6.

2 Exchange Rate Dynamics and Data

2.1 Exchange Rate Determination and Trends in Uganda

In a standard analysis free floating system the fundamental value of a country's currency should closely mirror its current account and international investments position (iip) developments (Rankin, 1998). In Uganda though, there are some other dynamics that may influence movement of the exchange rate. These include donor resource flows and disbursement patterns given that about half of government spending is donor funded. There are also noticeable seasonal patterns that seem to influence short term exchange rate movements. These emanate from various sources such as the seasonal nature of Uganda's agricultural exports and remittances from Ugandan's living abroad that tend to coincide with the festive calendar seasons of Easter and Christmas and the beginning of school terms (Ating-Ego and Egesa, 2003). Seasonal patterns in exchange rate movement have also been noted at those times of the year when profit and dividend payments to parent companies from their Ugandan subsidiaries are being made. Such patterns are without doubt disruptive. Figure 1 shows the seasonal pattern of the short term exchange rate and suggests that the pattern is additive.

Figure 1: Exchange Rate Seasonal Pattern in Uganda



The influence of speculators on the market can in some cases have considerable and destabilizing influence on short term exchange rate movements most especially if they are reacting to surprising information (Rankin, 1998) since their positions last for just a few hours or days. It is perhaps the destabilizing effects these traders can have on the market that the Bank of Uganda has always threatened to take measures to ensure that the exchange rate is not a one way bet (Mutebile, 2001).

There has also been a substantial increase in inflows following liberalisation of the capital account in 1997. These have mainly taken the form of foreign direct investment (FDI). Of late, there has also been an increasing interest in Uganda shillings denominated assets by foreign fund managers. This has tended to create transitory but potentially disruptive variability tendencies in the exchange rate. Off the trend depreciation tendencies have coincided with times of high oil prices. A few appreciation tendencies have also been noted at times of relatively strong export performance.

2.2 The Data and their Characteristics

The study employed daily data on the Uganda shilling/US dollar nominal exchange rate data covering the period 3rd January 2000 to 31st December 2004. Graphs of the log exchange rate and log of exchange rate changes are presented in Figures 2 and 3, respectively. They suggest that there are instances of sharp spikes in both directions in the nominal exchange rate.

Figure 2: Daily Exchange Rate Movements

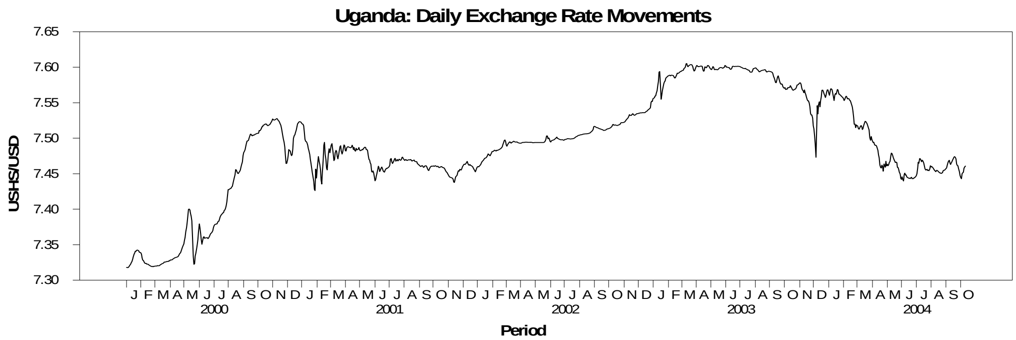
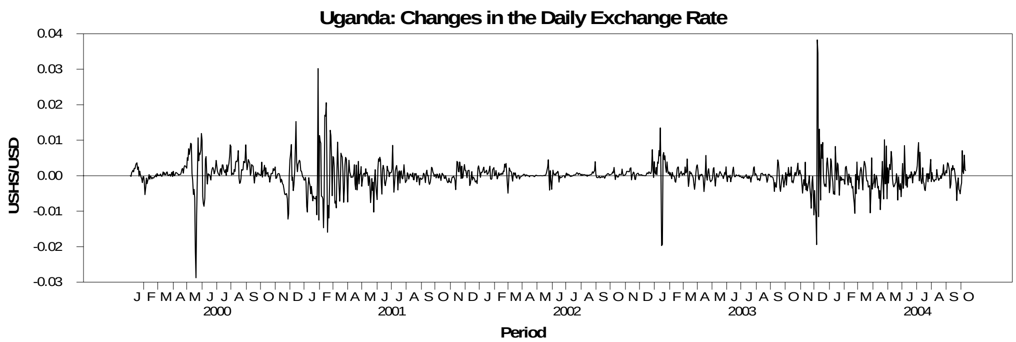


Figure 3: Daily Changes in the Exchange Rate



A statistical summary of the exchange rate data is given in Table 1.

Table 1: Exchange Rate Descriptive Statistics

	$\left(e_t - e_{t-1}\right)$
Mean	0.00011466605
Minimum	-0.028751278396
Maximum	0.038266343171
Std deviation	0.000111
Skewness	1.04087*
Kurtosis	20.80077*
Jarque-Bera	22687.87076*
t-Statistic	1.03498

* indicates significance at the 1 percent test level.
e is the natural logarithm of the daily exchange rate.
Source: Computed.

The distribution of the series is leptokurtic, they depict a high probability of more values clustering near the mean and a high probability of fat tails. The right tail appears to be particularly extreme. The statistics also suggest that appreciations of the nominal exchange rate over the sample have largely been insignificant. The single largest appreciation recorded over the sample was about 3 percent in one day compared to a depreciation of about 4 percent.

Table 2 suggests that the autocorrelation of exchange rate changes dies off after four days. The partial autocorrelations decay more quickly but depict a wave-like cyclical pattern.

Table 2: Exchange Rate ACF and PACF

Autocorrelation	Partial Correlation		AC	PAC
|** |	|** |	1	0.310	0.310
| |	*| |	2	0.012	-0.093
| |	| |	3	-0.027	-0.003
*| |	*| |	4	-0.128	-0.130
| |	| |	5	-0.050	0.034
| |	| |	6	0.036	0.036
|* |	|* |	7	0.086	0.068
| |	| |	8	0.044	-0.020
| |	*| |	9	-0.048	-0.062
| |	| |	10	0.003	0.055
| |	| |	11	0.020	0.020
| |	| |	12	0.045	0.045
| |	| |	13	0.011	-0.043
| |	| |	14	-0.055	-0.054
*| |	| |	15	-0.065	-0.027
| |	| |	16	-0.038	0.010
| |	| |	17	-0.031	-0.029
| |	| |	18	0.012	0.005
| |	| |	19	0.041	0.019
| |	| |	20	-0.006	-0.028
| |	| |	21	-0.041	-0.020
| |	| |	22	-0.010	0.018
| |	| |	23	-0.021	-0.024
| |	| |	24	0.007	0.020
| |	*| |	25	-0.040	-0.067
| |	| |	26	-0.012	0.026
| |	| |	27	0.015	0.014
| |	| |	28	-0.022	-0.022
| |	| |	29	0.015	0.017
|* |	| |	30	0.069	0.055
| |	| |	31	0.039	0.006
| |	| |	32	0.010	-0.001
| |	| |	33	0.022	0.038
| |	| |	34	0.031	0.021
| |	| |	35	0.018	0.014
| |	| |	36	0.024	0.016

Source: Computed.

3.1 Literature Review

The application of Markov chain type models to understand regime switching behaviour of macroeconomic and financial time series can be traced to the pioneering work of Hamilton (1989) and Engel and Hamilton (1990). Regime switching specifications allow for the possibility that a time series process may follow different state spaces over different sub-samples. The approach originally developed by Hamilton (1989) and Engel and Hamilton (1990) primarily relied on the assumption of a homogenous Markov chain with constant transition probabilities across the different state spaces.

Subsequent work by Filardo (1994), Diebold et al. (1994) and Engle and Hakkio (1996) allows for time varying transition probabilities. The transition probabilities may be specified either as functions of some information set or duration dependence or even both (Bazdresch and Werner (2005); Taylor, 2004; Diebold et. al., 1994). Specifications based on duration dependence to analyse regime switching behaviour of exchange rates make a rather strong assumption that markets clearly understand the different regimes and models. Specifications based on underlying economic fundamentals appear to be more convincing, save for the usual controversies surrounding the in-sample performance of structural models of exchange rates.

In the literature, two variants of Markov chain models have been used. The first assumes different normal distributions over the different sub-samples with constant parameters constant across the regimes. This is the mixture *iid* normals (Hamilton, 1989, Engel and Hamilton, 1990). The second variant is the more general regime switching approach. This allows the possibility that some parameters can change as the process switches from one regime to another (Taylor, 2004; Bazdresch and Werner, 2005).

Markov chain models are basically non linear and as such it is not possible to obtain the log likelihood estimates of the population parameters analytically. There are two possible solution methods; the numerical methods and the EM algorithm. The idea of the numerical methods is to make different guesses for the population parameters, compare the value of the log likelihood for each guess, and infer the population estimates for which the log likelihood is largest (Hamilton, 1994). The general idea of the EM algorithm involves maximizing the sample log likelihood function using the conditional density of the dependent variable evaluated as the sum of the conditional likelihood values in each possible combination of the current and past regime (Sarantis and Piard, 2004).

Markov chains have also been employed in the literature to obtain full sample probabilities for purposes of in-sample fitting (Hamilton and Engel, 1990; Taylor, 2004) and for out of sample forecasting (Engel and Hakkio, 1996; Bazdresch and Werner, 2005) though Marsh (2000) questions the forecasting ability of Markov chains.

Hamilton and Engel (1990) employed regime switching techniques to examine long swings in nominal exchange rates. Bazdresch and Werner (2005) employ the techniques to examine appreciation and deprecation episodes of the nominal exchange rate of the Mexican Peso. Bollen et. al. (2000) apply the techniques to understand the different exchange rate policy regimes whereas Vigfusson (1996) used it study existence of chartist and fundamentalist regimes. Simon van Norden (1996) employed the techniques to understand the regime switching behavior of exchange rate bubbles. Cheung and Erlandsson (2004) test the predictive ability of a simple random walk model versus a Markov chain specification.

All the studies have been able to identify two distinct regimes. This is quite interesting especially if viewed against the fact that empirical studies in economics rarely achieve consensus.

4.1 Methodology and Estimation Technique

Given that observed nominal exchange rate data may follow different state spaces over different sub-samples, a complete description of the data generating process should involve understanding the different regimes that the process may follow. The Markov chain methodology was employed to analyse the possibility of regime changes in the nominal exchange rate. The different processes that a variable may follow over different sub-samples are referred to as states or regimes, s_t .

A two-state Markov chain was assumed such that the process was said to be in state 1 if $s_t = 1$, and the process was said to be in regime 2 for $s_t = 2$. The probabilities of switching among the various possible states are defined by the transition probabilities, P_{ij} . The transition probabilities pij define the probabilities that state i will be followed by another state j . The value that the regime or state takes on at some date t will depend, in some probability on the values it has taken in the past. The realized state at time t is assumed to be related to past realizations only through its most recent values,

$$P\{s_t = j \mid s_{t-1} = i, s_{t-2} = k, ...\} = P\{s_t = j \mid s_{t-1} = i\} = P_{ij} . \quad (1)$$

The transition probabilities for a two-state Markov chain in matrix representation can be denoted as;

$$P = \begin{bmatrix} P_{11} & 1 - P_{21} \\ 1 - P_{11} & P_{22} \end{bmatrix}. \tag{2}$$

The process of obtaining inference about the state space that governed the process for each observation involves three major steps. First, using observed data, the conditional densities and transition probabilities are employed to generate parameter estimates of the variables. These are obtained by the method of maximum likelihood estimation. If the process is governed by regime $s_t = j$ at date t, then the conditional density of y_t is assumed to be given by

$$f\left(y_t \mid s_t = j, x_{t,} y_{t-1}; \alpha\right), \tag{3}$$

where α is a vector of parameters characterizing the conditional density. These densities can then be collected in an $(N \times 1)$ vector η_t. Since in our case $N = 2$,

$$\eta_t = \begin{bmatrix} f\left(y_t \mid s_t = 1, y_{t-1}; \alpha\right) \\ f\left(y_t \mid s_t = 2, y_{t-1}; \alpha\right) \end{bmatrix} = \begin{bmatrix} \dfrac{1}{\sqrt{2\pi\sigma}} \exp\left\{ \dfrac{-\left(y_t - \mu_1 - \phi_1 y_{t-1}\right)^2}{2\sigma^2} \right\} \\ \dfrac{1}{\sqrt{2\pi\sigma}} \exp\left\{ \dfrac{-\left(y_t - \mu_2 - \phi_2 y_{t-1}\right)^2}{2\sigma^2} \right\} \end{bmatrix}. \tag{4}$$

For purposes of having a tractable and simple notation, let the values of the conditional density parameters and the transition probabilities be put together in a ‘new’ population parameter vector θ whose value can then be estimated based on observation of the data series y_T. Hamilton (1994) has shown that maximum likelihood estimates of the transition probabilities will be given by

$$\hat{p}_{ij} = \frac{\sum_{t=2}^{T} P\left\{s_t = j, s_{t-1} = i \mid Y_T; \hat{\theta}\right\}}{\sum_{t=2}^{T} P\left\{s_{t-1} = i \mid Y_T; \hat{\theta}\right\}}, \tag{5}$$

where $\hat{\theta}$ denotes the full vector of maximum likelihood estimates. Thus, the estimated transition probability $\hat{p}_{ij}$ is essentially the number of times state i seems to have been followed by state j divided by the number of times the process was in state i. These counts are estimated on the basis of the smoothed probabilities.

The maximum likelihood estimate of the vector α that governs the conditional density is characterized by

$$\sum_{t=1}^{T}\left(\frac{\partial \log \eta_t}{\partial \alpha'}\right)' \hat{\xi}_{t|T} = 0. \tag{6}$$

Here η_t is the $(N \times 1)$ vector obtained by vertically stacking together the densities for $j = 1,2,...,N$ and $(\partial \log \eta_t)/\partial \alpha'$ is the $(N \times k)$ matrix of derivatives of the logs of these densities, where k represents the number of parameters in α. $\hat{\xi}_{t|T}$ denotes the conditional probability that the process at time t is in regime j.

The second step employs estimated values of the population parameters to form probabilistic inference $P\{s_t = j \mid y_t;\theta\}$ about the most likely regime the process was in at each date t in the sample. This inference takes the form of a conditional probability that is assigned to the possibility that the tth observation was generated by regime j. Let $\hat{\xi}_{t|T}$ represent the $(N \times 1)$ vector whose j^{th} element is $P\{s_t = j \mid Y_T;\theta\}$. The values for $t < \tau$ define the smoothed inference about the regime the process was in at date t based on data obtained through some later date τ. Since we assumed that state space follows a first order Markov chain in which the conditional density depends on past regimes only through the most current, then the smoothed inferences can then be calculated by using Kim's (1993) algorithm

$$\hat{\xi}_{t|T} = \hat{\xi}_{t|t} \otimes \left\{ P' \cdot \left[\hat{\xi}_{t+1|T} (\div) \hat{\xi}_{t+1|t} \right] \right\}, \tag{7}$$

where $(\div)$ denotes element by element division. The smoothed probabilities $\hat{\xi}_{t|T}$ are found by iterating (7) backward for $t = T-1, T-2, \ldots, 1$. Since the equations in θ are nonlinear, it is not possible to solve them analytically, however, their values can be obtained through a sequence of iterations.

Given an initial parameter estimate one can iterate to get $\theta^{(1)}, \theta^{(2)}, \ldots$. The iteration process continues until such a point when the change between any two estimates are smaller than some specified convergence criterion. If the iterations reach a point such that the two are equal the algorithm has found the maximum likelihood estimate of the sample parameters.

The following switching model was fitted to daily exchange rate data by maximum likelihood:

$$y_t - \mu_{st^*} = \phi_1 \left(y_{t-1} - \mu_{s^*_{t=11}} \right) + \phi_2 \left(y_{t-2} - \mu_{s^*_{t-2}} \right) + \phi_3 \left(y_{t-3} - \mu_{s^*_{t-3}} \right) + \phi_4 \left(y_{t-4} - \mu_{s^*_{t-4}} \right) + \varepsilon_t, \tag{8}$$

with $\varepsilon_t \sim i.i.d. N(0, \sigma^2)$ and with s_t^* presumed to follow a two state Markov chain with transition probabilities p_{ij}^*.

5.1 Estimation Results

The study employed the BFGS algorithm to obtain Maximum Likelihood estimates of the parameters in the exchange rate switching model. The BFGS is a variant of the numeric methods. The idea of the numerical methods is to make different guesses for the population parameters, compare the value of the log likelihood for each guess, and infer the population estimates for which the log likelihood is largest (Hamilton, 1994). The maximum likelihood estimates of parameters are reported in Table 3.

Table 1: BFGS Estimated Parameters for the Markov Switching Model

Parameter	Estimate	Std. error
μ_1	1.934000721	0.073939659
μ_2	-0.027601565	0.021420225
$\phi(1)$	0.620606392	0.028617755
$\phi(2)$	-0.220024907	0.034555714
$\phi(3)$	0.131863422	0.035584568
$\phi(4)$	0.083527460	0.029079418
P_{11}	0.598314451	0.100563891
P_{22}	0.991832766	0.002568646
σ	0.290861244	0.005846701

Function Value -302.26430381; Convergence achieved in 21 Iterations
Diagnostic measure (0=perfect) 0.0055

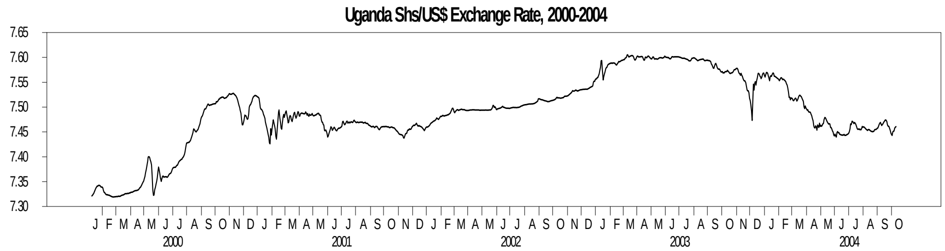
The convergence criteria used was based on change in the log likelihood during the iterations. Convergence was attained in 21 iterations. The function value or the log likelihood increased from -756.203489 to -302.26430381.

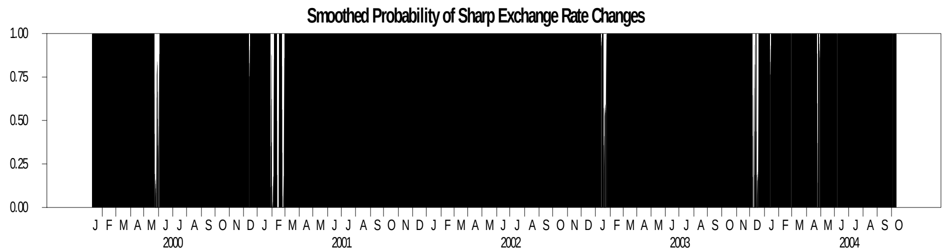
The regime $s_t = 1$ depicts an average depreciation of 1.9 percent per day (μ_1=1.9) whereas regime $s_t = 2$ depicts an average appreciation of about 0.03 percent per day (μ_2=-0.028). The probability that an episode of a large and sharp depreciation will be followed by another is approximately 0.6 (P_{11} =0.598). A regime charaterised by such sharp and large depreciations will typically persist for about two and a half days with an ergodic probability of 0.02. The probability that a tranquil and orderly state space will be followed by another is 0.992 (P_{22} =0.992) and the process will stay in this regime for an average of 125 days. This state space is persistent and has an ergodic probability of 98 percent.

The persistence of the regimes is asymmetric. Large and abrupt depreciations are characterized by very sharp but short lived episodes. This can be seen from the fact that the mean term for this regime is positive and relatively large (μ_1 =1.9) but with a smaller transition probability (P_{11} =0.598). The mean for regime two is negative and small (μ_2 =-0.028) but the regime transition probability is large (P_{22} =0.992). In other words, appreciations are small, gradual and prolonged but interestingly, they seem unable to reverse the effects of the sharp depreciation episodes. The Markov chain is irreducible and both states can be accessed from each other. The overall time varying stochastic volatility is indicates relative calm in the market (σ =0.29).

In addition, a probabilistic inference of the form $P\{s_t = j \mid y_t ; \theta\}$ was calculated for each date in the sample. These probabilities give the inference about the state space the process is in for each date in the sample. The resulting series is plotted as a function of time in the bottom panel of Figure 4. The full sample probabilities suggest the ability of the model to identify sharp spikes in the nominal exchange rate.

Figure 4: Exchange Rate and Smoothed Probabilities of Exchange Rate Changes





6.0 Summary and Conclusions

A two state Markov chain was employed to fit a regime switching model using daily Uganda shilling/US dollar nominal exchange rate data covering the period 3rd January 2000 to 31st December 2004. The maximum likelihood parameter estimates were obtained using the BFGS iteration algorithm. Our results validate the hypothesis that nominal exchange rate data generating process in Uganda over the study sample evolves according to two distinct state spaces. The full sample probabilities lead to the same conclusion. One state is characterized by sharp and disruptive, but short-lived depreciations and the other is characterised by quite small appreciations but taking place over a long period. The ergodic probabilities suggest that in as much the appreciations are persistent, they are nonetheless so small and unable to reverse the strong depreciation episodes. The results also suggest that the Markov chain is irreducible and that both states can be accessed from each other. The overall time varying stochastic volatility is low and appears to be driven largely by the sharp depreciation episodes. The results highlight the need to mitigate the disruptive effects of the sharp depreciations.

References

Atingi-Ego, M. and K.A. Egesa, (2003), "Compiling Trade in Services in a Fully Liberalised Country: the Case of Uganda", *Mimeo* Bank of Uganda.

Bazdresch S. and A. Werner (2005), "Regime Switching Models for the Mexican Peso", *Journal of International Economics*, 65:185-201.

Bollen P.B.N., Gray, S.F. and Whaley, R.E. (2000), "Regime Switching in Foreign Exchange Rates: Evidence from Currency Option Prices", *Journal of Econometrics*, 94:239-276.

Cheung Y. and Erlandsson U.G. (2004), "*Exchange Rates and Markov Switching Dynamics*", CESIFO Working Paper 1348.

Diebold, F.X., J.H. Lee and G. Weinbach (1994), "Regime Switching with Time-Varying Transition Probabilities" in Hargreaves C.P. (ed.), *Non-Stationary Time Series Analysis and Cointegration*, Oxford University Press.

Engel C. and Hakkio C. (1996), "The Distribution of Exchange Rates in the EMS", *Journal of International Finance and Economics*, 1:55-67.

Engel C. and Hamilton J.D., (1990), "Long Swings in the Dollar: Are They in the Data and Do Markets Know It?", *American Economic Review*, 80(4):689-713.

Filardo, A.J. (1994), "Business Cycle Phases and their Transitional Dynamics", *Journal of Business and Economic Statistics*, 12:299-308.

Frenkel, J.A. (1976), "A Monetary Approach to the Exchange Rate: Doctrine Aspects and Empirical Evidence", *Scandinavian Journal of Economics*, 78(2):200-24.

Goodhart Charles (1988), "The Foreign Exchange Market: a Random Walk with a Dragging Anchor", *Economica*, 55(220):437-60.

Hamilton, J.D., (1989), "A New Approach to the Economic Analysis of Non-stationary Time Series and Business Cycles", *Econometrica*, 57:357-384.

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

Malkiel, B.G., (2003), "The Efficient Market Hypothesis and its Critics", *Journal of Economic Perspectives*, 17(1):59-82.

Marsh, I.W. (2000), "High-Frequency Markov Switching Models in the Foreign Exchange Market", *Journal of Forecasting*, 19:123-134.

Mclachlan G., and D. Peel, (2001), *Finite Mixture Models*, John Wiley and Sons, New York.

Meese, Richard and Kenneth Rogoff, (1983), "Empirical Exchange Rate Models of the Seventies: Do they fit the Sample?", *Journal of International Economics*, 14 (1/2), 3-24.

Mutebile, T.E., (2001), Speech by the Governor, Bank of Uganda, at the Inauguration of the Uganda Foreign Exchange Bureau Operators Association Held on 27th January, 2001 at the Grand Imperial Hotel Kampala.

Norden S.V., (1996), "Regime Switching as a Test for Exchange Rate Bubbles" 11: 219-251.

Rankin, Bob (1998), "The Exchange Rate and the Reserve Bank.s Role in the Foreign Exchange Market", http:// www.rba.gov.au/Publications and Research/Education/Exchange_Rate.html.

Sarantis, N. and S. Piard (2004), "Credibility, Macroeconomic Fundamentals and Markov Regime Switches in the EMS", *Scottish Journal of Political Economy*, 51(4):453-476.

Shiller R.J., (2003), "From Efficient Markets Theory to Behavioral Finance", *Journal of Economic Perspectives*, 17(1):83-104.

Taylor, M.P. (2004), "Is Official Exchange Rate Intervention Effective?", *Economica* 71:1-11.

Taylor, M.P. (1995), "The Economics of Exchange Rates", *Journal of Economic Literature*, 83(1):13-47.

Vigfusson, R. (1996), "Switching Between Chartists and Fundamentalists: A Markov Regime Switching Approach, *Bank of Canada Working Paper 96-1*.