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by

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MARKOV SWITCHING GARCH MODELS OF CURRENCY CRISES IN SOUTHEAST ASIA

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Abstract

This paper develops a model which is able to forecast exchange rate turmoil. Our starting point relies on the empirical evidence that exchange rate volatility is not constant. In fact, the modeling strategy adopted refers to the vast literature of the GARCH class of models, where the variance process is explicitly modeled. Further empirical evidence shows that it is possible to distinguish between two different regimes: "ordinary" versus "turbulence". Low exchange rate changes are associated with low volatility (ordinary regime) and high exchange rate devaluations go together with high volatility. This calls for a regime switching approach. In our model we also allow the transition probabilities to vary over time as functions of economic and financial indicators. We find that real effective exchange rate, money supply relative to reserves, stock index returns and bank stock index returns and volatility are the major indicators.

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1 Introduction

The decade of the nineties witnessed several bank and currency crises: Europe in 1992-93 (the European Exchange Rate mechanism), Mexico in 1994-95, Turkey in 1994 and 2000-01, East and Southeast Asia in 1997, Russia in 1998, and more recently, Argentina, Uruguay and Brazil. The severity of the crises have motivated researchers to develop early warning systems in order to forestall similar crises. Such early warning systems typically involve some precise definition of a crisis and a mechanism for predicting it. A currency crisis is usually identified as an episode in which there is a sharp depreciation of the currency, a large decline in foreign reserves, a dramatic increase in domestic interest rates or a combination of these elements.

This paper develops a model which is able to forecast exchange rate turmoil. Our starting point relies on the empirical evidence that exchange rate volatility is not constant. In fact, the modeling strategy adopted refers to the vast literature of the GARCH class of models, where the variance process is explicitly modeled. Further empirical evidence shows that it is possible to distinguish between two different regimes: "ordinary" versus "turbulence". Low exchange rate changes are associated with low volatility (ordinary regime) and high exchange rate devaluations go together with high volatility. This calls for a regime switching approach. In our model we also allow the transition probabilities to vary over time as functions of economic and financial indicators.

The contribution of the paper is to recognize the importance of volatility dynamics in forecasting turbulent regimes.

The analysis is applied to four Southeast Asian countries: Thailand, Singapore, the Philippines and Malaysia. Model results will support our intuition for modeling exchange rate volatility.

Empirical studies of currency crises employing multi-country data were initiated by Eichengreen, Rose, and Wyplosz 1994, 1995 and 1996. The initial work was on developed countries that had pegged exchange rates, examining the behavior of a number of macroeconomic variables during crisis and non-crisis periods. The main finding was that, these macroeconomic indicators had very different patterns across periods in the European Exchange Rate Mechanism (ERM) countries, while this was not the case for non-ERM countries. These findings led to the conclusion that there were no clear early warning signals of speculative attacks.

Subsequent researchers focused on trying to predict currency and banking crises in developing countries. In the existing literature, there are three methods or approaches for predicting currency crises.

One class of models for predicting currency crises is the probit regression approach by Frankel and Rose (1996). They used probit analysis on a panel of annual data for 105 developing countries from 1971-92. The hypothesis tested was that currency crashes are positively linked to certain characteristics of capital inflows, such as low shares of foreign direct investments (FDI); low shares of concessional debt or debt from multilateral development banks; high shares of public-sector, variable short-term, and commercial bank debt. The finding was that currency crises were more likely when foreign interest rates are high, domestic credit growth is high, the real exchange rate is overvalued, the current account deficit and fiscal deficit are large (as a share of GDP), external concessional debt is small, and FDI is small in relation to the total volume of external debt. However, when the model was used to generate out-of-sample predictions for the 1997 Asian Crisis, the forecasts were not successful (Berg and Patillo, 1999a, p.118).[1]

A second class of models (Tornell, 1998; IMF, World Economic Outlook, 1998; Radelet and Sachs, 1998; Corsetti Pesenti and Roubini,1998) follows Sachs, Tornell and Velasco (1996) who used cross-country regressions to explain the Tequila (Mexican) Crisis of 1995. Using a crisis index defined as the weighted sum of the percentage decrease in foreign reserves and the percentage depreciation of the peso, they concluded that countries had more severe attacks when they had low foreign reserves, their banking systems were weak and their currencies overvalued. Berg and Patillo (1999a) extended the data to 23 other countries and concluded that the Sachs, Tornell and Velasco (1996) model proved to be largely unstable. Specification uncertainty appeared to be as important as parameter uncertainty.

The third class of models, attributed to Kaminsky, Lizondo and Reinhart (1998), is the 'signals approach'. A crisis is defined as a situation in which a weighted average on monthly percentage depreciations in the currency and monthly percentage declines in reserves exceeds its mean by more than three standard deviations. They used 15 monthly variables to monitor for unusual behavior during a 24-month window prior to a crisis. Threshold levels, beyond which signals would be generated, are specified. Using variants of the signals approach, Kaminsky (1998a and1998b), Kaminsky and Reinhart (1999) and Goldstein, Kaminsky and Reinhart (2000) claimed some success in predicting the Asian crisis.

Edison (2000) concluded that research into early warning systems has provided insights into the more important indicators of vulnerability, such as, a marked appreciation of the real exchange rate, a high ratio of short-term debt to reserves, a high ratio of M2 to reserves, substantial losses of foreign exchange reserves, and sharply declining equity prices.

Mariano et al. (2002) used a Markov switching regime approach to compute the forecast probabilities of getting into a crisis. We also use a Markov switching approach. However, we account for the fact that the volatility of exchange rate returns is not constant over time. This creates the need for a modeling strategy which includes a GARCH specification.

[1] See also Berg and Patillo (1999b). A more recent paper by Kumar, Moorthy and Perraudin, 2002, applied logit models to pooled data on 32 developing countries for the period January 1985 to October 1999. The results confirm those of earlier studies that factors such as declining reserves, exports and declining real activity are the most important explanatory variables for currency crashes.

2 Motivating our Approach

The goal of the paper is to develop an early warning methodology to predict episodes of high risk and high exchange rate movements.

Our approach consists in modeling the conditional mean and the conditional variance of exchange rate devaluation. The first and the second order moments of exchange rate devaluation are driven by the same Markov process governed by an unobservable state variable. The underlying assumption is quite simple: low mean values of exchange rate devaluation are associated with low volatility of the exchange rate devaluation and high devaluation is associated with high volatility. We refer to the latter regime as "turbulence" and the former as describing "ordinary" market conditions. In addition, the transition probabilities in the Markov process are a functions of macroeconomic and/or financial variables. This captures the idea that large exchange rate devaluations and high risk might be driven by exogenous variables.

This approach might lead to identify currency crises. In fact, there is empirical evidence (see below) showing that, at least for the four Southeast Asian countries analyzed in this paper, high risk and high exchange rate devaluation correspond indeed to the 1997 currency crises.

The countries considered are Thailand, Singapore, Malaysia and Philippines. The sample period runs from November 1984 to December 2001.

What distinguishes our approach from the previous literature[2] is the emphasis on the volatility process of exchange rate devaluation (we adopt GARCH models which are models for the volatility process). To motivate our accent on the volatility of exchange rate returns, we compute a volatility proxy. The volatility process is not directly observable. Many volatility proxies have been proposed in the literature. Most of them are functions of the return process (squared returns, absolute returns). We adopt a non-standard proxy: the range. Drawing on the results of Feller (1951), Parkinson (1980) shows that the range (properly rescaled) is an unbiased estimator of the volatility process. Moreover, Brunetti and Lildholdt (2002a) demonstrate that the range is superior to volatility proxies based on returns. The range is defined as the difference between the maximum value of the (log of) the price process over a given interval of time and the minimum value of the (log of) the price process over the same interval

$$l = \max_{0 \leq n \leq N} [\ln(P_n)] - \min_{0 \leq n \leq N} [\ln(P_n)] \tag{1}$$

Our data set is composed of monthly observations. The use of monthly data is due to the fact that many macroeconomic data used as explanatory variables for the time varying Markov probabilities, are available only at monthly frequencies. However, nominal exchange rate data is also available at daily frequencies. For each month and for each exchange rate analyzed we selected the highest (log) price and the lowest (log) price to compute the monthly range (see Chou, 2002). Therefore, the time interval $0 \leq n \leq N$ in our set up corresponds

[2] See also Mariano et al. (2002).

to a month. Finally, the volatility (standard deviation) proxy is computed as

$$\hat{\sigma}_{i,t} = \sqrt{\frac{\pi}{8}}\, l \tag{2}$$

where i indicates the four different exchange rates analyzed in the paper and t refers to the monthly observation.

Figures 1, 2, 3 and 4 graph the volatility proxy for the exchange rate devaluations of the four countries analyzed.[3]

2.1 Time-Varying Volatilities Approach

Since Mandelbrot (1963a, 1963b) and Fama (1965) it has been a well know fact that asset return volatility is not constant over time. Moreover, there is a large empirical evidence (among others see Brunetti and Lildholdt, 2002b) showing volatility clustering: large (small) changes in the nominal exchange rate tend to be followed by large (small) changes of either sign. These features are confirmed by our data. Figures 1, 2, 3 and 4 show that volatility changes over time and evolves in clusters.

The GARCH model is able to capture both time varying volatility and volatility clustering. Baillie and Bollerslev (1989) shows that the GARCH class of models is able to capture the volatility dynamics of exchange rates at daily, weekly and monthly frequencies. Even if the GARCH effect dissipates as the length of the sampling interval increases, there is still heteroskedasticity and volatility clustering at monthly frequencies. GARCH(1,1) models have proved to adequately describe exchange rate volatility dynamics.[4] This is the approach we follow in this paper.

2.2 Markov Regime Switching Approach

As already stated, we model jointly the conditional mean and the conditional variance (volatility) of exchange rate devaluations. The Markov switching regime model adopted relies on two assumptions: i) the volatility process is characterized by two regimes, high volatility and low volatility; ii) the high volatility regime is associated with large exchange rate deviations (high values of the mean process) and the low volatility regime is associated with small exchange rate movements (low values of the mean process). The first assumption is confirmed by Figures 1 to 4. For all the four countries analyzed, the volatility process exhibits periods of very low volatility and periods of very high volatility. Interestingly, the highest volatilities coincide with the 1997 crisis which is the major currency crisis that took place during our sample. Therefore this crisis represents our benchmark.

[3] Note that the volatility proxy for Malaysia covers the period November 1984 - October 1998. In fact, after this date the currency was pegged to the US Dollar.

[4] For a review of the literature on GARCH models see Bera and Higgins (1993) and Bollerslev, Engle and Nelson (1994).

The onset of the crisis in Thailand, the first country to be hit by the crisis, was on July 1997. The average monthly volatility (standard deviation) in the 12 months after the crisis (July 1997 - June 1998) is more than seven times bigger than in the previous 12 months (July 1996 - June 1997). Similar results also apply to Singapore and Malaysia. For the Philippines the volatility in the twelve months subsequent the beginning of the crisis increased by a factor of 55.

The second assumption simply implies that the same Markov process drives both the mean and the variance of exchange rate returns. Figure 5 displays the scatter plot of exchange rate devaluation and the volatility proxy for Thailand. It is evident that periods of zero or low exchange rate devaluation/appreciation are associated with low risk and periods of severe devaluations are associated with very high exchange rate risk. In the twelve months after the onset of the 1997 crisis the level of the exchange rate devaluation increased by a factor of 8 compared to the 12 months before.

Figures 6, 7 and 8 graph the scatter plots of exchange rate devaluation and risk for Singapore, Malaysia and the Philippines, respectively. Again, high devaluation and high risk go together (turbulence regime) as well as low devaluation and low risk (ordinary regime). The exchange rate devaluation increased by a factor of 12, 59 and 54 in Singapore, Philippines and Malaysia respectively, when comparing the twelve months before and after the crisis.

It is interesting to note the asymmetry of exchange rate devaluation and volatility: in periods of high risk the currency devaluates. The largest outliers in Figures 5 to 8 refer to the 1997 crisis.

The presence of two regimes - low devaluation and low volatility versus high devaluation and high volatility - motivates the Markov switching approach adopted. It is also evident that within the two regimes volatility is not constant. Hence the need for a GARCH approach.

2.3 Turbulence and Crisis

The modeling strategy adopted is able to identify turbulent periods. Do turbulent periods correspond to currency crises?

A currency crisis is not necessarily a "turbulence" period, and *vice versa*. There can be a crisis without any exchange rate devaluation (and of course without any volatility of the exchange rate devaluation). In fact, the government might be able to absorb exchange rate pressures using foreign reserves, interest rates, etc. On the same base the exchange rate might experience "turbulence" without being in a crisis.

Citing Kaminsky and Reinhart (1999): "Most often, balance-of-payments crises are resolved through a devaluation of the domestic currency or the floatation of the exchange rate. But central banks can and, on occasion, do resort to contractionary monetary policy and foreign-exchange market intervention to fight speculative attack." (p.475-6).

Figures 1 - 4 and Figures 5 - 6 provide overwhelming evidence that the 1997 crisis resolved in a large exchange rate devaluation and high volatility.

Our model predicts turbulent periods. Being the 1997 crises characterized by turbulence (high volatility and large exchange rate devaluation) we should be able to predict it.

3 Time varying probabilities Markov switching GARCH models

Let y_t be the first difference of the log nominal exchange rate. The simple GARCH(1,1) model may be written as follows:

$$\begin{aligned} y_t &= \mu + \sum_{i=1}^{k} \theta_i X_{i,t} + u_t && (3) \\ u_t &= \sigma_t \varepsilon_t,\ \varepsilon_t \sim nid(0,1) && (4) \\ \sigma_t^2 | \Omega_{t-1} &= \omega + \alpha u_{t-1}^2 + \beta \sigma_{t-1}^2 && (5) \end{aligned}$$

where X_i are the exogenous and/or lagged variables for the mean of the returns, θ is the corresponding parameter vector and Ω_{t-1} is the information set available at time $t-1$. For simplicity we are assuming that the innovation term follows a normal distribution. The model is very flexible and many extensions have been proposed in the literature.

As shown in the previous section, in periods of currency turbulence, exchange rate volatility is often very high and we may distinguish between two regimes: a "ordinary" regime and a "turbulence" regime. Dueker (1997) introduced the Markov Switching GARCH model and we adopt his approach. Equations 3-5 can be written as

$$\begin{aligned} y_t &= \mu_t + \sum_{i=1}^{k} \theta_i X_{it} + u_t && (6) \\ u_t &= \sigma_t \varepsilon_t,\ \varepsilon_t \sim nid(0,1) && (7) \\ \sigma_t^2 \left(S_t, S_{t-1} ... S_0\right) &= \omega\left(S_t\right) + \alpha\left(S_{t-1}\right) u_{t-1}^2 + \beta\left(S_{t-1}\right) \sigma_{t-1}^2 \left(S_{t-1} ... S_0\right) && (8) \end{aligned}$$

The constant, μ_t, in the conditional mean equation is allowed to switch between two regimes - high mean (μ_1) and low mean (μ_0),

$$\begin{aligned} \mu_t &= \mu_1 S_t + \mu_0 \left(1 - S_t\right) && (9) \\ S_t &\in \{0, 1\}, \quad \forall t && (10) \\ \Pr\left(S_t = 0 | S_{t-1} = 0\right) &= p && (11) \\ \Pr\left(S_t = 1 | S_{t-1} = 1\right) &= q && (12) \end{aligned}$$

where S_t is the latent Markov chain of order one. We are assuming that the parameter vector θ in the conditional mean equation is constant (i.e. it does not switch according to the Markov process) but this assumption can be easily relaxed. The innovation term, u_t, follows a normal distribution. Dueker (1997) adopted a student-t distribution for the error term. We started our empirical analysis assuming a student-t distribution for the innovations. The estimated degrees of freedom were very high, for this reason we decided to use the normal distribution.

The conditional variance, σ_t^2, is a function of the entire history of the state variable. This is due to the autoregressive term, σ_{t-1}^2, in the conditional variance equation - see Dueker (1997), Cai (1994) and Hamilton and Susmel (1994). Obviously, it is very demanding to account for all the past history of the state variable. Following Dueker (1997), we adopt an approximation procedure that seems not to cause any problems in the evaluation of the likelihood function. This procedure implies that the conditional variance is a function of only the most recent values of the state variable. Dueker (1997) shows that in a GARCH(1,1) model we need to consider only the most recent four values of the state variable. This means that the conditional variance, σ_t^2, is function only of the current state (S_t) and the previous state (S_{t-1}): $\sigma_t^2(i,j) = \sigma_t^2(S_t = i, S_{t-1} = j)$. By integrating out S_{t-1}, the conditional variance can be written as

$$\sigma_t^2(i,j) = \omega(S_t = i) + \alpha \left[u_{t-1}^2(j)\right] + \beta \left[\sigma_{t-1}^2(j)\right] \tag{13}$$

Equation (13) implies that the constant in the conditional variance equation is allowed to switch. In the GARCH(1,1) specification, the unconditional variance is given by $\frac{\omega}{1-\alpha-\beta}$. Therefore, equation (13) allows two unconditional variances: high unconditional variance in "turbulence" regimes and low unconditional variance in "ordinary" regimes. Following Dueker (1997), $\omega(S_t)$ is parameterized as $g(S_t)\,\omega$ such that $g(S=0)$ is normalized to unity.

In this setup the transition probabilities are constant. This seems over-restrictive. Transition probabilities may depend on economic variables. For this reason we introduce time varying probabilities. In our setup transition probabilities are probit functions of economic variables denoted by Z_t

$$\Pr(S_t = 0|S_{t-1} = 0) = p = \Phi\left(Z_{t-1}^{\prime}\zeta\right) \tag{14}$$

$$\Pr(S_t = 1|S_{t-1} = 1) = q = \Phi\left(Z_{t-1}^{\prime}\nu\right) \tag{15}$$

where Φ denotes the *cdf* of the normal distribution. A Markov switching regime GARCH model with time varying probabilities is also developed in Grey (1996).

This approach allows forecasting the conditional probability of being in a given regime (i,j) at time $t+1$ given the information available at time t.

Denote $\hat{\xi}_{t|t}$ the $(N \times 1)$ vector of conditional probabilities of being in state $(0,1)$ conditional on the data until date t. Define η_t as the $(N \times 1)$ vector of the density of y_t conditional on S_t. Following Hamilton (1994), the optimal forecast for each t, is computed by iterating the following two equations

$$\hat{\xi}_{t|t} = \frac{\left(\hat{\xi}_{t|t-1} \odot \eta_t\right)}{\mathbf{1}'\left(\hat{\xi}_{t|t-1} \odot \eta_t\right)} \tag{16}$$

$$\hat{\xi}_{t+1|t} = \mathsf{P}_{t+1} \cdot \hat{\xi}_{t|t} \tag{17}$$

where $\mathbf{1}$ is the unit vector, P_{t+1} is the $(N \times N)$ Markov transition probability matrix and $\odot$ denotes the element-by-element multiplication.

Recall that P_t is time varying and depends on the previous period values of explanatory variables. We are mainly interested in the turbulent regime. Our approach allows us to compute the probability of moving to a turbulence regime in period $t+1$ given all the available information at time t.

The log-likelihood function is given by

$$\ln L_t(i,j) = -\frac{1}{2}\ln\left[\sigma_t^2(j)\right] + \ln\left(\frac{u_{t-1}^2(i)}{\sigma_t^2(j)}\right) - \ln\left[\sqrt{2\pi}\right] \tag{18}$$

where $i \in \{0,1\}$ relates to $S_t \in \{0,1\}$ and $j \in \{0,1\}$ relates to $S_{t-1} \in \{0,1\}$. The function is maximized following Hamilton (1994).

4 Data Description

Currency crises most often reveal themselves in an actual devaluation of the domestic currency or the floatation of the exchange rate. Nevertheless, there are occasions in which central banks wind up adopting contractionary policies. In these cases, crises manifest themselves in interest rate hikes, depletion of reserves, etc. Also, currency crisis are sometimes linked to banking/financial sector distresses.[5]

To take into account all the facets of currency crises, we consider a number of macroeconomic and financial variables: M2/reserves, real domestic credit, real effective exchange rate, banking sector stock index returns and volatility, general stock market index returns and volatility.[6] In order to get a clearer view of the evolution of turbulent periods we use monthly data. Recall that our model delivers the probability of getting into turbulence in period t given the information available up until $t-1$ and for this reason lower frequencies might not be advantageous.

Real effective exchange rate (REER) and interest rate differentials (IRDIFF) are *external sector* indicators. In particular, the percentage deviation of the REER from a trend is a current account indicator while the domestic-US real interest rate differential on deposits represents an indicator associated with the

[5] For a literature review on the link between banking and currency crisis see Kaminsky and Reinhart (1999).

[6] See appendix for a description of how those series were created.

capital account. REER is considered as deviation from a trend because not all real appreciations/depreciations necessarily reflect disequilibrium phenomena.

M2/reserves (M2 ratio) together with real domestic credit/GDP (RDC) are *financial sector* indicators. Both variables are considered in deviation from a trend. In fact, not all the changes in those indicators are symptomatic of a troublesome situation.

Stock index returns (GENRET) and volatility (GENVOL) are indicators of the *real sector*[7] linking currency crisis to economic activity.

In order to stress the link between currency crises and *banking* problems we introduce returns and volatility of a stock index based on a portfolio (weighted by the capitalization) of banks listed on the stock market (BANKRET and BANKVOL respectively).[8] We believe these variables could be important indicators for the Southeast Asian crisis we study in this paper.

Citing Kaminsky and Reinhart, "Of course, this is not an exhaustive list of potential indicators." (p.481) We have considered only some of the indicators that they suggest and add some others, based on the empirical evidence of the countries that we analyze.

Figure 9-24 display the evolution of the above indicators for Thailand, Singapore, Philippines and Malaysia.

In all the countries the real effective exchange rate is appreciating relative to its trend during the period before the onset of the 1997 crisis, showing evidence of overvaluation. (Note that the real effective exchange rate follows the UK quotation - i.e. US Dollars per local currency). For Thailand, the Philippines and Malaysia the REER is 9-10% above the trend in the 12 months preceding the crisis. This is in line with previous literature on currency crises. Domestic-US real interest rate differentials do not indicate any rising expectations of devaluation as the 1997 currency crisis approaches. For all the countries analyzed, in the 12 months before the crisis, IRDIFFs are flat.

Turning now to the financial sector variables, it is possible to note that in Thailand and Malaysia the M2/reserves deviation from trend is positive and significative in size during the period before the onset of the 1997 crisis. This is in line with both a large expansion in M2 and a sharp decline in foreign currency reserves as also pointed out in Kaminsky and Reinhart (1999) for banking and currency crises. In Singapore and Philippines the M2 ratio does not display any considerable deviation from trend.

RDC is above its trend before the 1997 crisis in the Philippines and Malaysia but it is around trend in Thailand and Singapore.

The returns on the stock market index in the 12 months before the 1997 crisis are, on average, negative for all the markets considered. Particularly severe is the drop in the general stock market index in Thailand: the monthly return averages to -7%. Stock market volatility is also very high. The stock

[7] The classification of these variables as external, financial and real sector indicators is based on Kaminsky and Reinhart (1999). They do not include any volatility measures as possible indicators.

[8] The volatility of the general stock market index and the volatility of the banking index are computed using the range - equations (1) and (2).

market represents the real sector therefore, the stock market returns volatility may be interpreted as the uncertainty/risk related to the real sector. In the twelve months before the crisis, stock market volatility in Thailand doubles with respect to the average value over the whole sample. Also for Singapore, the Philippines and Malaysia stock market volatility increases.

Currency crises are sometimes evidence of banking sector distress. For this reason we use the banking sector index. In Thailand the average monthly return of the banking sector is -8% in the 12 months before July 1997. Evidence of banking sector distress is also present in Singapore and Malaysia. In Thailand the volatility of the banking index return more than doubles in the months before the crisis. Similar results hold for Singapore and Malaysia, but not for the Philippines.[9]

5 Empirical Results

For each country we estimated several models. To distinguish among models we use the number of explanatory variables in the time varying Markov probabilities. We started from the Switching Regime GARCH with constant transition probabilities. This is "Model(1,1)" because it includes only a constant for each probability. The model including an explanatory variable in the time varying Markov probability of the "ordinary" state (p) is referred to as "Model(2,1)" because there is a constant plus an explanatory variable in p and only a constant in q.

To select among the different models we use the following criteria:

1. Analysis of the statistical properties of the estimated parameters - i.e. parameters should be well-determined. On this regard, it is important to note that GARCH models, to work properly, require many data points. Unfortunately, the use of monthly frequencies is problematic in this respect. For this reason we consider 90% significance level.

2. The estimated coefficients in the probit representation of the time varying probabilities should have the right sign so that they can have a proper economic interpretation;

3. Forecasting performance. Our goal is to produce "early warnings" for turbulence periods. If the model delivers an increase in the probability of getting into the turbulent regime before the onset of the turbulence, we will consider the model as satisfactory. All the turbulent periods in the data set will be considered. However, we will pay particular attention to the 1997 crisis;

4. Models will be compared in terms of the value of the likelihood function.

[9] We computed summary statistics for all the variables analyzed. However, to conserve space we do not report them.

In what follows we analyze the estimation results and the forecasting performance of the estimated models. For the forecasting performance we report both the graph of the forecast probabilities and tables showing the behavior of these probabilities over turbulent periods. Providing a formal definition of turbulent periods, is beyond the scope of this paper. We identify turbulent periods with severe devaluations. The tables reporting the forecast probabilities aim to provide evidence about the performance of the estimated models.

Our analysis of the empirical results starts from Thailand, the first country involved in the 1997 crisis.

5.1 Thailand

5.1.1 Estimation Results

Table 1 reports the selected models for Thailand. For comparison we also report the simple Model(1,1) where the Markov probabilities are constant. The simple Model (1,1) reveals the average exchange rate devaluation during "ordinary" market conditions is not statistically different from zero and it is associated with a very low volatility (variance) level. In the "turbulence" state the average devaluation jumps to 9% (per month) which is associated with a volatility level which is more than 500 times bigger than the "ordinary" state. The GARCH parameters, α and β, are statistically well-defined and in line with the values reported in the literature on exchange rate volatility. In the third column of Table 1 we report the estimated parameters for Model(2,1). This model is characterized by the fact that REER is added as explanatory variable in p, the probability of being in the ordinary state at $t+1$ given the information available at time t. As for the simple Model(1,1) the two regimes are evident: low devaluation goes with low volatility and high devaluation goes with high volatility. Interestingly, in the conditional variance equation, α is negative, nevertheless the conditional variance is always positive[10] - this is also true for Model (3,1). REER is significant and has the correct sign. Well before the onset of the crises the REER is moving as to anticipate the forthcoming exchange rate devaluation.

Model (3,1) contains REER and M2 ratio as explanatory variables in p while q contains only a constant. Both indicators have the correct sign and are significant. For this model, the volatility in the turbulent regime shifts by a factor of 715. Finally, the two indicators in the last model are REER and the banking index returns. BANKRET has a positive sign. In fact, when the banking sector is performing well (positive returns), the probability of staying in the ordinary state increases. Notice that, for the last model, we were forced to use less observations because the data on the banking index starts in February 1987. Nevertheless, the likelihood of the last model is much higher than the likelihood of the other models implying that the information content of the banking sector is remarkable.

[10] See Nelson and Cao (1992).

5.1.2 Forecasting

For Thailand, in the period analyzed, the major turbulence was due to the 1997 crisis which started in July. Table 2 contains the forecast probabilities of getting into a turbulent period at time $t+1$, given the available information up until time t (equation 17), for the selected models - see Table 1.

The second row shows the average of that probability during ordinary periods. The simple Model(1,1) is able neither to anticipate nor to provide any warning of the 1997 crisis. The situation changes when considering Model(2,1). In June 1997, Model (2,1) gives a 14% probability of getting into a crisis in the next month. In absolute terms, the value of 14% is not high. However, in relative terms - i.e. when compared to the average probability in tranquil periods - 14% represents a noticeable jump in the probability level. Including the M2 ratio improves our forecast - in June 1997 the probability of getting into a crisis in the next period is 34%. However, the best forecast comes from the last model which tells us that the probability of getting into a crisis in the next period is equal to 82%.

Figures 25 and 26 show the forecasting probabilities of the last two models in Table 1. Signals of the 1997 crisis are already apparent in January 1997. We consider this a very good result.

For Thailand the indicators that proved to be important are REER, M2 ratio and bank index returns. It is interesting to note that all the model selected contain the REER as explanatory variable. Moreover, all models have just a constant in q - the probability of moving from turbulence to ordinary regime - while all the action is in p - the probability of moving from an ordinary regime to a turbulent one.

5.2 Singapore

5.2.1 Estimation Results

Table 3 reports the five selected models for Singapore. The simple Model(1,1) reveals that the exchange rate devaluation exhibits two regimes. In the ordinary regime the currency is, on average, appreciating and the volatility is low. In the turbulent regime the currency is depreciating and the volatility shifts by a factor of 6. The parameter β in the GARCH specification is not significantly different from zero. Therefore, all the models in Table 3 follow an ARCH(1) specification. Model(2,1) includes REER in p. All the parameters are well-defined. If REER is appreciating, the probability of being in the ordinary period decreases while the probability of being in the turbulent regime increases. This is the reason why in Model (2,2) the REER coefficient is negative in p and positive in q. For Singapore, both the banking index returns and the banking index returns volatility are important indicators (jointly with REER). They indeed display the expected sign and are significant.

5.2.2 Forecasting

The forecasting probabilities of the selected models for Singapore are reported in Table 4. We identify three periods of turbulence. The more severe turbulent period coincides with the 1997 crisis which started in August. The other two turbulent periods are April 2001 and October 2001. Model(1,1) is not able to predict the 1997 crisis. However, it performs satisfactorily for the other two turbulent periods.

Model(2,1) tells us in June 1997 that the probability to move to turbulent period in July is 35%. This probability is 57% in the next period. Model(2,2) performs even better - in June 1997 the probability of getting into turbulence is 55%. Also the models which include the banking return index and the banking return index volatility perform well in forecasting not only the 1997 crisis but also the 2001 turbulent periods.

Figures 27 and 28 graph the forecasting probabilities of Model(2,2) with REER in both p and q, and Model(3,1) with REER and BANKSTD in p. It is evident how both models are able to anticipate the turbulent periods experimented by the Singaporean Dollar. Model(3,1) with REER and BANKSTD, already shows symptoms of the 1997 crisis in February 1997.

Real effective exchange rate, bank index returns and volatility are the important indicators for Singapore. Model(2,2) indicates that REER is important in modeling both the probability of being in the ordinary regime and staying in that regime and the probability of being in a turbulent regime and staying in that regime. This is the only model, for all the countries analyzed, where it is important to model q - i.e. q is not constant but varies over time. Combining REER and banking indicators in modeling p, produces very interesting results in terms of forecasting.

5.3 The Philippines

5.3.1 Estimation Results

For the Philippines, the parameter β in the conditional variance equation is not statistically important, therefore the models analyzed reduce to an ARCH specification. Table 5 contains the three selected models. In Model(1,1) all the coefficients are significant at standard significance level. The only two indicators that are important for this country are REER and general stock index returns. The real effective exchange rate in Model(2,2) has the expected negative sign but it is not statistically important. REER is also not significant in Model(3,1). However, the forecasting performances of the two models increases considerable when the real effective exchange rate is included. Notice that Model(3,1) has been estimated using less observations (178) than the other two models (205). This is due to the fact that we have less data on the general stock index. Nevertheless, the log-likelihood of Model(3,1) is the highest of all the models considered indicating that the general stock index return is an important indicator in modeling time varying probabilities.

5.3.2 Forecasting

The forecasting performances of the three selected models for the Philippines are reported in Table 6. We distinguish four turbulence periods: November 1990, the 1997 crisis which started in July, July 2000 and April 2001. The simple Model(1,1) produces early warnings for the 1990, 2000 and 2001 turbulences but fails to predict the July 1997 crisis. On the other hand, predictions probabilities for Model(2,1) and Model (3,1) for the 1997 crisis, provide signals for the impending crisis. Once again, it is important to note that, these prediction probabilities are not in absolute terms very high but still significant relative to their value in tranquil periods.

Figures 29 and 30 show the forecasting probabilities for the last two models in table 5. The exchange rate devaluation of the Philippine Pesos is very volatile and shows several periods of appreciation/depreciation. The forecasting probabilities exhibit a similar pattern.

Despite sound economic fundamentals (see Figures 17 - 20) both REER and GENRET are gathering signs of the forthcoming crisis.

5.4 Malaysia

5.4.1 Estimation Results

The last country analyzed is Malaysia. The data sample is shortened to account for the pegging regime that started in November 1998. Table 7 reports the four selected models. As usual high volatility goes with exchange rate devaluation. Model(2,1) shows that REER has the correct sign and is significant. This is in line with the evidence provided for the other countries. The M2 ratio[11] reveals to be an important indicator and the bank index returns standard deviation provides also very interesting results. The log-likelihood of the Model(3,1) with REER and BANKSTD shows the highest value despite the small number of observations.[12]

5.4.2 Forecasting

We identify four periods of turbulence: January 1994, August 1997,[13] May 1998. Model(2,1)-REER, Model(3,1)-REER and M2 ratio and Model(3,1)-REER and BANKSTD already show in June 1997 the *limbo* of the crisis. This is not the case for Model(1,1). The performance in predicting the 1997 crisis is spectacular for two models: Model(3,1)-REER and M2 ratio and Model(3,1)-REER and BANKSTD. All the models analyzed, including Model(1,1), do a very good job in predicting the May 1998 turbulent period. These results are confirmed by figures 31 and 32.

[11] For Malaysia, the first difference of the M2 ratio is used. The deviation from trend for M2 ratio resulted to be very noisy.

[12] Data on the bank stock index are available only from February 1986.

[13] As in Kaminsky and Reinhart (1999) we identify the onset of the Malaysian crisis with August 1997.

5.5 Summary of the Empirical Results

The results for all the countries analyzed show interesting common features. First, modeling p as time varying produces the best results. Only once - Model(2,2) for Singapore - we select a model with both p and q as time varying. Our intuition relies on the fact that $(1-p)$ gives the probability of getting into turbulence from the ordinary regime. In our methodology $(1-p)$ represents the first channel through which changes in the explanatory variables affect the forecast probabilities.

Second, the real effective exchange rate displays an enormous explanatory and predicting power in all the countries. In addition, M2 ratio, BANKRET, BANKSTD, GENRET contain valuable information which improves the performance of the models.

Third, all the selected models for each country are very parsimonious. This is a very nice feature.

Finally, we would like to stress that the selected models exhibit excellent forecasting performances.

6 Conclusions

In this paper we propose a new methodology for early warning systems. Following Mariano et al (2002) we use a Markov switching regime model. However, we recognize that exchange rate devaluation is characterized by heteroskedasticity. Indeed, financial asset returns variances are not constant over time. Our emphasis is on the volatility process. The approach consists of jointly modeling the conditional mean and the conditional variance of exchange rate devaluation. This implies not only that volatility switches between two regimes, but also that within each regime we allow volatility to follow a GARCH process. The estimated parameters confirm that our intuition is right. More importantly, the approach developed in the paper is able to produce very good forecasting performance, at least for the countries analyzed and for the period considered. It is interesting to note how the stock market and the banking sector indexes play an important role in forecasting turbulences.

We should also underline that our approach exhibits several limitations:

1. It is not applicable to countries that are pegging their exchange rate. In fact, in this case, there will not be any variation of the exchange rate and any volatility of the exchange rate.

2. We are able to distinguish turbulence and ordinary regimes. As already discussed, turbulence does not always coincides with currency crises.

3. The probabilities analyzed are one-step-ahead forecasts. This short horizon may not be optimal for central banks who want to take measures well in advance in order to (at least) try to avoid the crisis. On the other hand, it is good for last minute interventions and it might represent the main horizon for financial market participants.

4. If you have a longer horizon this approach might not be your best bet.

5. We only consider four countries and only one major currency crisis. It remains to validate how this methodology will work with other countries and other currency crises.

In on going research we are developing a model which is able to account for contagion effects among countries. The use of data at higher frequencies (weekly) may provide useful information for out-of-sample forecasts at longer horizons.

7 Appendix

7.1 Data

We created a data set for Malaysia, Philippines, Singapore and Thailand composed by five variables: exchange rate return/devaluation, M2 ratio, real domestic credit/GDP, real effective exchange rate devaluation, domestic-US real interest rate differential on deposits, stock index returns and volatility, banking sector return and volatility.

All data, with exception of the real effective exchange rate and stock index and banking sector index, are retrieved from the International Financial Statistics (IFS) database. The real effective exchange rate is from JP Morgan, while stock data are from Bloomberg.

All the variables are constructed accordingly with the literatures on currency crises, see Kaminsky and Reinhart (1999).

M2 ratio is given by the sum of M1 (IFS line 24) and quasi money (IFS line 25) divided by Reserves (IFS line 1l.d) converted into national currency.

Real domestic credit is domestic credit (IFS line 52) divided by CPI (IFS line 64) to obtain domestic credit in real terms and then divided by GDP (IFS line 99b.p.). Monthly GDP is obtain by interpolating quarterly data.

Interest rate differentials are computed as difference between domestic and US real interest rates on deposits. Real rates are deposit rates (IFS line 60) deflated using consumer prices (IFS line 64).

Real effective exchange rate is a measure of competitiveness and rises if for example domestic inflation exceeds that abroad and the nominal exchange rate fails to depreciate to compensate.

General stock index returns are first difference of the natural logarithm of the stock index.

General index returns volatility is computed using equations (1) and (2).

Banking index returns are first difference of the natural logarithm of the banking index.

Banking index returns volatility is computed using equations (1) and (2).

References

[1] Baillie, R.T. and Bollerslev, T. (1989), "The Message in Daily Exchange Rates: A Conditional Variance Tale", *Journal of Business and Economic Statistics*, 7, 297-305.

[2] Bera, A. K., and M. L., Higgins (1993), "ARCH Models: Properties, Estimation and Testing", *Journal of Economic Surveyes*, 7, 305 - 362.

[3] Berg, A. and Pattillo, C. (1999a),"Are Currency Crises Predictable? A Test", *IMF Staff Papers, 46-2, 107-138.*

[4] Berg, A. and Pattillo, C. (1999b),"Predicting Currency Crises: The Indicators Approach and An Alternative", *Journal of International Money and Finance, 18-4, 561-586.*

[5] Bollerslev, T., Engle, R.F. and Nelson, D.B. (1994), "ARCH Models", in *Handbook of Econometrics, Volume IV*, 2959-3038, eds. R.F. Engle and D. McFadden, Amsterdam: North-Holland.

[6] Brunetti, C. and Lildholdt, P. (2002a), "Return-based and range-based (co)variance estimation - with an application to foreign exchange markets", Mimeo, Univeristy of Pennsylvania.

[7] Brunetti, C. and Lildholdt, P. (2002b), "Time Series Modeling of Daily Log-price Ranges for the SF/USD and USD/GBP", *PIER Working Paper* 02-017.

[8] Cai, J. (1994), "A Markov model of switching-regime ARCH", *Journal of Business & Economic Statistics*, 12, 309-316.

[9] Chou, R. (2001), "Forecasting financial volatilities with extreme values: The conditional autoregressive range (CARR) model", mimeo.

[10] Corsetti, G., Pesenti, P. and Roubini, N. (1998), "Paper Tigers? A Model of the Asian Crisis", *NBER Working Paper,* Cambridge, Massachusetts: National Bureau of Economic Research, No.6783.

[11] Ding, Z., Granger, C. and Engle, R. (1993), "A long memory property of stock returns and a new model", *Journal of Empirical Financ,e* 1, 83106.

[12] Dueker, M.J. (1997), "The Econometrics of Ultra-High Frequency Data", *Journal of Business and Economic Statistics,* 15-1, 26-34.

[13] Edison, H.J. (2000), "Do Indicators of Financial Crises Work? An Evaluation of An Early Warning System", *International Finance Discussion Papers*, Board of Governors of the Federal Reserve System, 675.

[14] Eichengreen, B., Rose, A. and Wyplosz, C. (1994), "Speculative Attacks on Pegged Exchange Rates: An Empirical Exploration With Special Reference to the European Monetary System", *NBER Working Paper,* Cambridge, Massachusetts: National Bureau of Economic Research, No.4898.

[15] Eichengreen, B., Rose, A. and Wyplosz, C. (1995), "Exchange Market Mayhem: The Antecedents and After-math of Speculative Attacks", *Economic Policy,* October, 249-312.

[16] Eichengreen, B., Rose, A. and Wyplosz, C. (1996), "Contagious Currency Crises", *NBER Working Paper,* Cambridge, Massachusetts: National Bureau of Economic Research, No.5681.

[17] Fama, E.F. (1965), "The Behaviour of Stock Market Prices", *Journal of Business*, 38, 34 - 105.

[18] Feller, W. (1951), "Two Singular Diffusion Problems", *Annals of Mathematics* 54, 173-182.

[19] Frankel, J. and Rose, A. (1996), "Currency Crashes in Emerging Markets: An Empirical Treatment", *International Finance Discussion Papers,* Board of Governors of the Federal Reserve System, 534.

[20] Goldstein, G., Kaminsky, L. and Reinhart, C.M. (2000), "Assessing Financial Vulnerability: An Early Warning System for Emerging Markets", Washington: Institute for International Economics.

[21] Grey, S.F. (1996), "Modeling the conditional distribution of interest rates as a regime-switching process", *Journal of Financial Economics*, 42, 27-62.

[22] Hamilton, J. (1994), *Time Series Analysis,* Princeton University Press, Princeton.

[23] Hamilton, J.D. Susmel, R. (1994), "Autoregressive Conditional Heteroskedasticity and Changes in Regime", *Journal of Econometrics*, 64(1-2), 307-33.

[24] IMF (1998),"World Economic Outlook", Washington D.C.: International Monetary Fund, May.

[25] Kaminsky, G. (1998a), "Currency and Banking Crises: A Composite Leading Indicator", *IMF Seminar Series*, 6.

[26] Kaminsky, G. (1998b), "Financial Crises in Asia and Latin America: Then and Now", *American Economic Review, Papers and Proceedings*, 88, 44-48.

[27] Kaminsky, G., Lizondo, S. and Reinhart, C.M. (1998), 'Leading Indicators of Currency Crises', *IMF Staff Papers*, March.

[28] Kaminsky, G. and Reinhart, C.M. (1999), "The Twin Crises: The Causes of Banking and Balance-of-Payment Problems", *American Economic Review,* 89, 473-500.

[29] Kumar, M.S., Moorthy, U. and Peraudin, W. (2002), "Predicting Emerging Market Currency Crashes", *IMF Working Paper*, Research Department, International Monetary Fund.

[30] Mandelbrot, B. (1963a), "The Variation of Certain Speculative Prices", *Journal of Business*, 36, 394 - 419.

[31] Mandelbrot, B. (1963b), "New Methods in Statistical Economics", *Journal of Political Economy*, 71, 421 - 440.

[32] Mariano, R.S., Abiad, A.G., Gultekin, B., Shabbir, T. and Tan, A. (2002), "Markov Chains In Predictive Models of Currency Crises - With Applications to Southeast Asia", *PIER Working Paper* 02-013.

[33] Nelson, D.B. and Cao,C.Q. (1992), "Inequality Constraints in the Univariate GARCH Model", *Journal of Business and Economic Statistics*, 10, 229 - 235.

[34] Parkinson, M. (1980), "The Extreme Value Method for Estimating the Variance of the Rate of Return", *Journal of Business*, 53, 61-65.

[35] Radelet, S. and Sachs, J. (1998), "The East-Asian Financial Crisis: Diagnosis, Remedies, Prospects", *Brookings Papers on Economic Activity*, 1, p.1-90.

[36] Sachs, J., Tornell, A. and Velasco, A. (1996), "Financial Crises in Emerging Markets: The Lessons From 1995", *Brookings Papers on Economic Activity*, 1, 147-215.

[37] Tan, A.H.H. (1999), "The Asian Economic Crisis: The Way Ahead For Singapore", Chapter 2 in *Singapore Inc., Public Policy Options In The Third Millennium*, edited by Linda Low & Douglas Johnston, Asia Pacific Press, Singapore, 2001, pp.17-34.

[38] Tornell, A. (1998), "Common Fundamentals in the Tequila and Asian Crises", Mimeo, Harvard University.

Thailand	Model(1,1)	Model(2,1) REER	Model(3,1) REER M2ratio	Model(3,1) REER BANKRET
μ_0	-0.002 (0.036)	-0.005 (0.042)	-0.119 (0.039)	0.010 (0.042)
μ_1	9.380 (2.291)	6.983 (2.424)	6.773 (2.425)	4.227 (2.90)
ω	0.023 (0.007)	0.04 (0.006)	0.034 (0.005)	0.049 (0.014)
g	597.844 (414.207)	525.816 (103.844)	715.100 (164.832)	488.721 (323.025)
α	0.093 (0.045)	-0.047 (0.027)	-0.0509 (0.021)	0.168 (0.092)
β	0.804 (0.046)	0.849 (0.027)	0.873 (0.018)	0.6182 (0.072)
p_{const}	2.364 (0.268)	2.378 (0.314)	2.852 (0.538)	6.839 (3.856)
p_{REER}		-0.117 (0.066)	-0.168 (0.084)	-0.332 (0.216)
$p_{M2ratio}$			-0.725 (0.695)	
$p_{BANKRET}$				0.189 (0.121)
q_{const}	1.809 (0.755)	0.929 (0.499)	1.362 (0.539)	0.226 (0.870)
θ	0.237 (0.064)	0.298 (0.062)	0.272 (0.065)	0.282 (0.074)
log L	-257.6	-257.1	-254.2	-223.2
nobs	205	205	205	178

Table 1: Thailand: Estimation Results

Thailand	ERDEV	Model(1,1)	Model(2,1) RERR	Model(3,1) RERR M2ratio	Model(3,1) REER BANKRET
ordinary period $_{average}$	0.078	0.02	0.03	0.03	0.02
Jun-1997	-0.35	0.01	0.14	0.37	0.82
Jul-1997	16.22	0.96	0.82	0.91	0.53
Aug-1997	6.88	0.92	0.54	0.77	0.62
Sep-1997	11.12	0.94	0.77	0.88	0.40
Oct-1997	2.99	0.83	0.50	0.72	0.17
Nov-1997	4.96	0.77	0.37	0.62	0.08
Dec-1997	14.19	0.93	0.68	0.80	0.26
Jan-1998	17.24	0.95	0.75	0.85	0.27

Table 2: Thailand: Forecast

Singapore	Model(1,1)	Model(2,1) REER	Model(2,2) REER REER	Model(3,1) REER BANKRET	Model(3,1) REER BANKSTD
μ_0	-0.141 (0.078)	-0.156 (0.081)	-0.192 (0.078)	-0.148 (0.077)	-0.135 (0.772)
μ_1	0.348 (0.377)	0.375 (0.370)	0.450 (0.301)	0.229 (0.291)	0.208 (0.315)
ω	0.725 (0.123)	0.698 (0.120)	0.677 (0.110)	0.591 (0.105)	0.626 (0.113)
g	6.37 (2.375)	5.723 (2.102)	4.710 (1.388)	5.741 (1.679)	5.906 (1.866)
α	0.153 (0.147)	0.191 (0.146)	0.239 (0.126)	0.222 (0.129)	0.190 (0.133)
$\underset{const}{p}$	2.067 (0.336)	2.615 (0.775)	2.950 (0.895)	4.683 (3.789)	3.656 (1.794)
$\underset{REER}{p}$		-0.523 (0.365)	-0.590 (0.406)	-0.932 (-0.943)	-0.662 (0.508)
$\underset{BANKRET}{p}$				0.369 (0.295)	
$\underset{BANKSTD}{p}$					-0.182 (0.110)
$\underset{const}{q}$	1.294 (0.453)	1.275 (0.431)	2.182 (1.507)	1.004 (0.335)	1.108 (0.379)
$\underset{REER}{q}$			0.481 (0.487)		
θ	0.267 (0.074)	0.256 (0.074)	0.240 (0.073)	0.282 (0.073)	0.276 (0.073)
log L	-319.6	-316.2	-316.0	-314.6	-316.1
nobs	205	205	205	205	205

Table 3: Singapore: Estimation Results

Singapore	ERDEV	Model(1,1)	Model(2,1) REER	Model(2,2) REER REER	Model(3,1) REER BANKRET	Model(3,1) REER BANKSTD
ordinary period *average*	0.15	0.04	0.14	0.15	0.09	0.13
Jun-1997	-0.70	0.03	0.35	0.55	0.37	0.30
Jul-1997	1.39	0.08	0.57	0.57	0.56	0.50
Aug-1997	3.39	0.55	0.85	0.85	0.79	0.82
Sep-1997	1.32	0.42	0.73	0.73	0.62	0.66
Oct-1997	2.60	0.80	0.87	0.87	0.84	0.84
Nov-1997	1.27	0.66	0.75	0.75	0.67	0.68
Dec-1997	4.34	0.90	0.90	0.90	0.84	0.87
Jan-1998	5.88	0.89	0.87	0.87	0.85	0.85
Mar-2001	1.71	0.11	0.24	0.23	0.98	0.42
Apr-2001	2.23	0.17	0.33	0.35	0.83	0.49
Sep-2001	-0.57	0.61	0.68	0.88	0.87	0.73
Oct-2001	3.37	0.90	0.90	0.95	0.84	0.87

Table 4: Singapore: Forecast

The Philippines	Model(1,1)	Model(2,1) REER	Model(3,1) REER GENRET
μ_0	0.089 (0.038)	0.088 (0.038)	0.077 (0.041)
μ_1	0.634 (0.304)	0.637 (0.300)	0.508 (0.254)
ω	0.119 (0.026)	0.119 (0.026)	0.098 (0.026)
g	46.545 (12.717)	45.962 (12.529)	41.347 (12.713)
α	0.429 (0.168)	0.421 (0.167)	0.517 (0.176)
p_{const}	1.453 (0.205)	1.511 (0.238)	1.558 (0.328)
p_{REER}		-0.020 (0.034)	-0.027 (0.051)
p_{GENRET}			0.002 (0.038)
q_{const}	1.240 (0.253)	1.271 (0.253)	1.675 (0.389)
θ	0.404 (0.058)	0.402 (0.0597)	0.458 (0.068)
log L	-321.7	-321.6	-282.9
nobs	205	205	179

Table 5: The Philippines: Estimation Results

The Philippines	ERDEV	Model(1,1)	Model(2,1) REER	Model(3,1) REER GENRET
ordinary period *average*	0.06	0.08	0.07	0.08
Oct-1990	1.57	0.61	0.61	0.76
Nov-1990	8.38	0.89	0.90	0.95
Jun-1997	0.04	0.08	0.11	0.12
Jul-1997	4.77	0.89	0.90	0.95
Aug-1997	5.83	0.82	0.83	0.92
Sep-1997	9.92	0.86	0.87	0.93
Oct-1997	6.19	0.78	0.79	0.89
Nov-1997	0.17	0.74	0.74	0.92
Dec-1997	7.40	0.89	0.90	0.95
Jan-1998	13.78	0.83	0.84	0.92
Jun-2000	1.99	0.66	0.66	0.85
Jul-2000	3.89	0.88	0.89	0.95
Aug-2000	1.26	0.76	0.77	0.89
Sep-2000	1.85	0.87	0.88	0.92
Oct-2000	5.05	0.89	0.90	0.95
Mar-2001	0.37	0.80	0.81	0.91
Apr-2001	3.49	0.82	0.83	0.90
May-2001	0.69	0.70	0.71	0.84
Jun-2001	1.86	0.81	0.82	0.87
Jul-2001	3.30	0.86	0.87	0.92

Table 6: The Philippines: Forecast

Malaysia	Model(1,1)	Model(2,1) REER	Model(3,1) REER M2ratio	Model(3,1) REER BANKSTD
μ_0	-0.020 (0.074)	0.015 (0.072)	-0.040 (0.076)	-0.025 (0.076)
μ_1	1.101 (0.992)	1.370 (1.071)	1.232 (0.962)	2.133 (1.542)
ω	0.424 (0.160)	0.531 (0.147)	0.528 (0.147)	0.445 (0.116)
g	37.66 (15.48)	37.716 (16.390)	34.084 (14.618)	65.055 (23.434)
α	0.238 (0.137)	0.201 (0.140)	0.195 (0.122)	0.000 (0.000)
β	0.155 (0.142)	0.157 (0.175)	0.129 (0.166)	0.376 (0.129)
p_{const}	1.885 (0.326)	2.498 (0.519)	3.442 (1.086)	4.166 (1.571)
p_{REER}		-0.101 (0.057)	-0.124 (0.095)	-0.189 (0.099)
$p_{M2ratio}$			-21.184 (10.326)	
$p_{BANKSTD}$				-0.117 (0.077)
q_{const}	0.925 (0.448)	1.209 (0.388)	1.101 (0.345)	1.462 (1.180)
θ	0.261 (0.088)	0.259 (0.087)	0.271 (0.085)	0.269 (0.269)
log L	-272.4	-271.0	-270.6	-239.5
nobs	167	167	167	152

Table 7: Malaysia: Estimation Results

Malaysia	ERDEV	Model(1,1)	Model(2,1) REER	Model(3,1) REER M2ratio	Model(3,1) REER BANKSTD
ordinary period average	0.05	0.05	0.01	0.01	0.005
Dec-1993	0.78	0.04	0.02	0.01	0.33
Jan-1994	5.30	0.82	0.88	0.86	0.93
Jun-1997	0.40	0.04	0.20	0.18	0.25
Jul-1997	1.96	0.15	0.45	0.94	0.49
Aug-1997	6.41	0.82	0.88	0.86	0.92
Sep-1997	9.40	0.78	0.86	0.84	0.91
Oct-1997	8.89	0.70	0.81	0.78	0.89
Nov-1997	2.99	0.53	0.66	0.61	0.74
Dec-1997	10.62	0.82	0.89	0.86	0.91
Jan-1998	15.68	0.77	0.86	0.84	0.92
Apr-1998	-0.53	0.37	0.50	0.45	0.63
May-1998	2.38	0.34	0.44	0.46	0.49
Jun-1998	4.35	0.57	0.69	0.71	0.67

Table 8: Malaysia: Forecast

Fig.1: Thailand - Volatility

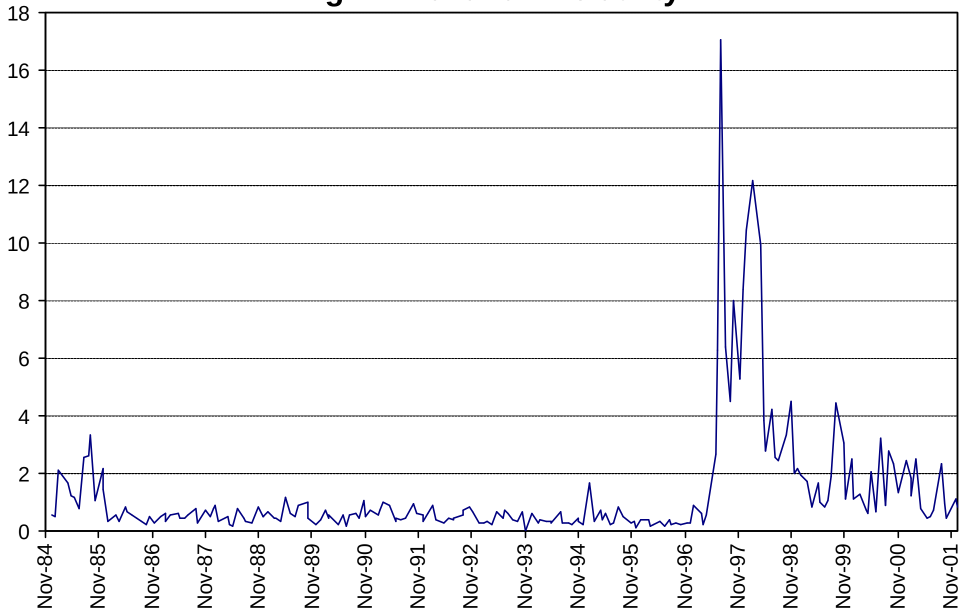


Fig.2: Singapore - Volatility

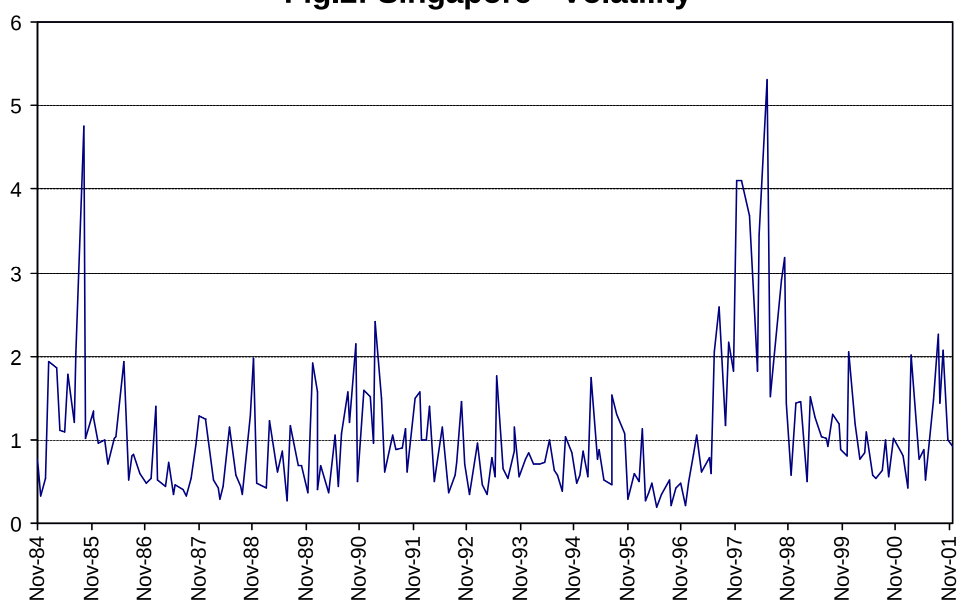


Fig.3: Philippines - Volatility

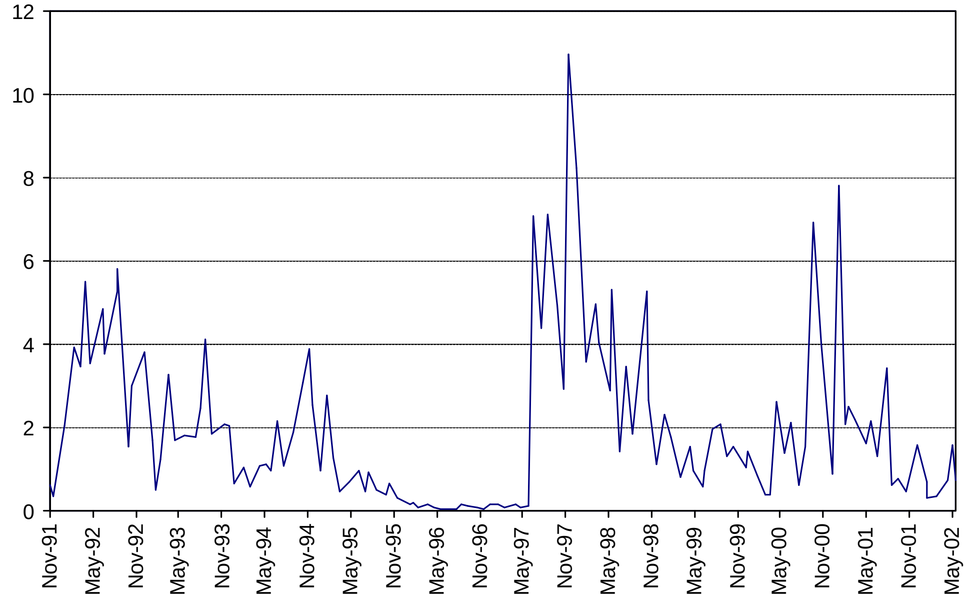


Fig.4: Malaysia - Volatility

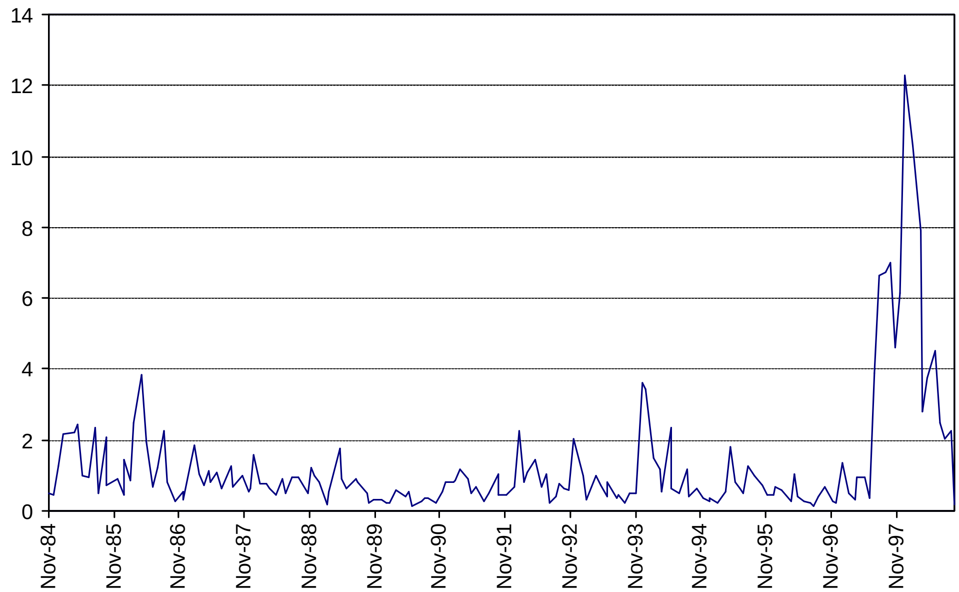


Fig.5: Thailand

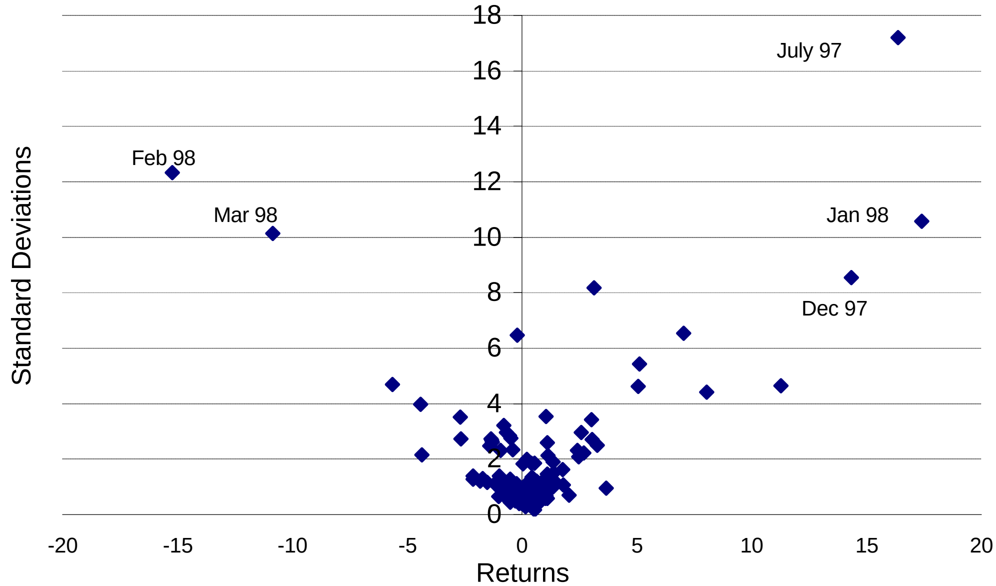


Fig.6: Singapore

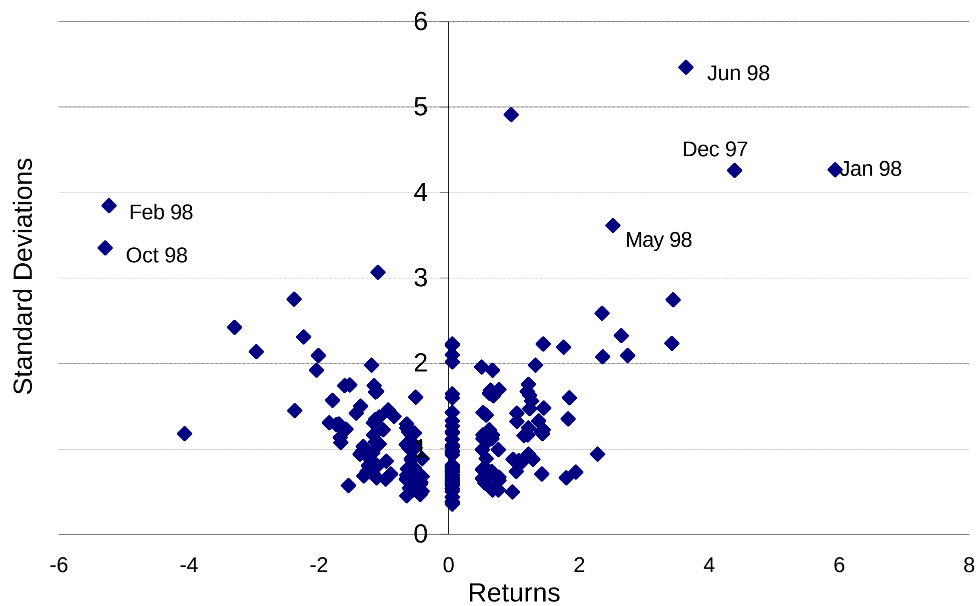


Fig.7: Philippines

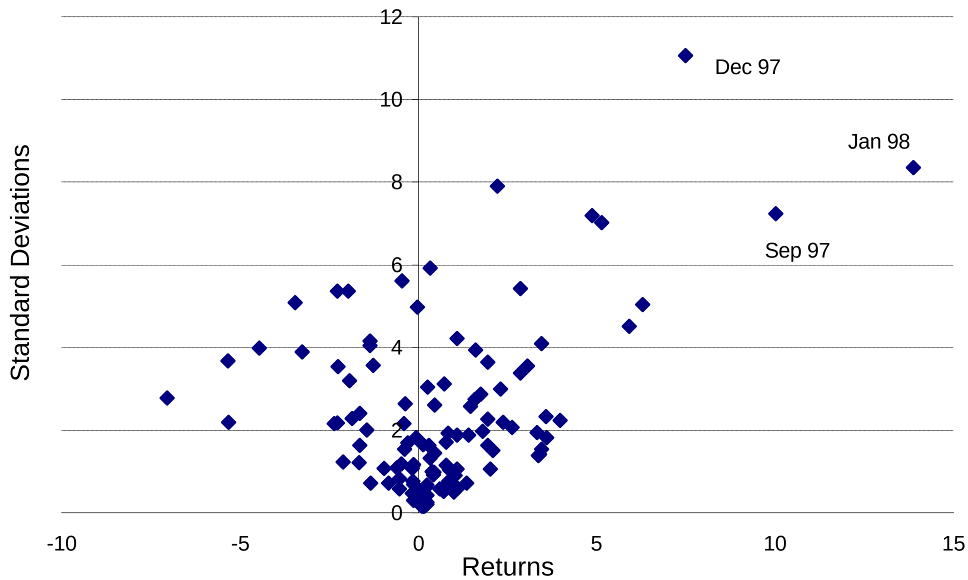
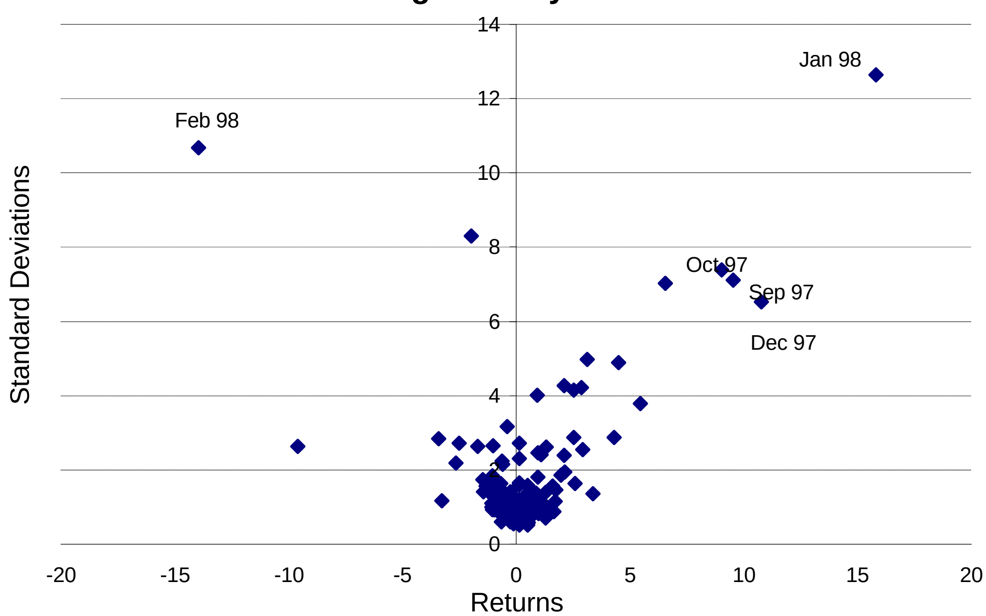


Fig.8: Malaysia



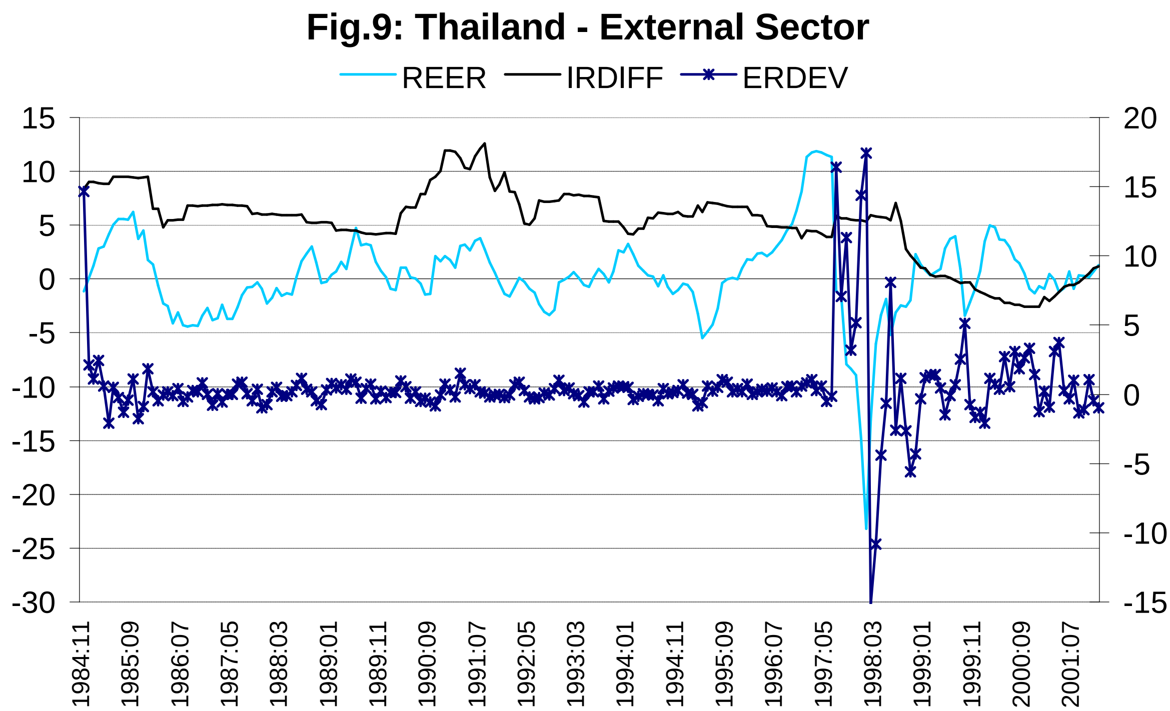


Fig.9: Thailand - External Sector
REER
IRDIFF
ERDEV
15
10
5
0
-5
-10
-15
-20
-25
-30
20
15
10
5
0
-5
-10
-15
1984:11
1985:09
1986:07
1987:05
1988:03
1989:01
1989:11
1990:09
1991:07
1992:05
1993:03
1994:01
1994:11
1995:09
1996:07
1997:05
1998:03
1999:01
1999:11
2000:09
2001:07

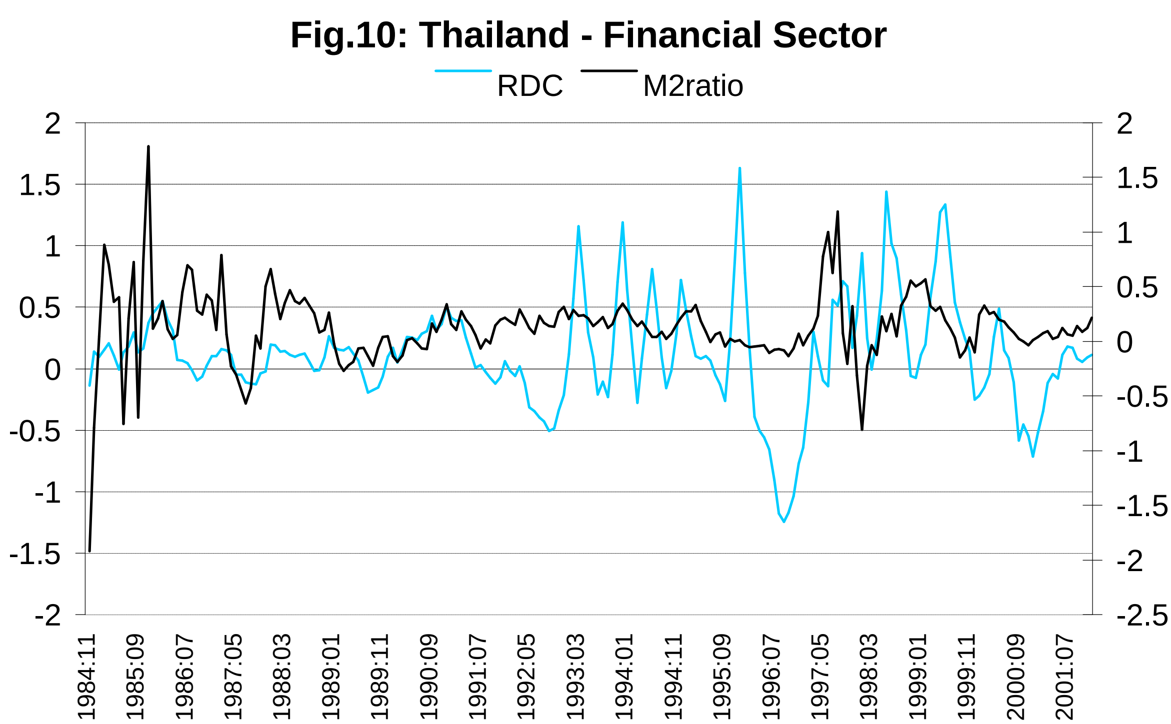


Fig.10: Thailand - Financial Sector
RDC
M2ratio
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
-2.5
1984:11
1985:09
1986:07
1987:05
1988:03
1989:01
1989:11
1990:09
1991:07
1992:05
1993:03
1994:01
1994:11
1995:09
1996:07
1997:05
1998:03
1999:01
1999:11
2000:09
2001:07

Fig.11: Thailand - Real Sector

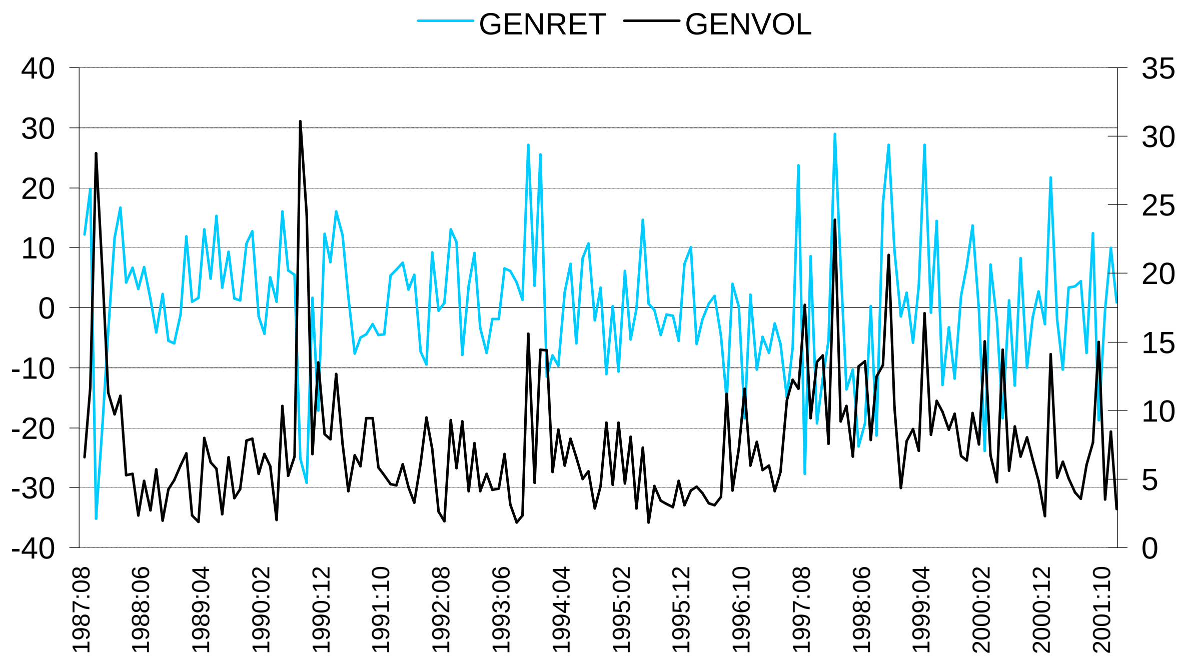


Fig.12: Thailand - Banking Sector

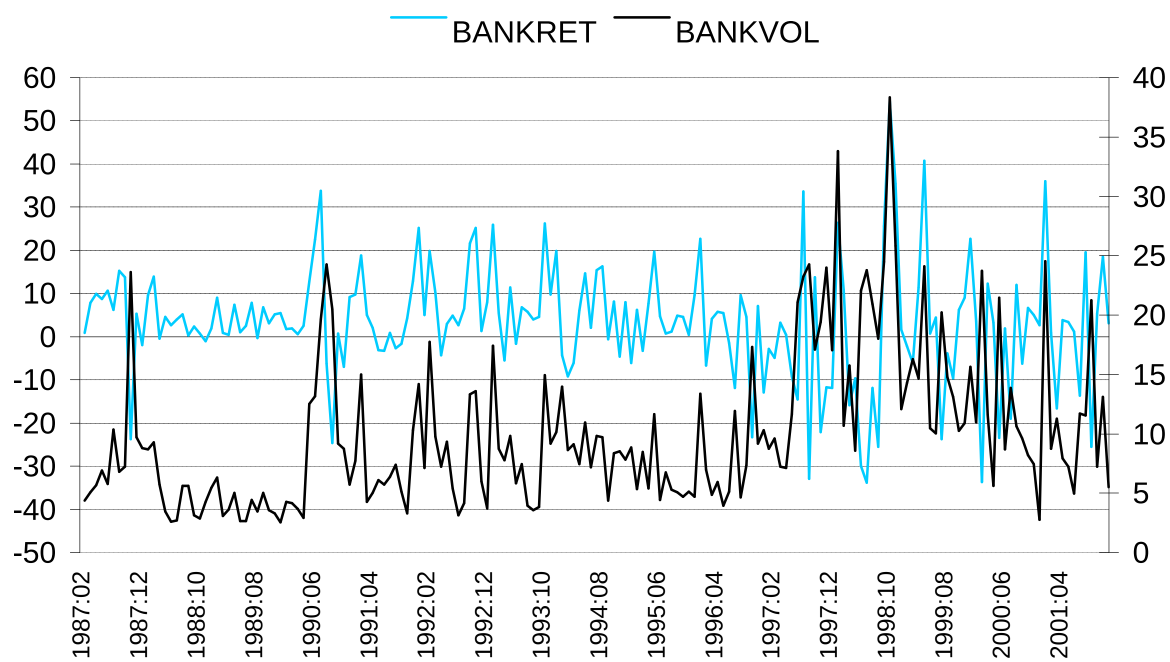


Fig.13: Singapore - External Sector

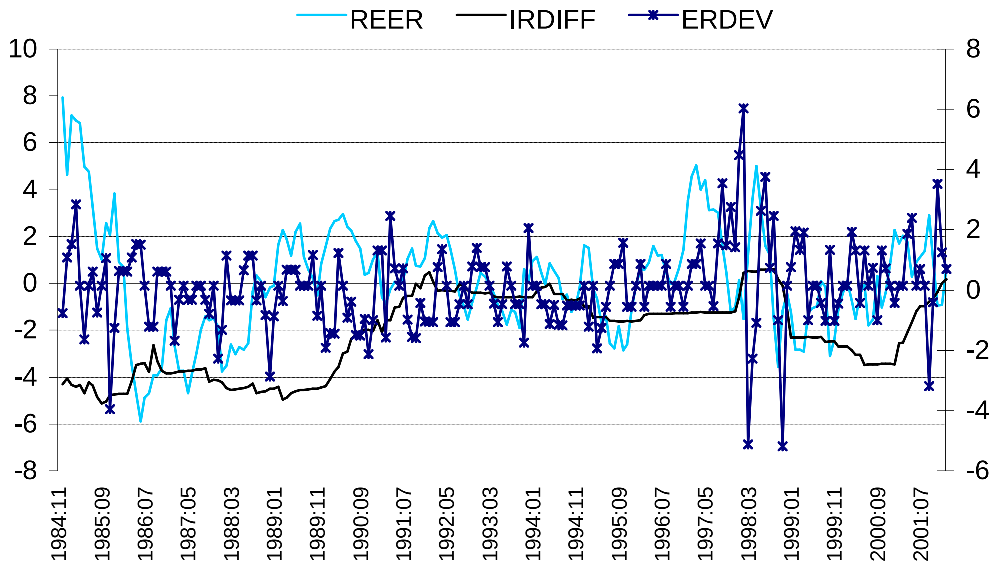


Fig.14: Singapore - Financial Sector

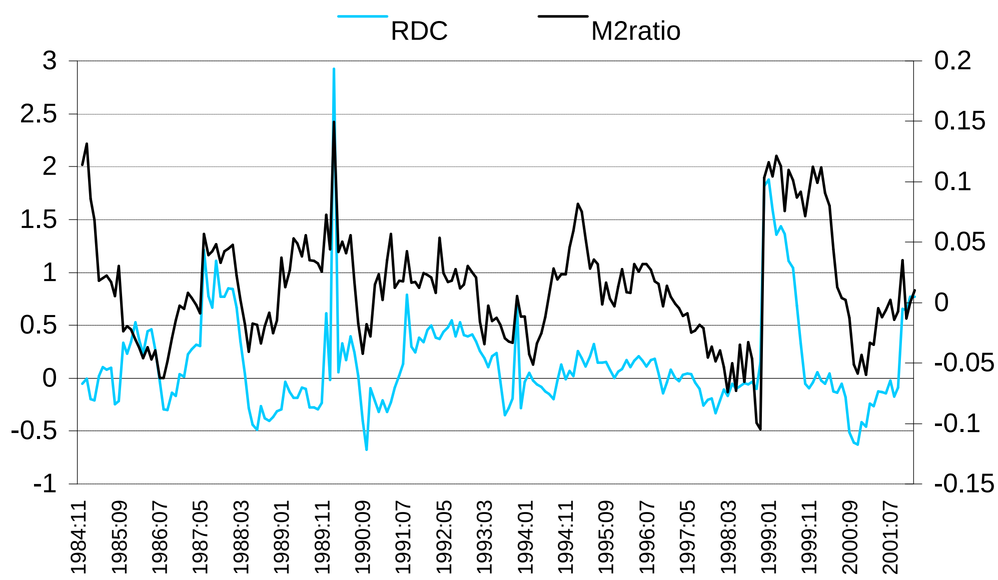


Fig.15: Singapore - Real Sector

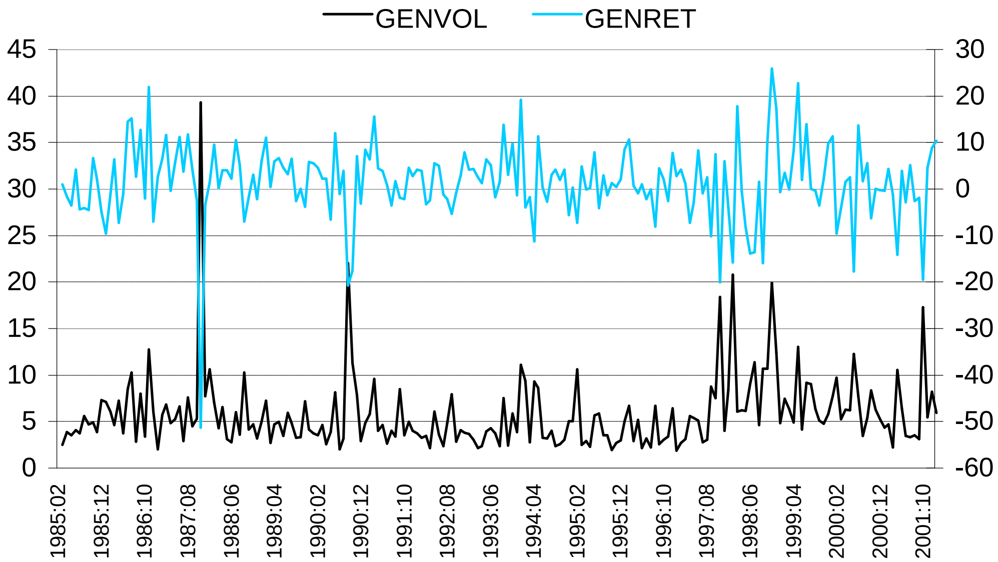


Fig.16: Singapore - Banking Sector

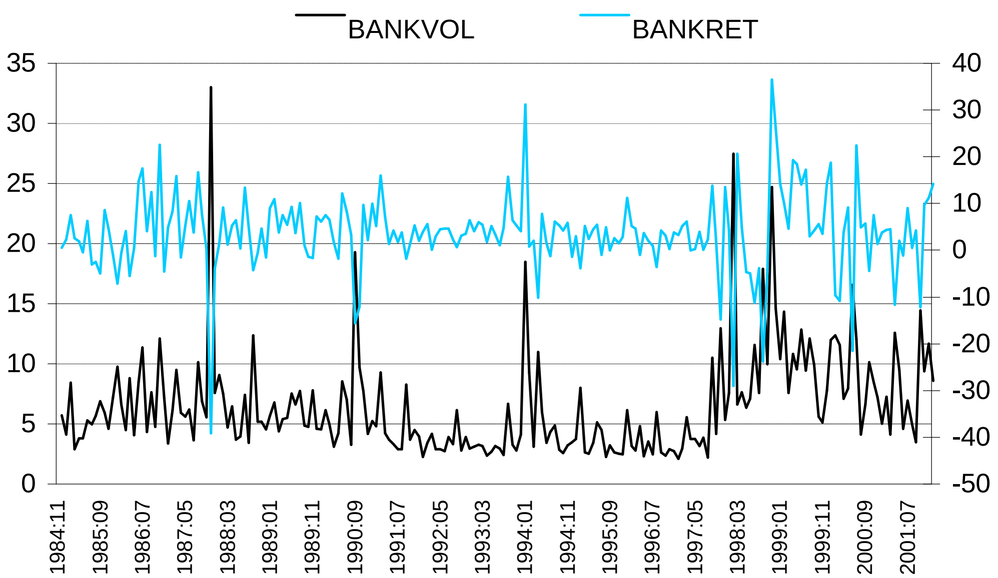


Fig.17: Philippines - External Sector

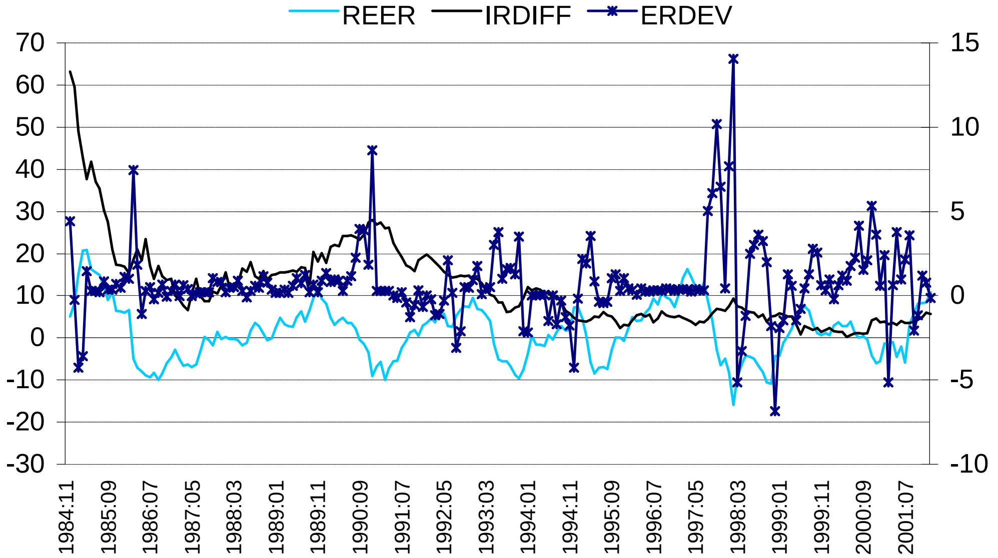


Fig.18: Philippines - Financial Sector

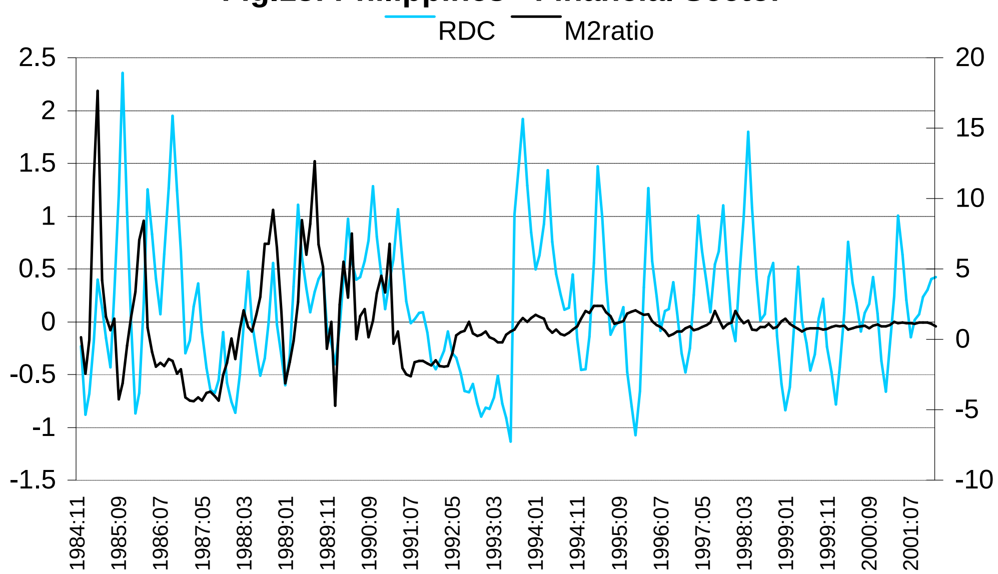


Fig.19: Philippines - Real Sector

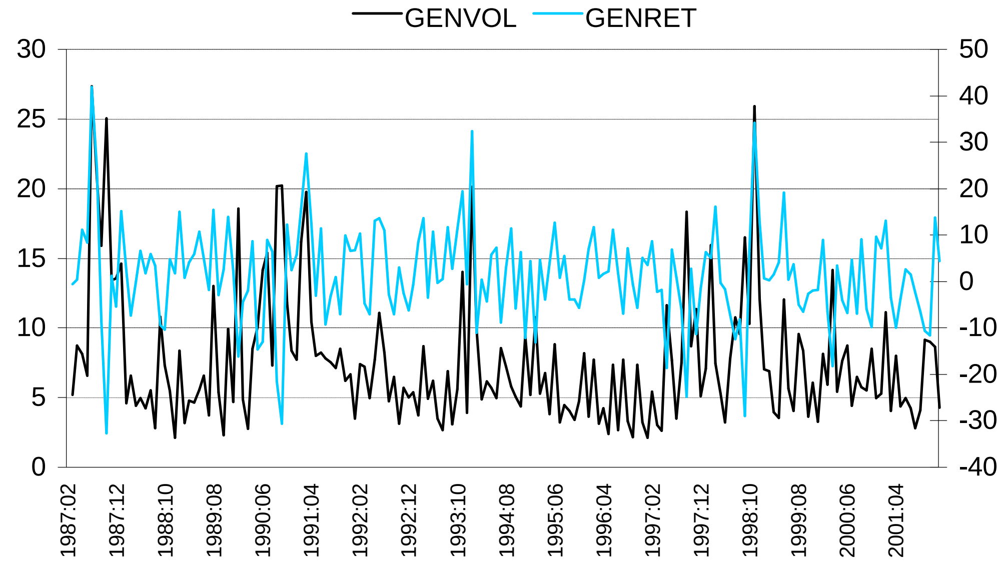


Fig.20: Philippines - Banking Sector

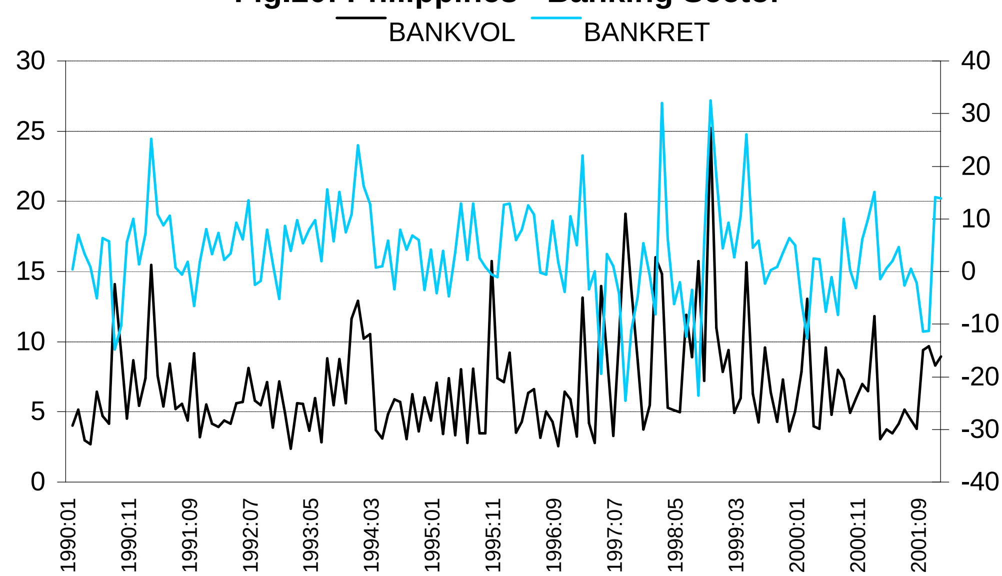


Fig.21: Malaysia - External Sector

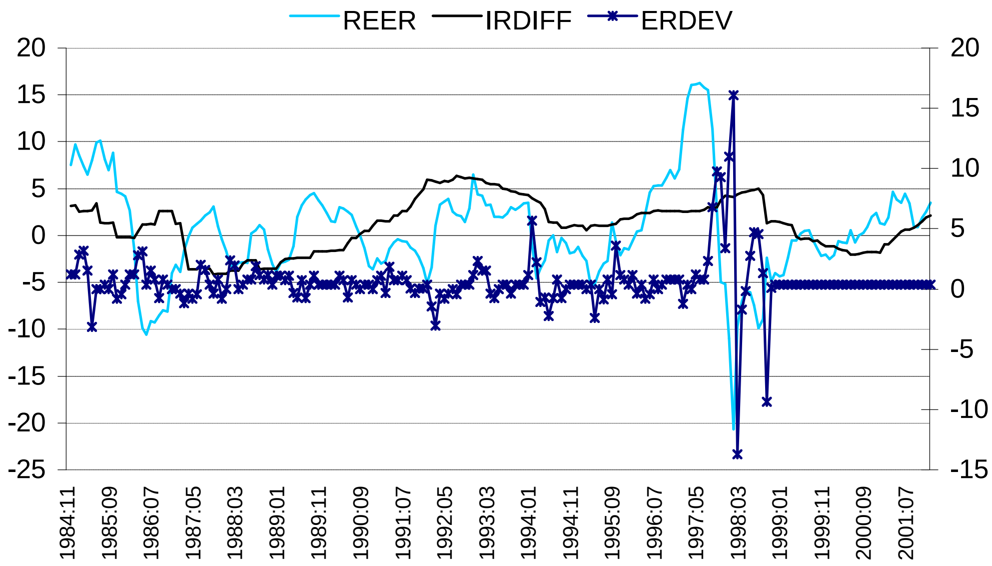


Fig.22: Malaysia - Financial Sector

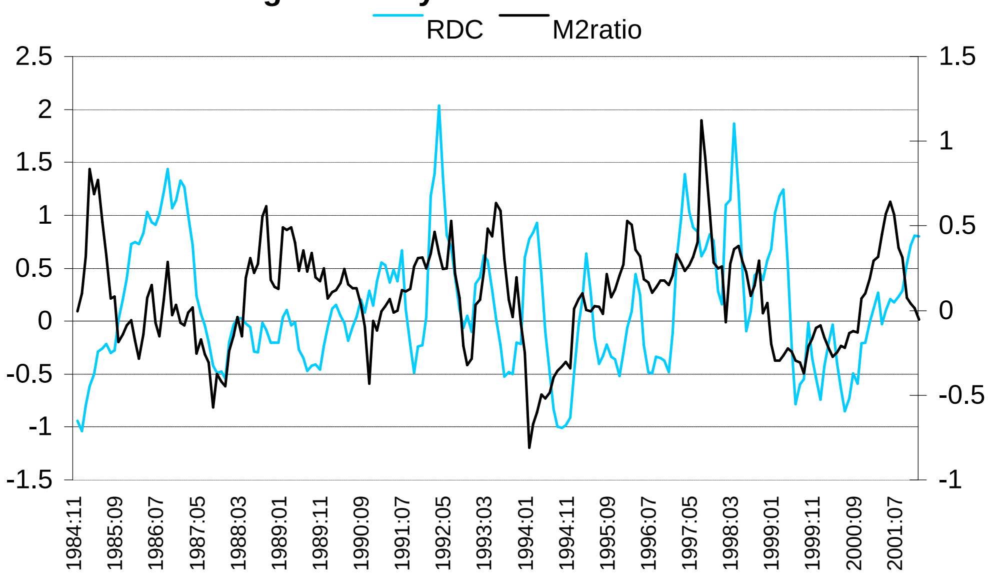


Fig.23: Malaysia - Real Sector

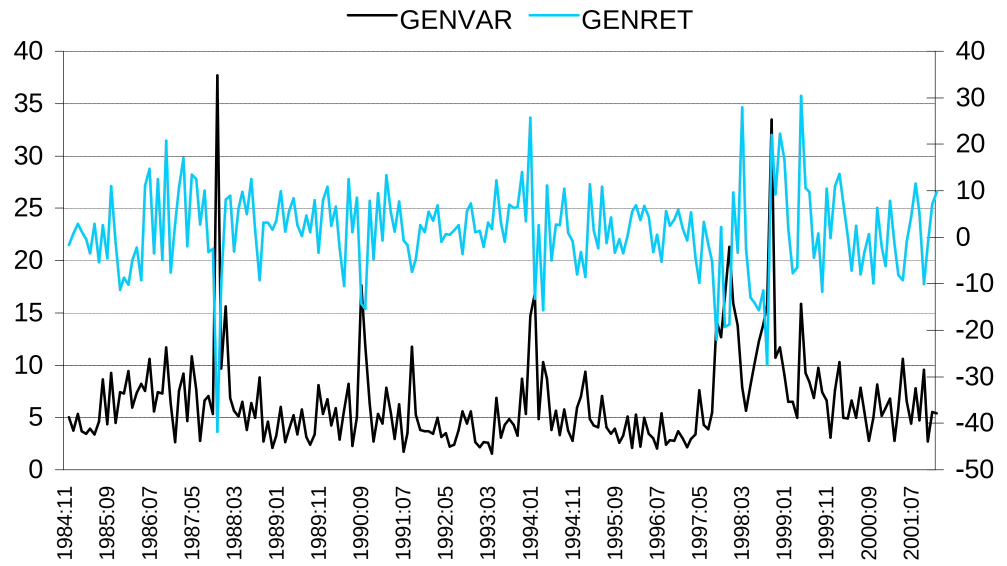


Fig.24: Malaysia - Banking Sector

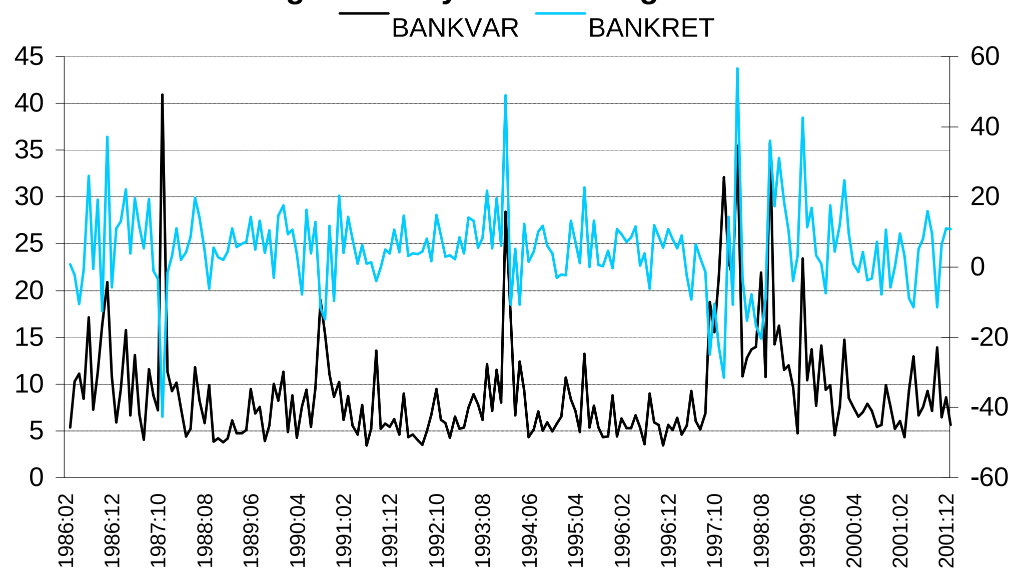


Fig.25: Thailand - Model31 (REER,M2ratio)

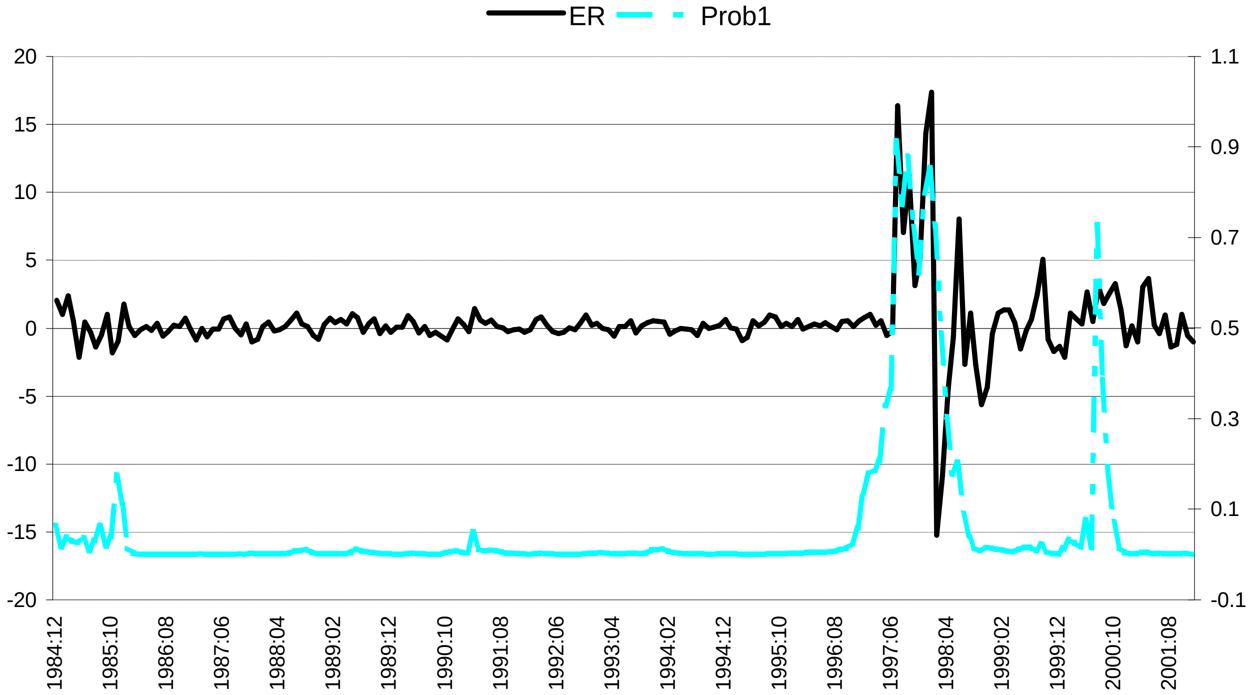


Fig.26: Thailand - Model31 (REER, BANKRET)

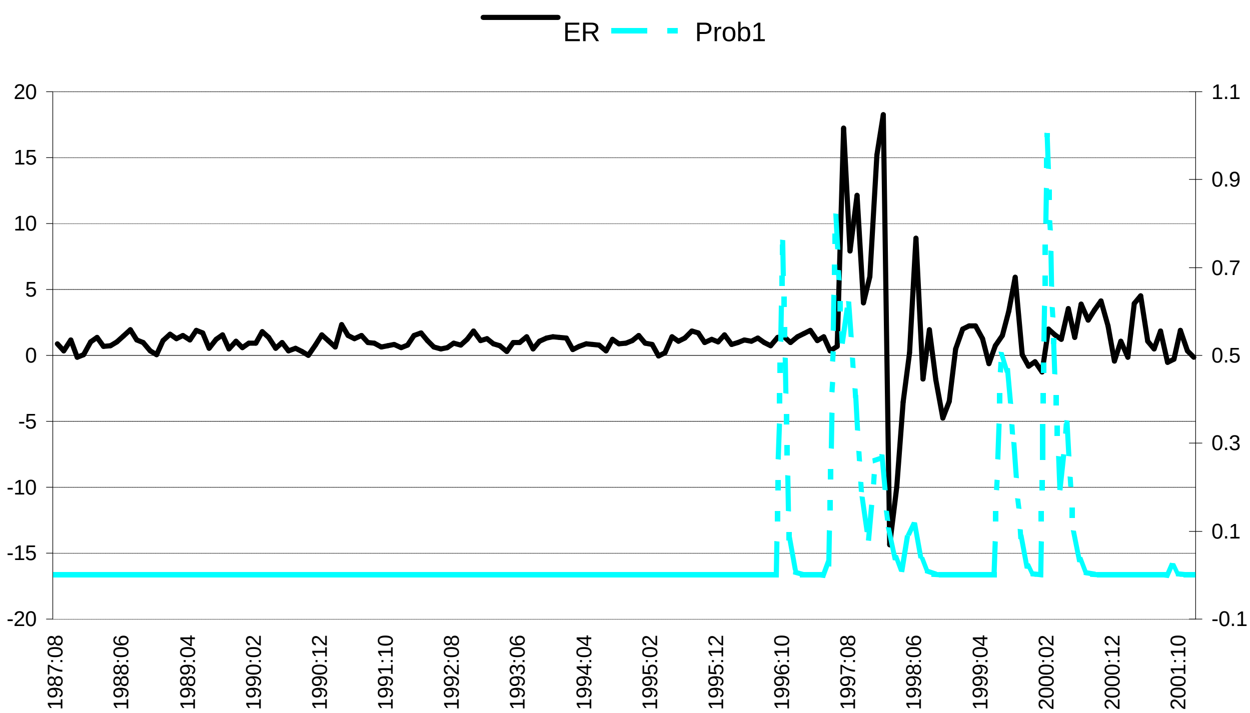


Fig.27 : Singapore - Model22 (REER)

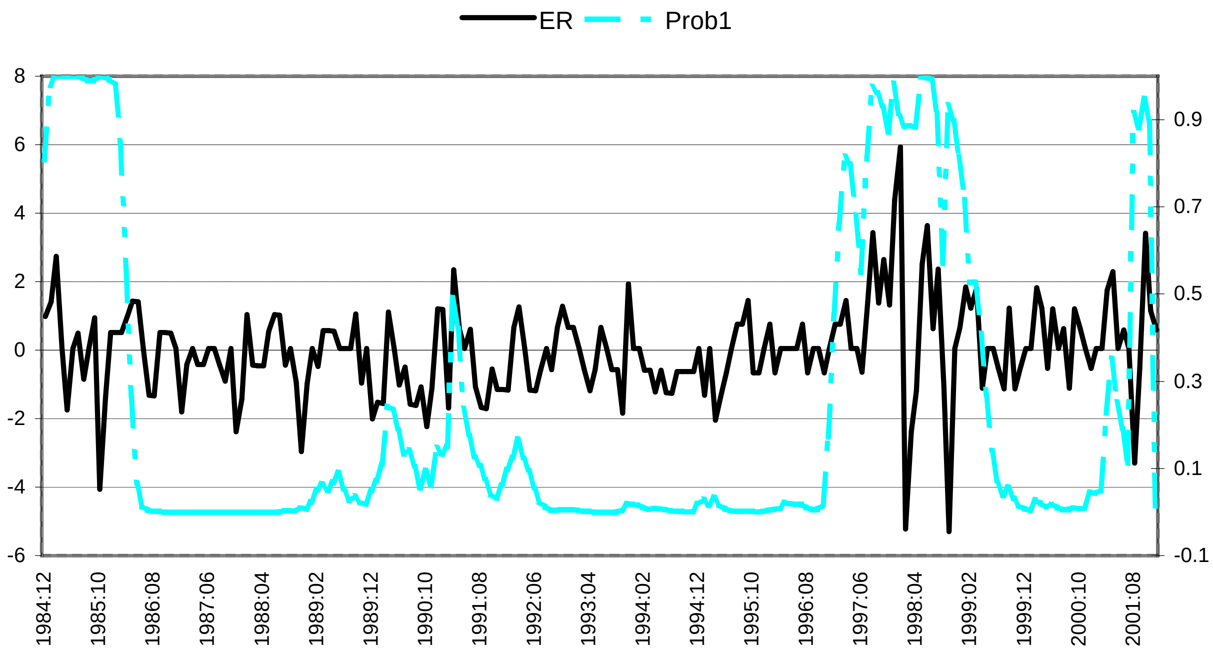


Fig.28: Singapore - Model31 (REER, BANKSTD)

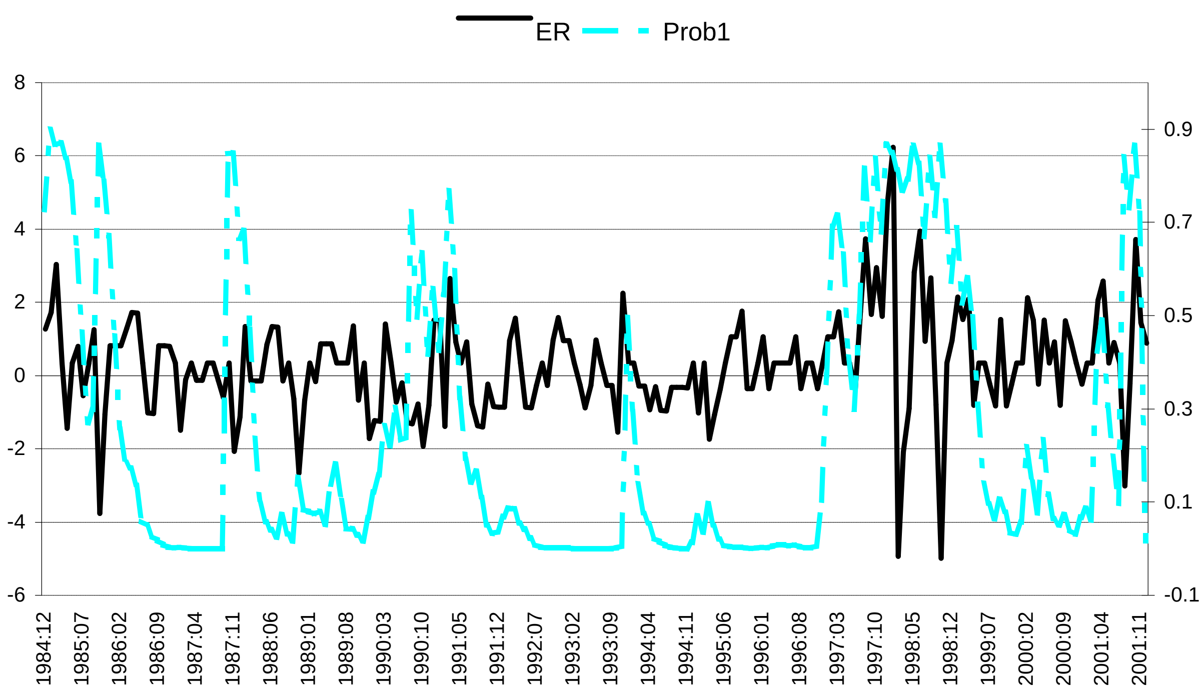


Fig.29: Philippines - Model21 (REER)

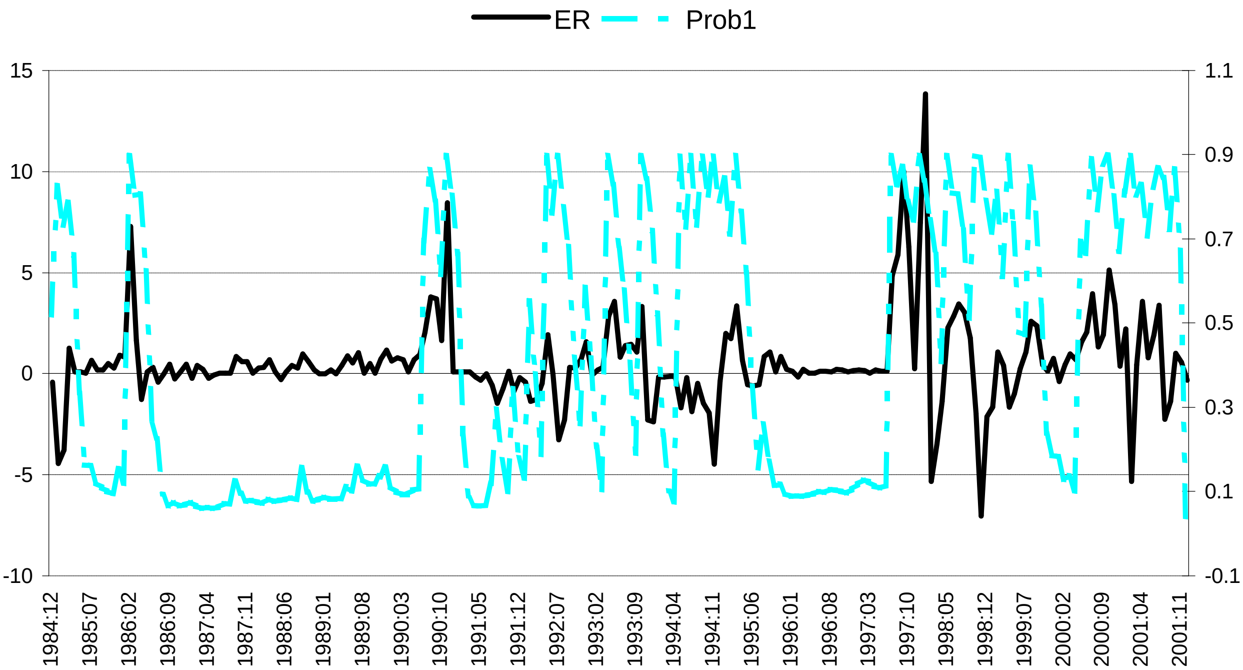


Fig.30: Philippines - Model31 (REER, GENRET)

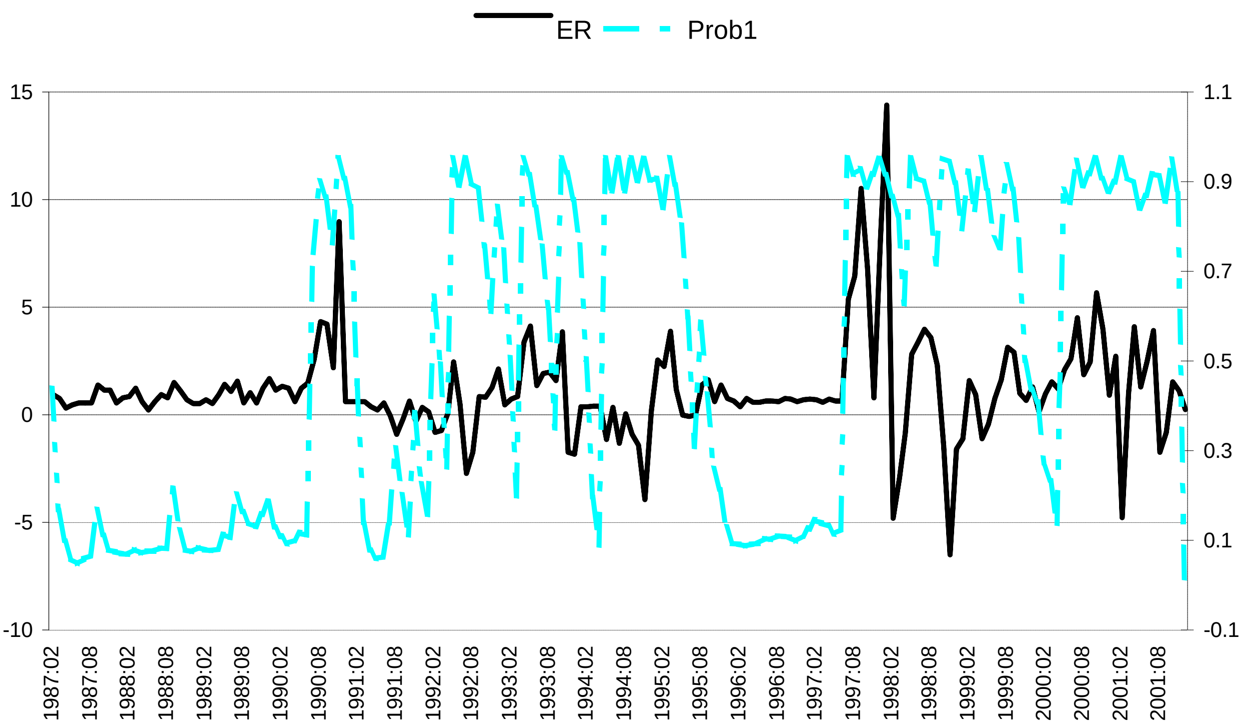


Fig.31: Malaysia - Model31 (REER,M2ratio)

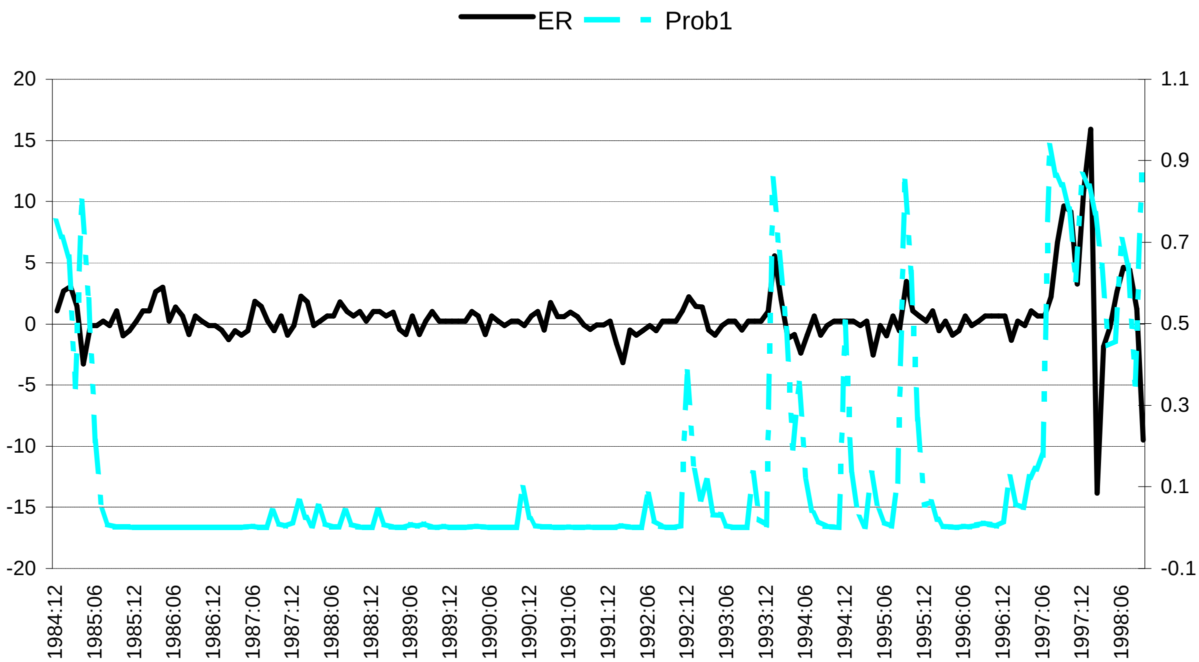


Fig.32: Malaysia - Model32 (REER,BANKSTD)