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# Modeling Country Risks: An Asian Perspective

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**Abstract**

This paper investigates the use of the Markov Regime Switching Model (MRSM) as a means to track changes in the levels of investor confidence. It also assesses the probabilities of a country switching between different regimes using the transition probability matrix. A maximum of three possible levels or regimes of risk – low, intermediate and high volatility regimes, is considered. From the smoothed probabilities calculated for different regimes, this paper makes inferences about timings of debt crisis. Comparing Brazil, Mexico, the Philippines and Indonesia in particular, we date the onset and subsequent dissolution of crisis-induced panic. We give interpretations of the results based on evidences of debt crisis. The objective is to investigate if there is information in the transition probability matrix and smoothed probabilities that country risk managers can use to make assessment on risk condition.

Key words: Debt crisis, Country risk assessment, Markov regime switching model

JEL Classifications: G15, C22

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## Modeling Country Risks: An Asian Perspective

## 1. Introduction

A country defaults on its loan when it is unable and/or unwilling to pay its obligations on interest and principal of its debt on time. Such an event can seriously impair banks' balance sheets and profitability. In a highly volatile business environment, it is therefore important that banks have the necessary resource and tools to assess the risk of default. One of the main responsibilities of country risk managers is to do country visits, partly to establish networking contacts and to access news on the ground. The process of making country risk assessment based on country visits alone however, can be subjective, so banks also rely on some forms of quantitative approach, or a systematic framework, to analyze country risk and improve their portfolio performance.

The rule-based reasoning spreadsheet model is one common method that commercial banks used to monitor historical and future outlook of the country's economic prospects, politics and social environment. The model gives a score to each indicator according to the criteria / rules set by the managers.[3] The scores are added up for different criteria and countries with low (high) risk of default will have high (low) scores. One advantage of the rule-based model is that it allows users to modify the model to meet their specific requirements. If particular risk factors have greater bearing on business or investments, composite risk ratings can be recalculated by giving greater weight to those factors. Because of the ease in use and design, the rule-based models have been widely adopted in commercial banks and risk rating agencies.

[3] For example, in assessing a current account deficit, the rule can be set that if a country has a current account deficit of say 3% of GDP in a particular year, that's in the safety zone, so a higher country score is assigned to the indicator in that year. If a country has a current account deficit of 5% of GDP, that's a reason for concern, so an average country score is assigned. If a country has a current account deficit of 8% of GDP that's cause for alarm, so a lower country score is assigned. Weights that summed up to 100% are attached to sub-categories of risk, for example political, financial and economic.

There is however a limitation with using the rule-based approach to model the country's risk of default. The model requires the managers to input changes in the economics, politics and social situation in a timely manner. Sometimes investors can change their expectations of economics, political and social fundamentals so quickly enough that they affect the whole economic landscape. And what make the job challenging for the managers is that that it is not easy to track these changes without a formal framework. Based on our experience, this point emphasizes the importance of having statistical models to track changes in the levels of investor confidence.

This study investigates the Markov Regime Switching Model (MRSM) as a means to track changes in the levels of investor confidence. A maximum of three possible levels or regimes of risk – low, intermediate and high volatility regimes, is considered. From the smoothed probabilities calculated for different regimes, this paper makes inferences of when 'panic' starts and when 'panic' ends. [4] We give interpretations of the results based on evidences of debt crisis. Using the transition probability matrix, this paper assesses the probabilities of a country switching between different regimes, and based on cross country comparison, the analysis makes inferences about the risk of investing in the country. The objective of the paper is to investigate if there is information in the transition probability matrix and smoothed probabilities that country risk managers can use to make assessment on risk.

The study will be on countries in Asia and Latin America, namely Indonesia, the Philippines, Brazil and Mexico in part because we wanted some basis of comparisons across international countries. These countries were used as case studies because both countries have large foreign debts that are predominantly owed by the government. Moreover, a large share of their public debts are denominated in, or

[4] Monthly data is used for the first experiment. Daily data is used for the second experiment.

linked to, the dollar, which makes the countries sensitive to movements to depreciation in the local currencies respectively. In the case of Philippines, accumulated public sector debt is estimated at 130% of GDP, of which two-thirds is government debt (half in foreign currency), and the rest that of state-owned quasi-commercial entities.

The remainder of this paper is structured as follows. Section 2 reviews factors that had contributed to debt crisis over the last three decades in some emerging countries. Section 3 reviews previous work on country risk modeling Section 4 describes the data and the econometric methodology. Section 5 presents the empirical results (the working paper currently focuses on Philippines and Brazil). Section 6 concludes by explaining how the results from using the MRSM methodology to capture volatility in a country's exchange rate can help industry practitioners such as country risk managers make better assessment on country risk. It also provides suggestions for future work.

## 2. International Debt Crisis in Emerging Economies

Two observations can be made when analyzing debt crisis in emerging countries over the last three decades. One, when debt crisis occurred they do not strike only one country in isolation, but a few emerging countries that are either geographically close to, or apart from, each other. These experiences suggest either the influence of contagion or the influence of common external factors on debt crisis.

We look at the effects of external influence, as seen from changes in oil price and related to this, monetary policy in the US. Periods of strong US dollar policy or rapid changes in oil prices have coincided with several international debt crises. For example during the periods of strong US dollar policy in the 1980's, the Eastern

Europe and Latin American countries experienced debt crisis. Likewise a strong US dollar policy between 1994 and 1998, coincided with a series of crisis that sparked the crisis in Latin America in 1994, followed by the Asian Financial crisis in 1997 and the crisis in Russia and Latin America in 1998.

Indeed rapid changes in price of oil are seen as catalyst for capital flows. For example, following the rapid increase in oil prices in the 1970's oil exporting countries in the Middle East deposited billions of dollars in profits they received from the oil commodities sold, in to US and European banks. These commercial banks were eager to make profitable loans to governments and state-owned entities (as well as private companies) in developing countries, using the dollars flowing from the Middle Eastern countries. And developing countries, particularly in Latin America, in turn were also eager to borrow relatively cheap money from the banks. The catalyst that triggered huge inflows into funds into emerging countries in the 1970s was caused by rapid rise in oil prices. In contrast, the period of low global oil prices as experienced by developed economies on the one hand, and the period of strong economic growth in emerging economies had caused differentials in interest rates between developed and developing economies. This in turn led to a new cycle of funds to flow from the developed economies to the emerging markets, as seen prior to the 1994 crisis in Latin America and prior to the 1997 crisis in Asia. Again, the fall in oil prices prior to the 1998 crisis in Russia and Brazil led to deterioration in the terms of trade for these oil-exporting countries, which meant debt repayment problems for these countries.

A second observation is that emerging markets had defaulted on their external debts repeatedly, over different periods in time, which suggest the influence of local or idiosyncratic factor that had made debtor countries susceptible to default not once or twice, but many times over. In total over the past two centuries Turkey has defaulted six times, Brazil seven times, Mexico eight times, Venezuela nine and Argentina five. These countries tend to have weak fiscal structures and weak financial systems. These countries tend to rely too much on foreign debt for their growth, after liberalization policies which had encouraged borrowing by the public or private sectors. When the global or local environment became no longer conducive to hold foreign debt, the debtor countries became susceptible to defaults. These countries have heavily relied on commodity exports as a major source of foreign earnings. Experiences have shown that debtor countries faced problems repaying their debts when commodity price fall.

Inconsistency in economic policies is another negative driver for defaults; this happens when the government became overly committed to keep the exchange rate pegged at a certain level, while experiencing uncontrollably large flows of foreign funds and keeping inflation and growth under check. To illustrate, when there is a large inflow of funds, the central bank's has to intervene in the foreign exchange market to prevent the exchange rate from appreciating. In which case, if it is an un-sterilized intervention, interest rates will fall and that itself will cause the central bank to worry about economy becoming overheated.[5] In contrast, when there is a large outflow of capital, the central bank has to intervene to keep the peg exchange rate from depreciating which makes interest rates increase; this will cause the central bank to worry about the economy going into a recession. From the experiences of countries such as Mexico in 1994, Asia in 1997, and Brazil in 1999 which went through financial crisis, central bank intervention to prevent the local currencies from

[5] If the intervention to buy foreign reserves is sterilized, that means the central bank has neutralized (or cancel out) the effect of intervention on money supply. For example, if the government increases reserves by buying foreign currency the domestic money supply will increase, but it can cancel out the effect on money supply by selling securities such as treasury bills to mop up the supply.

appreciating had been shown to lead to serious overheating problems (as seen in large current account deficits, high rate of inflation). When speculators speculated that the peg is no longer feasible in the light of unsustainable growth, they pulled the funds out which resulted in sharp correction in the economy. One lesson to be learnt is that it is important to trace the effects of exchange-market interventions and changes in foreign-exchange reserves on national monetary bases and other monetary aggregates relative to their counterparts in the target country or countries. A long buildup of foreign-exchange reserves should be taken as a danger signal, rather than as a sign of strength, for governments and central banks trying to manage exchange rates. Our discussion points to the weakness of soft pegs, especially for countries that are integrating into international capital markets. Debtor countries become subjected to perils of financial policy in US when they choose a peg exchange rate system. The impossible trinity, that a country cannot simultaneously maintain a fixed exchange rate, capital mobility and a monetary policy dedicated to domestic goals, clearly applies here. A country is better off exiting the soft peg when the currency is strong, as happens when reforms gain credibility and capital flows in.[6]

In sum, these idiosyncratic factors are specific (or, local) to each country. Generally speaking, the more unfavorable the idiosyncratic factor, the more adversely a country would react to shifts in external factors.[7]

## 3. Country Risk Literature

Some of the comprehensive surveys on country risk models can be found in earlier papers such as by Saini and Bates (1984) which focused on survey of the

[6] This happened in the case of Poland and Israel, where in each case the band widened as pressure for the currency appreciated.

[7] See Eichengreen, Rose and Wyplosz (1997) and Verma and Soydemir (2006) for investigations on influence of local and global risk factors on country risk

quantitative approaches of published empirical papers. Eaton and Taylor (1986) reviewed the theoretical aspects of numerous papers relating to least developed countries LDC debt and financial crisis, with an emphasis on the policy implications to be drawn. Rockerbie (1993) explained the interest spread on sovereign Eurodollar loans on the basis of various indicators on default risk in lesser developed countries and developed countries. He also provided a useful summary of risk indicators in the empirical papers examined.

A more recent survey by Hoti and McAleer's (2004) found more than half of the models used in empirical studies were probability-based models with the most popular model being the logit model, followed by the probit, discriminant and Tobit models. Their survey found the most frequently used dependent variable was the probability of debt rescheduling, followed by agency country risk ratings.[8] In these studies, three types of explanatory variables were used, namely economic, financial and political indicators, with economic and financial risks being the major components of country risk.[9] For economic and financial risks, they are represented by country's economic performance, terms of trade, exchange rates, monetary reserves, rapid increases in production costs and / or energy prices and unproductively invested foreign funds. Political risk, is seen to emerge from events such as wars, internal and external conflicts, territory disputes, revolution changes of government and terrorist attacks.

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[8] Agency country risk ratings are used as measures of country creditworthiness and hence serve as indicators of the probability of debt rescheduling.. The lower is a country's creditworthiness, the higher is the associated risk in investing in the country, and the higher is the probability that the country will reschedule its future debt payments. Some agencies such as Institutional Investor, Euromoney and ICRG provide quantitative country risk ratings which range from o (lowest) to 100 (highest creditworthiness), while Rundt & Associates ratings are rated on a scale of 1 (best) to 10 (worst). Other agencies such as Standard and Poor's, Moody's and EIU publish qualitative letter ratings. For example, country risk ratings for Moody's range from Aaa (highest) to C (lowest).

[9] In practice, these three groups are regarded as interdependent because businesses and individuals monitor the economic and financial consequences of political decisions.

## 4. Methodology: Regime-Switching Regressions

The methodology that we use to model regime-switches in mean follows Hamilton (1989) while that used to model regime-switches in volatility can be traced to Hamilton and Susmel (1994). The reader is referred to these key references for full details. Here, in order to motivate our argument that transition probabilities can be used to characterize the idiosyncratic risks of a country, we merely outline the key role played by the Markov chain in modeling regimes.

Structural break refers to sudden change in the behavior of a time series data. To incorporate the potential recurrence of such breaks into forecasts, nonlinear models such as Hamilton's (1989) regime-switching approach are often adopted. This allows the change in regime to be modeled as a random event that could potentially recur, and for which the probability of recurrence could be forecasted. Thus, the change in regime is itself a random variable, whose probability law is defined within the data generating process. Equivalently, the regime or state is modeled as a discrete process.

In this paper, we assume the unobserved regime can be modeled by a Markov chain, the simplest time series model for a discrete-valued random variable. We consider a maximum of three possible regimes. Let $s_t$ be a random variable that can assume only integer values {1, 2, 3}, where the probability that $s_t$ equals some particular value $j$ depends on the past only through the most recent value $s_{t-1}$

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

Such a process is described as an $N$-state Markov chain with transition probabilities given as $\{p_{ij}\}_{i,j=1,2,\ldots,N}$ . The transition probability $p_{ij}$ gives the probability that state $i$ will be followed by state $j$, so that $p_{i1} + p_{i2} + p_{i3} = 1$.

In a 3-state regime for example, the transition probabilities can be represented in a $(3 \times 3)$ matrix **P** known as the transition matrix, where the element in row $j$, column $i$ is the transition probability $p_{ij}$:

$$\mathbf{P} = \begin{bmatrix} p_{11} & p_{21} & p_{31} \\ p_{12} & p_{22} & p_{32} \\ p_{13} & p_{23} & p_{33} \end{bmatrix} \quad (2)$$

Let the regime that a given process is in at date $t$ be indexed by an unobserved random variable $s_t$, where there are $N$ possible regimes ($s_t$ = 1,2,.....$N$). When the process is in regime 1, the observed variable $y_t$ is presumed to have been drawn from a $N(\mu_1, \sigma_1^2)$ distribution. If the process is in regime 2, then $y_t$ is drawn from a $N(\mu_2, \sigma_2^2)$ distribution, and so on. Hence, the density of $y_t$ conditional on the random variable $s_t$ taking on the value $j$ is

$$f(y_t | s_t = j; \theta) = \frac{1}{\sqrt{2\pi}\sigma_j} \exp\left\{\frac{-(y_t - \mu_j)^2}{2\sigma_j^2}\right\} \quad (3)$$

for $j = 1, 2, \ldots,$ or $N$. For an $N$ regime case, $\theta$ is a vector of population parameters that includes $\mu_1, \ldots, \mu_N$ and $\sigma_1^2, \ldots, \sigma_N^2$.

The unobserved regime $\{s_t\}$ is presumed to have been generated by some probability distribution, for which the unconditional probability that $s_t$ takes on the value $j$ is denoted $\pi_j$, where $P\{s_t = j; \theta\} = \pi_j$ for $j = 1, 2, \ldots,$ or $N$. The probabilities $\pi_1, \ldots, \pi_N$ are also included in $\theta$; so that $\theta = (\mu_1, \ldots, \mu_N, \sigma_1^2, \ldots, \sigma_N^2, \pi_1, \ldots, \pi_N)'$. The joint density-distribution function of $y_t$ and $s_t$ is given by

$$p(y_t, s_t = j; \theta) = \frac{\pi_j}{\sqrt{2\pi}\sigma_j} \exp\left\{\frac{-(y_t - \mu_j)^2}{2\sigma_j^2}\right\}. \quad (4)$$

Summing (4) over all possible values for $j$ then gives the unconditional density for $y_t$:

$$f(y_t;\boldsymbol{\theta}) = \sum_{j=1}^{N} p(y_t, s_t = j;\boldsymbol{\theta}) \tag{5}$$

Since the regime $s_t$ is unobserved, expression (5) is the relevant density describing the actual observed data $y_t$. If the regime variable $s_t$ is distributed i.i.d. across different dates $t$, then the log likelihood for the observed data can be calculated from (5) as

$$L(\theta) = \sum_{j=1}^{T} \log f(y_t;\, \theta) \tag{6}$$

The maximum likelihood estimate of θ is obtained by maximizing (6) subject to the constraints that $\pi_1 + \pi_2 + \ldots + \pi_N = 1$ and $\pi_j \geq 0$ for $j = 1, 2, \ldots, N$.

Functions of the form of (5) can be used to represent a broad class of different densities. The joint density-distribution $p(y_t, s_t = 1; \theta)$ is $\pi_1$ times a $N(\mu_1, \sigma_1^2)$ density, while $p(y_t, s_t = 2; \theta)$ is $\pi_2$ times a $N(\mu_2, \sigma_2^2)$ density. The unconditional density for the observed variable $f(y_t; \theta)$ is the sum of these two magnitudes.

Once one has obtained estimates of θ, it is possible to make an inference about which regime was more likely to have been responsible for producing the date t observation of $y_t$. Again, from the definition of a conditional probability, it follows that

$$P\{s_t = j \,|y_t;\, \theta\} = \frac{p(y_t,\, s_t = j;\, \theta)}{f(y_t;\, \theta)} = \frac{\pi_j \cdot f(y_t|s_t = j;\, \theta)}{f(y_t;\, \theta)} \tag{7}$$

Given knowledge of the population parameters **q**, it would be possible to use (3) and (5) to calculate the magnitude in (7) for each observation $y_t$ in the sample. This number represents the probability, given the observed data, that the unobserved regime responsible for observation $t$ was regime $j$.

The mixture density (5) has the property that a global maximum of the log likelihood (6) does not exist. A singularity arises whenever one of the distributions is imputed to have a mean exactly equal to one of the observations ($\mu_1 = y_1$, say) with no variance ($\sigma_1^2 \to 0$). At such a point the log likelihood becomes infinite.

Such singularities do not pose a major problem in practice, since numerical maximization procedures typically converge to a reasonable local maximum rather than a singularity. The largest local maximum with $s_j > 0$ for all $j$ is described as the *maximum likelihood estimate*.

Hamilton and Susmel (1994) suggested an extension to the above model which would allow for changes in regimes to affect the residual variance through

$$u_t = \sqrt{g_{s_t}} \times \tilde{u}_t \tag{8}$$

Here, $\tilde{u}_t = h_t \cdot v_t$ is said to follow an ARCH-L(q) process, in a reference to the "leverage" effect proposed by Glosten, Jagannathan and Runkle (1989), when $v_t$ is white noise and $h_t$ is given by (see Hamilton and Susmel's equation (3.4))

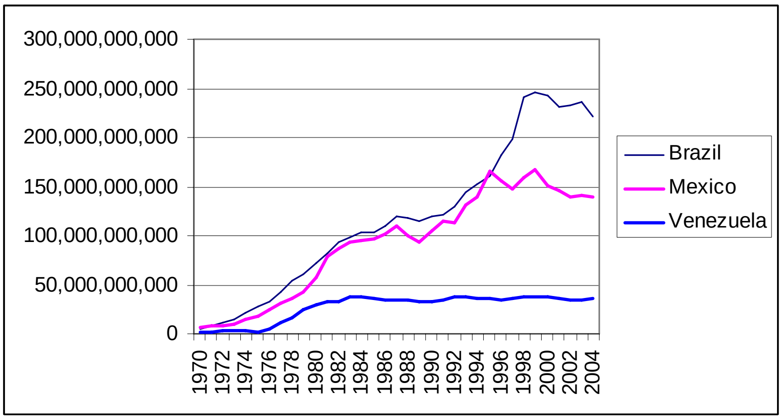
$$h_t^2 = \alpha_0 + \alpha_1 \tilde{u}_{t-1}^2 + \alpha_2 \tilde{u}_{t-2}^2 + \ldots + \alpha_q \tilde{u}_{t-q}^2 + \xi \cdot d_{t-1} \cdot \tilde{u}_{t-1}^2 \tag{9}$$

with $d_{t-1} = 1$ = 1 for $\tilde{u}_{t-1} \leq 0$ and $d_{t-1} = 0$ otherwise.

## 5. Empirical results

Brazil is an interesting case study of how its debt problem had evolved and what the government had done to overcome the problem. A significant portion of its foreign borrowing in the 1970's had been by state enterprises to import sophisticated equipments. They had borrowed to finance their investments, as part of the nation's import-substitution industrialization strategy to reduce dependency on imported oil, raw materials and production goods. By 1980 the foreign-debt problem grew to US$72 billion, prompting the government reduce economic growth and with it, the country's imports, so that trade surpluses could grow to service the country's foreign debt. The economy contracted further when its access to international financial markets was cut off after Mexico announced a moratorium on its debt service payments in August 1982. Growth on average slowed to 2.2% during the period 1980- 1989, down from 8.6% during the period 1970 – 1979.

Chart : Total global debt (private and public)




Source: IMF

Brazil defaulted on its debt payment on April 1994. Earlier in the 1990's, external debt ballooned with private capital representing the most important source of financing current account deficits, which have risen as a natural consequence of the attractiveness of investments and the sluggishness with which domestic savings have recovered. At the end of 1993, Brazil's external debt totaled approximately $146 billion. Of this total, about $34 billion is medium-term commercial bank debt owed by the government. In 1994, Brazil's net public debt as a share of gross domestic product was 30 per cent, and by 2002 it has soared to 60%. In April 1994, the government concluded a debt renegotiation agreement with foreign commercial banks, where it restructured $35 billion in defaulted bank loans.[10] Unlike past Brady Plan debt exchanges, the Brazilian deal was closed without the support of the official international financial community since the Brazilian government was unable to reach an agreement with the IMF for a standby program. According to the data of the Banco Central do Brasil, Brazil's gross external debt was $210.8 billion in 2001. Brazil did not reach an agreement with the Paris Club during 1994 to reschedule official debt. Under Brazil's 1992 agreement with the Paris Club, further debt rescheduling is contingent upon the government concluding a standby agreement with the IMF. Two months after Brazil defaulted on its debt payment on April 1994, the currency was changed on June 1st 1994, the old "cruzeiro real" was abandoned and the new currency, Real (symbol R$) was set equivalent to R$1=US$1. Leading to the default period, the currency had been depreciating. Of interest to us in the paper is whether the MRSM model recognizes those periods as state of high exchange rate volatility?

To answer this question (and similarly for other periods of default in Philippines) we chose the exchange rate as dependant variable in the MRSM. The 2-state and 3-state Markov switching models in mean and ARCH are used on rate of change of the exchange rates for Brazil and the Philippines. Tables 1 and 2 tabulate the estimated parameters of the model for regime switch in mean and ARCH process,

[10] Early in the1990s, foreign capital began to return but it took a rather different form from the capital inflows of the 1970s. They were smaller and were no longer dominated by loans from international banks. Instead, foreign lenders sought equity investments in Brazilian enterprises. Foreign firms with the capacity to manage direct investments in Brazil began to replace commercial banks as the primary source of foreign capital.

respectively, over the period Jan 1991 to 2006 for Brazil exchange rates. We will focus on Figure 1 which shows what the smoothed probabilities look like, as computed using the 2-state MRSM in mean, as well as, Table 3 which shows the transition probability matrix for a 2-state MRSM in ARCH.

**Table 1**
**Brazil exchange rates: 2- and 3-state Markov regime-switching in mean**

For vector of coefficients parameterized as follows

| Parameters | 2-State | 3-State |
|---|---|---|
| $\phi_{01}$ (state 1) | 0.81669708 (0.68065066) | 25.407313 (7.9507125) |
| $\phi_{02}$ (state 2) | 28.526341 (1.2050712) | 1.9681327 (7.6964441) |
| $\phi_{03}$ (state 3) | | -8.8397458 (7.9150066) |
| $\phi_1$ | 0.23088258 (0.076706789) | 0.25468823 (0.081042334) |
| $\phi_2$ | 0.64493820 (0.072919056) | 0.70417325 (0.095716954) |
| $\phi_3$ | -0.37784452 (0.074037527) | -0.066189749 (0.086040506) |
| $\phi_4$ | -0.11834924 (0.076772947) | 0.042887599 (0.092629168) |
| $\sigma^2$ | 24.158351 (2.7276962) | 30.376019 (3.4748320) |
| $p_{11}$ | 0.97038181 (0.014680544) | 0.25298719 (0.31248720) |
| $p_{22}$ | 0.88279609 (0.053850995) | |
| $p_{21}$ | | 0.027060649 (0.015163082) |
| $p_{23}$ | | 0.19338502 (0.10529877) |
| Log-likelihood | -366.74456 | -380.79013 |

*Note: Standard errors in parentheses.* $\phi_{0i}$ *i=1,2 are means for each state,* $\phi_i, i = 1,2,3,4$ *are autoregressive coefficients,* $\sigma^2$ *is disturbance variance and* $p_{ij}$ *are transition probabilities. Except first one, all the other estimates are highly significant.*

**Table 2**
**Brazil exchange rates: 2- and 3-state Markov regime-switching ARCH**

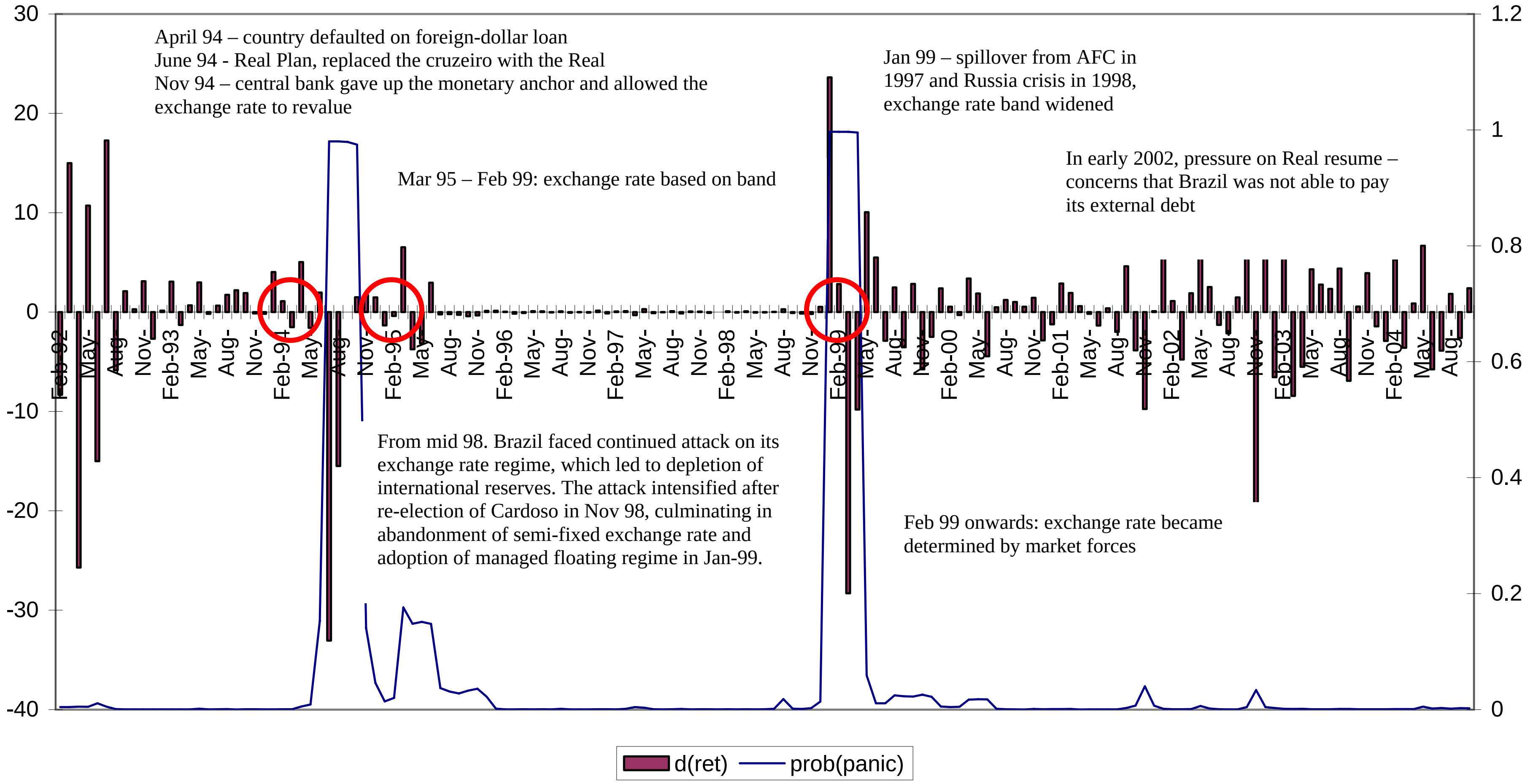
For vector of coefficients parameterized as follows

| | 2-State | | 3-State | |
|---|---|---|---|---|
| **Parameters** | **Est Coef** | **Std error** | **Est Coef** | **Std error** |
| Constant term in regression | 0.001398 | 0.014319 | -0.00068 | 0.01508 |
| $\phi_1$ | -0.39822 | 0.080697 | -0.32743 | 0.046198 |
| $\phi_2$ | -0.27808 | 0.049048 | -0.23135 | 0.037022 |
| $\phi_3$ | -0.22216 | 0.046189 | -0.11317 | 0.031486 |
| $\phi_4$ | -0.03816 | 0.045491 | -0.04986 | 0.020324 |
| Constant term in ARCH | -0.00591 | 0.006477 | -0.0044 | 0.003512 |
| $\alpha_1$ | 1.136291 | 0.656693 | 0.964997 | 0.305492 |
| $\alpha_2$ | -0.19417 | 0.181628 | 0.138237 | 0.126326 |
| $\alpha_3$ | -0.4253 | 0.294132 | 0.280295 | 0.140642 |
| $\alpha_4$ | -0.45642 | 0.317642 | 0.270232 | 0.131912 |
| | 7.751217 | 3.038459 | 6.594891 | 1.976034 |
| | -1.73242 | 0.705339 | 419.7382 | 864.4072 |
| | | | -1.14E-06 | 0.066235 |
| | | | 419.3038 | 865.7632 |
| variance factors for state 2 | 216.0973 | 250.6664 | 373.849 | 306.0998 |
| variance factors for state 3 | | | 84.10411 | 65.02843 |
| df for t distribution | 1.078659 | 1.054343 | 3.142789 | 2.53236 |
| Log-likelihood | -329.65141 | | -325.72967 | |

*Note: Standard errors in parentheses. For the 2-state model, the transition probabilities are expressed in terms of* $\theta_1, \theta_2$ *as follows* $p_{11} = \theta_1^2 / (1+\theta_1^2)$, $p_{22} = \theta_2^2 / (1+\theta_2^2)$

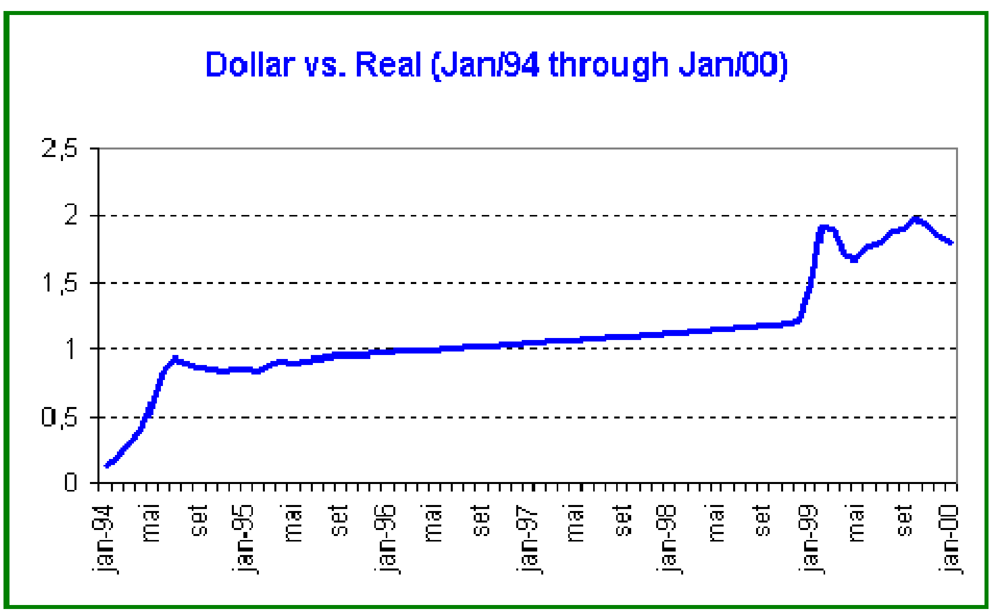
Figure 1 shows what the smoothed probabilities look like, as computed using the 2-state (high volatility state vs low volatility state) MRS in mean. Using the monthly data, the chart shows that the model captured two periods of large changes in the value of the exchange rate value (one in July 1994, Jan 1999 and Mar 1999), as state of high volatility, where the model showed the volatility lasted for three months (July to Sep 94) and (Jan to Mar 99). During the July 1994 period, the real appreciated by more than 30%. During the Jan 1999 period, the real depreciated by about 22%, and this was followed by a 30% appreciation in Mar 1999. In other periods there were also exchange rate volatilities but they are of more moderate magnitude, and the model did not trigger any state of panic. In each case, the results suggest that financial volatility lasted for three months before financial calm was restored again. We will explain these empirical results based on evidences in Brazil.

**Figure 1**
**Brazil Exchange Rate: 2-State Smoothed Probabilities**



In 1990, a floating exchange rate regime has been adopted, but two months after the country default on its loan in April 1994, it implemented a Real plan in June 1994 to make the currency a controlled currency. With this plan, the old "cruzeiro real" was abandoned and the new currency, Real (symbol R$) was set equivalent to R$1=US$1 on June 1st 1994. Despite it being a controlled currency, the real currency managed to gain value against the dollar (as sharp as 30% in July 1994) for the following reasons: the Central Bank had increased interest rates and there was liquidity in the international markets; most important of all, foreigner investors believed in the success of the Plan Real, which would (with the fall of inflation) cause redistribution of income, and Brazil saw a massive influx of foreigner investments. The MRSM triggered the period of appreciation of the Real during the period July to September 1994 as a state of high volatility. Indeed, inflation declined dramatically in the first two months of the plan. Brazil had the longest period of low inflation in its history; in several months, indexes were negative.

Chart 2: Dollar vs Real



Source: IMF

Pressures then started to come from politicians that Real had appreciated too much over the last 12 months, causing concerns that the country had been losing export competitiveness. From Mar 1995 to Feb 1999, a new exchange rate based on bands was introduced. During the period, the dollar would be adjusted downwards about 0.6-0.7% per month (7-8% per year), a process of gradual depreciations of the Real. From mid-1998 Brazil started facing continued attack on its exchange rate regime, which led to sustained depletion of its international reserves. The attack intensified after re-election of Cardoso in Nov 98, culminating in abandonment of semi-fixed exchange rate and adoption of managed floating regime in Jan-99.

In the year 1999, Brazil was involved in a currency crisis, as a result from the 1997 Asian crisis and the 1998 Russian crisis. The crisis led to several occasions of speculative attacks against the Real, during which time the central bank would react by selling dollars at official rate and increase interest rates, to punish those who did not believe in the Real. In 13 Jan 1999 the exchange rate band was widened to R$1.20 – R$1.32 per US$1. There was record capital outflows $14 bn within a few days. The interest rates were again raised, but that did not stop the attacks. The Central Bank had to sell tens of billions of dollars at official rate. At that time, the Government decided that the protection of the Real with high interest rates was too expensive at the expense of halting the economy, and that the Real should float freely. The exchange rate devalued by more than 20%. Our model captured the events in January 1999 as a high volatility state that lasted for three months before financial calm was restored again. By Feb 1999, the exchange rate became determined by market forces. The currency has been set into an independently floating regime since 1999, with inflation targeting framework set as a guide for monetary policy. This explains why from 1999 onwards the Real has become more erratic versus the dollar.

There were subsequently some more exchange rate volatilities. In 2001 when public debt reached 70% of GDP, there were concerns that the country will not repay foreign public debt and this had caused sovereign bond spreads to widen to 2000 basis points by October 2002. There were periods of depreciation (about 10% in some months), but it was not significant enough for the MRSM to capture that event as a state of high volatility. Then in Nov 2002 the exchange rate made an about turn and appreciated by about 20%, which coincided with a major rescue package announcement by the IMF, coupled with an unexpectedly prudent economic policy by the new administration in Brazil. Both probably succeeded in resolving most doubts and could explain the confidence in the currency. The chart in Figure 1above showed that the 20% appreciation was not significant enough for the MRSM to capture that event as a state of high volatility

Table 3 shows the transition probability matrix for a 2-state MRS in ARCH.

**Table 3**
**Transition Probability Matrix – Brazil exchange rates (Feb 1992 – Oct 2004) : SWARCH 2 State**

| | Low | High |
|---|---|---|
| Low | 0.983628 | 0.24992 |
| High | 0.016372 | 0.75008 |

The transition probability matrix in a 2-state model is interpreted as follows. First, there is a high 98% probability that a low volatility state will be followed by a similar state. There is a high 75% probability that a high volatility state will be followed by a similar state. Second, there is a higher probability that the state will switch from high to low volatility than for the reverse to occur (25% versus 1.6%). Both results suggest that that there is a greater tendency for the country to both stay in low volatility (than stay in high volatility) and revert to low volatility (than to revert to high volatility).

We relaxed the model and increase the number of states from a 2-state to 3-state. Figure 2 shows what the smoothed probabilities look like using the 3-state (high, moderate vs. low state) MRS in mean. The results look similar in terms of model's ability to define periods of exchange movements in Jul 1994 and Jan 1999 as highly volatile. One difference in the results is that the 3-state model additionally defined the periods Mar 1995 and May 1995 as at state of highly volatile exchange rate. Evidences showed that on 6th Mar 1995, a new exchange rate system based on bands was introduced. The band was set at R$0.86-R$0.98 per U.S. Dollar, wider from the previous band of 0.844 to 0.846. There were subsequent revisions that saw upward increase in both the min-max of the band (i.e. depreciation of Real) but it was not sufficient for the 3-state or 2-state model to trigger panic state. Interestingly, the 3-state model also did not capture the exchange rate movements in first half of 1992 as intermediate state of volatility. Likewise, the model also did not capture for most of periods between years 2001 to 2003 the exchange rate movements as intermediate state of volatility.

**Figure 2:**
**Brazil Exchange Rate: 3-State Smoothed Probabilities**

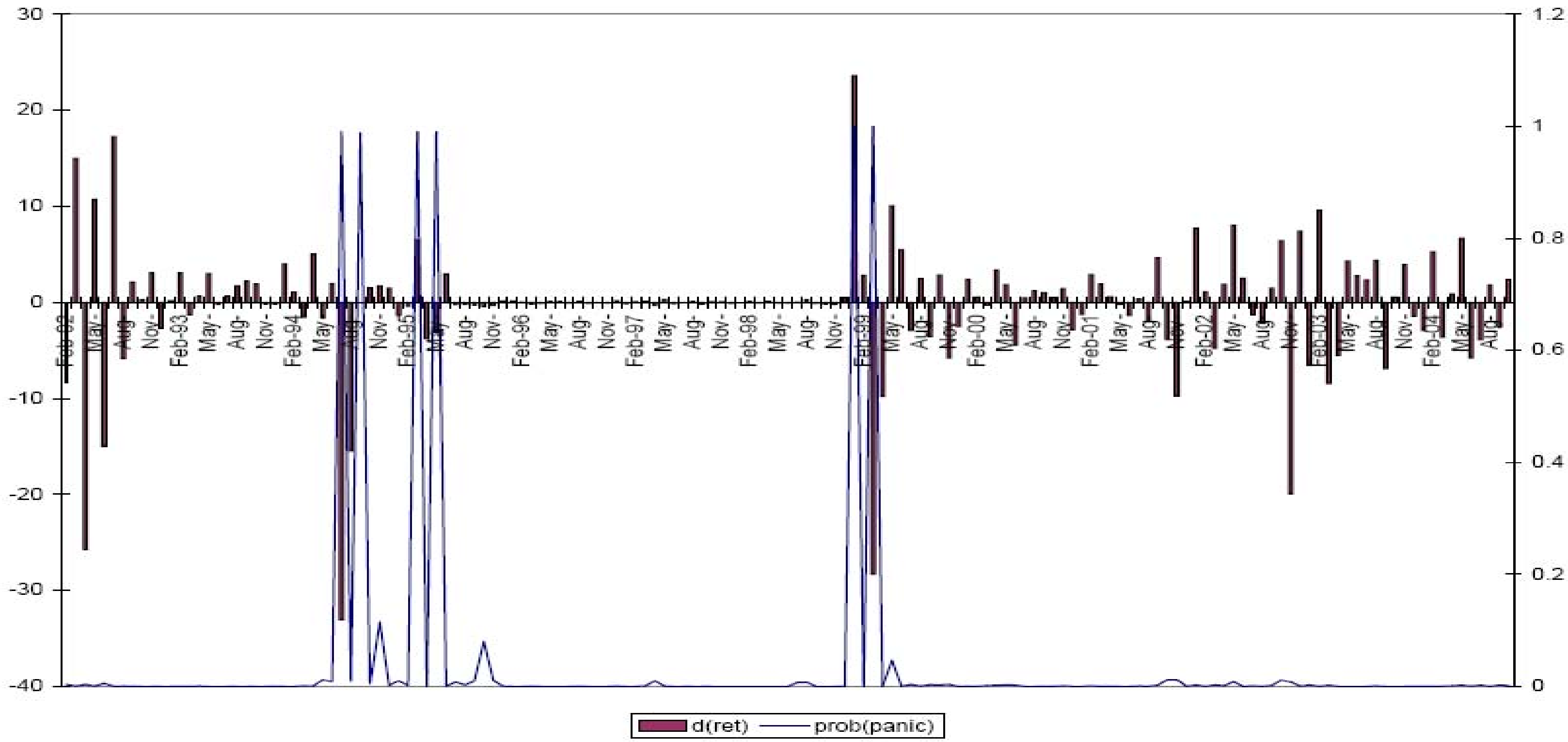


Table 4 shows the transition probability matrix for a 3-state MRS in ARCH.

**Table 4**
**Transition Probability Matrix – Brazil Exchange Rate (Feb 1992 – Oct 2004)**
**SWARCH 3-State**

| | Low | High | Intermediate |
|---|---|---|---|
| Low | 0.978 | 0 | 0.501 |
| High | 0.022 | 0 | 0.499 |
| Intermediate | 0 | 1 | 0 |

The interpretation of the results using a 3 state model is more interesting. Looking at the first column, the matrix says that there is a high 98% probability that a calm state can be followed by a similar state, and the remaining probability that a calm state can be followed by a high volatility state is low at 2%. According to the second column, the matrix says that there is a no chance that a high volatility state would be followed by either a high volatility state or a calm state. Instead, the estimates show that a high volatility state will always be followed by an intermediate state. Lastly, according to the third column, there is about an even chance that an intermediate state will move to either of the calm or high volatility states, and no chance that it will move to its own state. In this regard, the interpretation of the transition probability matrix of our experiment with a 3-state model is actually a lot more interesting and the information content is richer than what we saw with a 2-state model.

## Philippines Results

The 2-state and 3-state Markov switching models in mean and ARCH are used on rate of change of the exchange rates for the Philippines, and selected results are tabulated. Table 5 tabulates the estimated parameters of the model for regime switch in ARCH process, over the period Jan 1991 to 2006 for the Philippines exchange rates. For the purpose of the paper, we will focus on Figure 3 which shows what the smoothed probabilities look like, as computed using the 2-state MRS in ARCH and Table 6 which shows the transition probability matrix for a 2-state MRS in mean.

**Table 5:**
**Philippines exchange rate returns: 2- and 3-state Markov regime-switching ARCH**

For vector of coefficients parameterized as follows

| | 2-State | | 3-State | |
|---|---|---|---|---|
| **Parameters** | **Est Coef** | **Std error** | **Est Coef** | **Std error** |
| Constant term in regression | 0.003446 | 0.007269 | 0.08165 | 0.026836 |
| $\phi_1$ | 0.296109 | 0.031702 | 0.469773 | 0.044223 |
| $\phi_2$ | -0.06184 | 0.00917 | | |
| Constant term in ARCH | -0.00075 | 0.000671 | -0.02785 | 0.013973 |
| $\alpha_1$ | 0.464372 | 0.124378 | 0.357229 | 0.116594 |
| $\alpha_2$ | 0.409497 | 0.135976 | 0.221127 | 0.095581 |
| $\alpha_3$ | 0.165019 | 0.082286 | 0.212757 | 0.09574 |
| $\alpha_4$ | 0.452975 | 0.126977 | 0.650853 | 0.233105 |
| $\alpha_5$ | 1.14E-11 | 0.076169 | | |
| $\alpha_6$ | 0.285865 | 0.085091 | | |
| | 5.309918 | 0.898346 | 6.588735 | 1.375089 |
| | 1.368861 | 0.296751 | 3533.987 | 3421.994 |
| | | | -1.90712 | 0.467351 |
| | | | -2730.65 | 2657.393 |
| variance factors for state 2 | 321.8117 | 109.5413 | 84.01945 | 29.02991 |
| variance factors for state 3 | | | 1569.728 | 714.4381 |
| | 0.20821 | 0.446185 | | |
| df for t distribution | | | | |
| Log-likelihood | | | -521.193 | |

Figure 3 and 4 show what the smoothed probabilities look like, as computed using the 2-state MRS (high volatility state vs low volatility state) and 3-state MRS in ARCH. Using the monthly data, the charts show periods of high appreciation and depreciation in the peso. As a result of the volatilities in the exchange rate, the 2-state model captured several periods as being in state of high volatility (Jan-80, April-80, Nov-84, June-84, Nov-84 to Feb-85, Jan-96, July-87, Jun-90 to Jan-91, Jul-97 to Jan-98). We will for analysis purpose study two periods of high volatility as given by the 2-state model, first during 1984 to 1985 and second during 1990 to 1991, both of which coincide with periods of debt re-negotiations by the Philippines government. The 3-state model gives a more refined interpretation of the volatility with inclusion of the intermediate state, but makes the exercise more tedious hence we shall focus for clarity on the results of the 2-state model.

First, during 1984 to 1985 the peso depreciated by around 25%, which the MRS model captured as states of high volatility. The Philippines had turned to the IMF previously in 1962 and 1970 when it had run into balance of payments difficulties. It did so again in late 1982. An agreement was reached in February 1983 for an emergency loan, followed by other loans from the World Bank and transnational commercial banks. On October 17, 1983, it was announced that the Philippines was unable to meet debt-service obligations on its foreign-currency debt of US$24.4 billion and was asking for a ninety-day moratorium on its payments. Leading to the Oct 83 period, the exchange rate had showed some signs of volatility, and accordingly the 2-state MRS model registered state of panic in Dec 83 which lasted for one month. Calm set in for four months. The cycle repeats with the model registering another round of state of panic that similarly lasted for one month, followed by state of calm for one month and another cycle of state of panic for subsequent four months (Oct 84-Feb 85).

Subsequent requests were made for moratorium extensions. In each of these arrangements with the IMF, the Philippines agreed to certain conditions to obtain additional funding, generally including devaluation of the peso, liberalization of import restraints, and tightening of domestic credit (limiting the growth of the money supply and raising interest rates). The adjustment measures demanded by the IMF in the December 1984 agreement were harsh, and the economy reacted severely. Because of its financial straits, however, the government saw no option but to comply. Balance of payments targets were met for the following year, and the current account turned positive in FY 1986, the first time in more than a decade. But there was a cost; interest rates rose to as high as 40 percent, and real GNP declined 11 percent over 1984 and 1985. The dire economic situation contributed to Aquino's victory in the February 1986 presidential election.

Our second example refer to the period between June-90 to Jan-91, when the peso depreciated by around 5-10% per month, and the model during this period showed states of high volatility. In fact leading to the month February 1991, the Philippine government also said that it would ask the Paris Club for deferment of payment on US$1 billion in debts falling due from June 30, 1991 to July 31, 1992. In March 1991, Philippine officials raised the issue of "condonation," or debt forgiveness, of Philippine debt with United States officials, requesting that the United States accord the Philippines similar treatment to that accorded Egypt and Poland. The United States resisted the entreaty, pointing out that whereas US$33 billion of Poland's US$48 billion debt was official, all but 20 percent of the Philippine debt was owed to commercial banks.

**Figure 3:**
**Philippines exchange rate returns: 2- state Markov regime-switching ARCH**

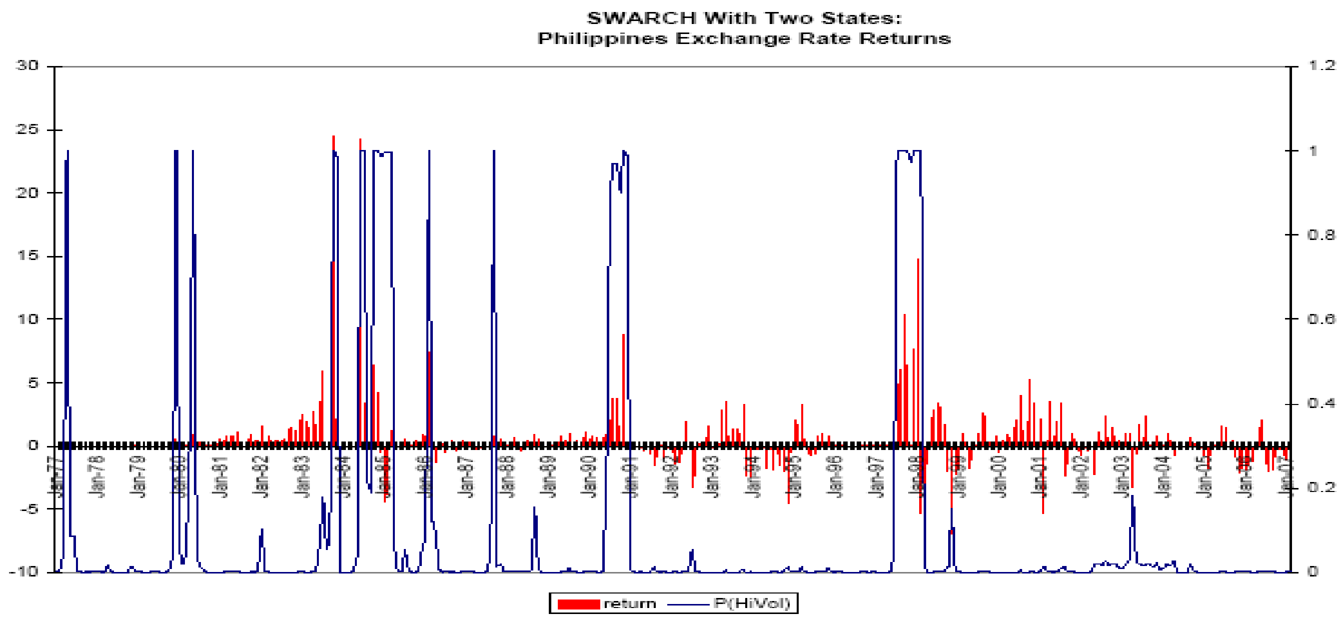


**Figure 4:**
**Philippines exchange rate returns: 3-state Markov regime-switching ARCH**

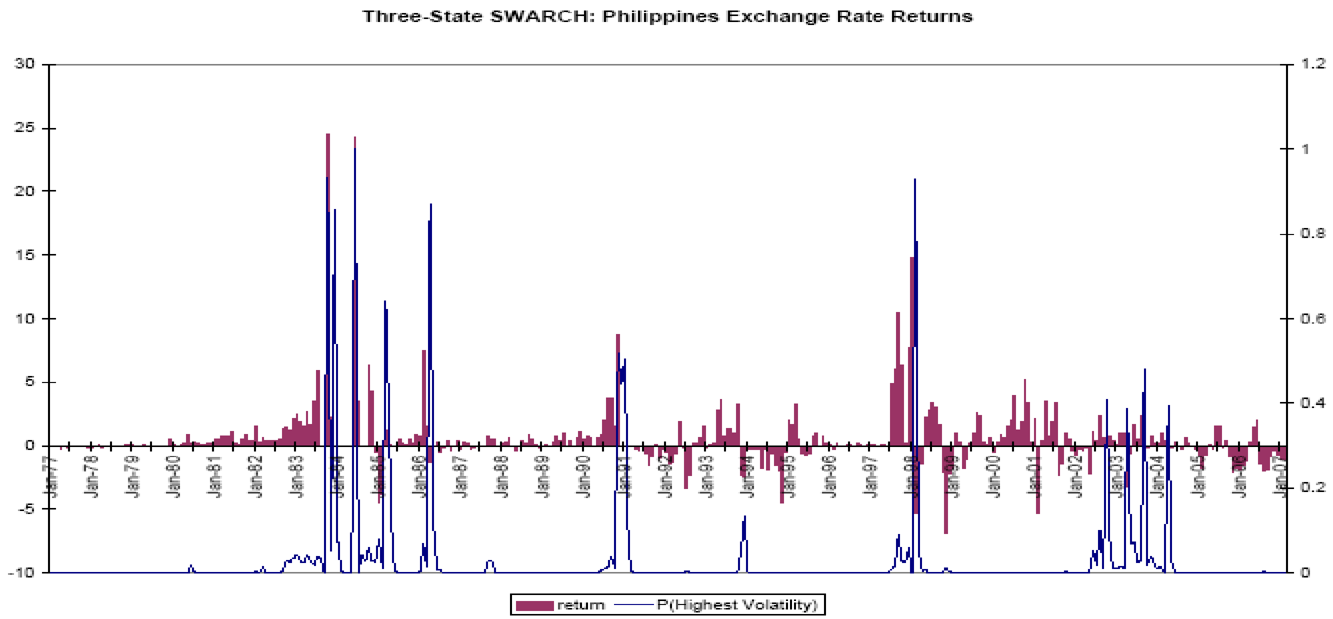


Table 6 shows the transition probability matrix for a 2-state MRS in ARCH for Philippines exchange rate.

**Table 6:**
**Transition Probability Matrix – Philippines (Jan 1977 – Feb 2007)**
**SWARCH 2 State**

| | Calm | Panic |
|---|---|---|
| Calm | 0.965748 | 0.347974 |
| Panic | 0.034252 | 0.652026 |

The transition probability matrix in a 2-state model is interpreted as follows. There is a high 97% probability that a calm state will be followed by a calm state. There is a moderately high 65% probability that a panic state will stay in a panic state. There is a higher probability that the state will switch from panic to calm than for the reverse to occur (35% versus 3%). In this regard, the interpretation of the transition probability matrix of our experiment with a 2-state model is interesting because it suggests that there is a greater tendency for the country to stay in calm (than stay in panic) and for the country to revert to calm (than to revert to panic)

We relaxed the model and increase the number of states from a 2-state to 3-state (high, moderate vs. low volatility states). Table 7 shows the transition probability matrix for a 3-state MRS in ARCH for Philippines exchange rate.

**Table 7**
**Transition Probability Matrix – Philippines (Jan 1977 – Feb 2007)**
**SWARCH 3 State**

| | Calm | Panic | Intermediate |
|---|---|---|---|
| Calm | 0.977483 | 0 | 0.62616 |
| Panic | 0.022517 | 0.784348 | 0.37384 |
| Intermediate | 0 | 0.215652 | 5.01E-08 |

The interpretation of the results using a 3 state model is more interesting. Looking at the first column, the matrix says that there is a high 98% probability that a calm state can be followed by a calm state, or the remaining low 2% probability that a calm state can be followed by a panic state. According to the second column, the matrix says that there is no chance that a panic state would be followed by a panic state; however there is a 78% chance that the panic state would stay at panic state, or 20% chance that it be followed by an intermediate state. The estimates suggest that a panic state will most likely stay in panic state. According to the third column, at the intermediate state, there is about 63% chance it will move to calm state and remaining 36% chance of staying in intermediate state. In this regard, the interpretation of the transition probability matrix of our experiment with a 3-state model is actually a lot more interesting and the information content is richer than what we saw with a 2-state model.

## 6. Conclusions

From a country risk analysis perspective, we found that applying the methodology of MRSM model yields potentially useful information. For Brazil, which had intermittent periods of flexible and controlled exchange rate, the model captured the transitional changes during periods of exchange rate appreciation and exchange rate depreciation as state of high volatility. However, during latter period of flexible exchange rate system, the model did not capture the volatility of the exchange rate movements as high, nor as intermediate volatility state (in the 3-state version of the model). In such instances, there were periods of depreciation (about 10% in some months), but it was not significant enough for the MRSM to capture that event as a state of high or even intermediate volatility. For Philippines, the 2-state model captured most of the peaks in peso depreciations as high state of volatility. For some periods, an exchange rate devaluation of around 5% is sufficient enough for the model to trigger these periods as a state of high volatility.

We also found the use of the MRSM yields potentially useful information for country comparisons. We compared the results in Brazil model with the Philippines model. One interesting interpretation of the transition probability matrix is its use as a measurement of risk. If we use the transition probability matrix as a gauge of level of risk in investing in currency asset, we observe that during the state of panic in either country, Philippines peso has a higher chance of staying in panic state as compared to Brazil.

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