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Arias, Guillaume; Erlandsson, Ulf

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GUILLAUME ARIAS AND ULF G. ERLANDSSON *

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Abstract

In this paper we develop an early warning system of currency crises based on the Markov switching methodology. Constructed data on speculative pressure from six Asian countries indicate that currency crises are mainly captured through volatility effects. Based on an extensive survey, we test potential determinants of exiting the tranquil state and find a number of variables with significant medians across the panel. Using these candidates, we obtain final specifications using a recently proposed penalized maximum likelihood methodology. The method enables us to extract smoother transition probabilities than in the standard case, reflecting the need of policy makers to have advance warning in the medium to long term rather than the short term. Our forecasting results indicate that the approach is useful in the early warning of currency crises setting.

KEYWORDS: Currency crisis, Early Warning System, Markov-Switching
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*Guillaume Arias, Centre d'Economie et de Finances Internationales (CEFI), Université de la Méditerranée Aix-Marseille II, Château Lafarge, Route des Milles, 13400 Les Milles, phone: +33(0)442935993, fax: +33(0)442389585, mail: garias@univ-aix.fr, and Ulf G. Erlandsson, Department of Economics, Lund University, Box 7082, S-220 07 LUND, Sweden, phone: +46 (0)462228677, fax: +46 (0)462224118, mail:ulf.erlandsson@nek.lu.se.

Introduction

In retrospect, the financial history of the 90s decade will be remembered as a period of massive capital flows and spectacular financial crises in emerging countries. Total net private capital flows to those economies in the 1990-96 period reached US$ 1,055 billion corresponding to more than seven times the amount they received over the 1973-81 period. However, the regular rise in capital inflows in the early 90s was suddenly stopped by currency crises in Mexico and its "Tequila effect", reflected by a switch from 61.7 billion US dollars in 1993 to 35.7 billion dollars in 1995 in Latin America, and a switch from 215.9 billions in 1996 to 147.6 billions in 1997 in Asian countries. If one adds the cases of Russia (1998) and Brazil (1999), the frequency of currency crises in the second part of the 90s is viewed as impressive and unique in the history of such financial events.[1] Even if currency crises are not new per se, most economists acknowledge the recent crises appeared very specific in terms of suddenness, spread and economic repercussions, which is reflected in the renewal of the theoretical and empirical works on speculative attacks.

Apart from the purely academic interest in modelling the causes, mechanism and effects of such financial turbulence, international and domestic official authorities as well as major private banks started to build early warning systems in order to detect the most significant alarm signals of potential future crises and derive estimated forecasts of the latter.[2] The motivation behind such empirical works is rather intuitive. Not only authorities desire to avoid crises that are costly in terms of economic and social welfare,[3] but also rational private investors dislike foreign exchange capital losses due to depreciations. However the evidence to date in this field is quite disappointing : "*(1) the leading indicators literature is still in its infancy and more rigorous and precise data (especially on financial fragility and investment efficiency) should be explored; and (2) researchers should refrain from creating and developing predictors of crises (after all, financial crises might perfectly be unpredictable) and focus instead on simpler early-warning indicators.*"[4]

The search for sophisticated econometric approaches led a majority of researchers to favour techniques such as linear regressions, probit/logit models or the non parametric signalling approach (Kaminsky et al. (1998)), instead of relying on former simplistic event studies. However, given the numerous hypotheses imposed by these methodologies, a growing body of economists is developing more flexible models built on the concept of regime-switching. This paper contributes to the empirical

[1]This observation is reinforced by the recent crises in Turkey and Argentina in early and late 2001 respectively.

[2]See Abiad (2003) for the International Monetary Fund, Hawkins and Klau (2000) for the Bank for International Settlements, Vlaar (2000) for the Dutch central bank, Subbaraman et al. (2003) for Lehman Brothers for example.

[3]For example, a recent empirical study (Hutchison and Neuberger (2002)) finds that currency crises in emerging countries were associated with average production's losses between 5 to 8% between 1975 and 1997 in a window of 2 to 4 years.

[4]Bustelo (2000, p. 248).

literature on currency crises by proposing an early warning system, modelled by a Markov-switching model as an alternative to more standard practice. The rest of the paper is organized as follows. The second and third sections present a brief overview of theoretical models of currency crises and a survey of empirical models dealing with emerging markets in the 90s period respectively. These constitute the theoretical and empirical foundations of our model that is detailed in the fourth section. Section 5 concludes.

Three generations of theoretical models: how theory adapts to facts

It is common to describe the different theoretical approaches of currency crises in terms of generations. The first generation of currency crisis models dates back to the works of Krugman (1979) and Flood and Garber (1984). In this framework, an incompatibility between the economic policy, e.g. an overly expansionary policy-mix (budgetary and/or monetary) and the targeting of the exchange rate in the domestic country lead to the abandonment of the corresponding fixed exchange rate regime after a sudden exhaustion of official foreign reserves.

These original models fit well to the Latin American episodes of currency crises in the early 80s, and were later extended to account for other unsustainable fundamentals such as current account deficits and the overvaluation of the real exchange rate (Agenor et al. (1992)).[5] However, an important drawback of these models is the mechanical behaviour of authorities that is considered exogenously with regard to speculators.

Declaring the failure of preceding traditional models to explain the sudden occurrence of crises without standard policy inconsistencies in the cases of the European Monetary system (1992-93) and Mexico (1994-95), a second generation of models appears in the early 90s (Rangvid (2001)).[6]

The distinctive feature of these new models is to formalize the preferences of authorities, i.e. the trade-offs between internal (the preservation of the society's welfare) and external (targeting of the exchange rate) policy objectives, through a loss function.[7] The decision to maintain or abandon the fixed exchange rate regime becomes the result of minimizing the loss function, influenced by the weights at-

[5]Other extensions include the consideration of uncertainty on the evolution of reserves and/or the credit policy, slower adjustments of commodity prices in the short run or imperfect substitutability of financial assets (Agenor et al. (1992)).

[6]Notice that some authors still maintain the European (Krugman (1996)) or Mexican (Flood et al. (1996)) could be explained in terms of the first generation models.

[7]On one hand, speculative attacks could well be self-validating and the deterioration of fundamentals unsustainable (Flood and Marion (2000)). On the other hand, the existence of multiple equilibria has been seriously questioned under specific conditions (Krugman (1996), Morris and Shin (1998)). For these reasons, we believe the optimisation of the authorities' loss function is the crucial distinctive feature of second generation models.

tached to each objective, the private anticipations of devaluation, and the net costs of sticking to the current fixed regime (especially given the worsening of domestic social welfare) or forgiving it (in terms of a credibility loss for example) respectively. Once fundamentals enter an intermediary zone of vulnerability with multiple equilibria, a shift in market anticipations towards devaluation, raises the net costs of maintaining the fixed parity, eventually leading to the optimal decision of abandoning the current fixed regime. In this case, the coordination of anticipations through a sunspot variable enables the jump from one equilibrium to another.[8]

As in the previous major episodes of currency crises in the 90s, the south-East Asian turbulence of 1997-98, beginning with Thailand in July 1997, exhibited particular characteristics that were difficult to explain in the traditional framework of currency crisis models, leading to a newer generation of models.[9] Two kinds of currency crisis models may be distinguished within this new category. On one hand, several economists believe the Thai crisis was an insurance crisis due to a policy inconsistency between the public guarantee of private investments (specifically the protection of the domestic financial system), or structural disequilibria to a more general extent, magnified by a moral hazard[10] problem between (domestic and international) official authorities and the (financial and non financial) private sector (Dooley (2000)).[11]

Even though both views of the Asian crises above provide reasonable explanations for the causes of the Thai turbulences, complementary features are needed to justify its aggravation[12] and regional spread through various contagion effects

[8]Since the jump between different equilibria remains largely unexplained, some authors propose justifications in terms of herding in the presence of imperfect information, contagion effects or the heterogeneous informational structure of financial markets (Masson (1999)).

[9]Not only policy-mixes were more prudent and the stock of official foreign reserves higher than in Mexico before the crisis, but also authorities did not seem to face any serious trade-offs between political and economic goals, political uncertainty was less obvious (before the Thai crisis at least) and unemployment levels were low. Eventually, contagion to the rest of the south-east Asian region was faster and more widespread than in the case of the Tequila effect, and the currency crisis of 1997-98 was only part of a large financial crisis including bankruptcies of financial intermediaries and companies. In other words, models built upon the conventional theory of currency crisis did not seem to justify the severity and spread of the Asian turbulence.

[10]At the macroeconomic level, the moral hazard problem generally results from some form of implicit or explicit official insurance on investments and/or financial debts that motivates excessive behaviour of domestic agents (especially public governments in case of an international official guarantee and the private sector in case of a domestic public guarantee).

[11]However, most partisans of this fundamental-based approach recognize the aggravation and fast extension of the initial crisis to other countries need some elements of over-optimism (reflected in over-lending and over-investment) from the private sector, and contagion to complete the story (Corsetti et al. (1999)).

[12]Such aggravating factors may include circular and self-reinforcing effects linked to borrowing and lending policies of companies and banks respectively, asset price movements, or the links between financial fragility and currency pressuresMicroeconomic elements such as information asymmetries between private lenders, borrowers and financial intermediaries at the domestic (Mishkin (1999)) and international levels

(Dornbusch et al. (2000)) as well as its transmission to the real sector (Krugman (1999)).[13]

Empirical evidence on emerging markets currency crises in the 90s

According to existing surveys,[14] one can range the different empirical methodologies into four categories : earlier simple qualitative comparisons with histograms and/or parametric tests only, standard linear or probit/logit regressions, estimations based on non parametric tests such as the signalling approach, and more specific methodologies applied to currency crisis like Markov-switching models or artificial neural networks for example.[15] Within this range, a majority of studies use either linear regressions to analyse contagion effects or the influence of several variables on the severity of currency crises (often through cross-section analysis), or probit/logit as well as signalling approaches to detect determinants of crisis' probabilities.

Not only the econometric methodologies, the countries' coverage, and the time frequencies of the analyses differ but also the empirical definitions of the crisis, as the dependent variable, are various. The latter are generally based on large increases in exchange rates to reflect only devaluation episodes or a combination of exchange rates and proxies for stabilizing measures of the domestic currency in the general case of speculative attacks. Short term interest rates and/or external reserves of the Central Bank are generally considered as such proxies.[16] Once a crisis dating

(Hermalin and Rose (1999)), with herding behaviour (Calvo and Mendoza (2000)), speculative behaviour of investors (Bisignano (1999)), and increased competition between financial intermediaries (Miotti and Plihon (2001)) also contributed to the severity of the crises. Negative impacts of ineffective policy measures of foreign exchange interventions (higher interest rates according to Radelet and Sachs (1998), of capital outflows' controls in Thailand according to Edison and Reinhart (2000)), or prudential standards imposed on banks in the midst of the crisis, could be quoted as other contributing factors as well.

[13]Krugman (1999) suggests the real depreciation of domestic currencies, as a counterpart of the significant capital outflows (due to a sudden loss of foreign investors' confidence), i.e. the "transfer problem", had a dramatic impact on domestic firms' balance sheets. The latter being characterized by an important share of external debts denominated in foreign currency and a borrowing constraint proportionate to the net value of assets, real depreciation led to a reduction of firms net worth and a corresponding lowered capacity of borrowings to invest, self-validating ex-post the former loss of confidence, i.e. the "balance sheet problems".

[14]See Kaminsky et al. (1998), Hawkins and Klau (2000), and Abiad (2003) for example.

[15]See Abiad (2003, pp. 7-19) for an exhaustive survey.

[16]Notice that such simple measures are imperfect. The influence of capital flows' sterilization, capital account restrictions, or interventions on derivative markets through swaps or forwards are not considered for example. The empirical use of reserves or interest rates may also not be appropriate. Not only reserves' movements could reflect debt and reserve management rather than exchange rate's stabilization (and reserves' data could be distorted by valuation changes for example), but also the effects of interest rate increases on speculative attacks are not clear-cut. Specifically, a rise in interest rate might well have negative effects on investment in the context of a recession. Furthermore, since a large nominal

scheme is defined, and a methodology is chosen to estimate the statistical significance of potential crisis' determinants, most empirical models compare the effective estimated dates of crises with their predicted counterparts.

In order to draw critical lessons concerning the empirical determinants of currency crises and in accordance with our empirical investigation in the next section, we chose to concentrate on pooled and panel studies analysing developing and emerging markets in the 90s on a monthly basis, contrary to existing surveys in this field.[17] This discriminating procedure brought 25 articles and 27 corresponding studies. We reported in the appendix the total proportion of statistically significant determinants of currency crises in all those studies. We classified the explanatory variables in major economic categories (budgetary policy, monetary and financial sector, real sector, relations with the foreign sector...) in the spirit of Kaminsky et al. (1998, pp. 48-49). Some lessons can be drawn from our selective survey.

- Among variables that appear at least 5 times in our selection, the most significant determinants of currency crisis seem to be banking credit, production, stock indexes, current account deficit, increase in- or overvaluation of- the real exchange rate,[18] total and short term external debt, the ratio of official external reserves to short term external debt, and the occurrence of a crisis elsewhere or in the past.
- Even though they are relatively less used according to our survey, some categories seem to be promising such as the "institutional/structural or the political sectors", microeconomic variables specific to firms, determinants related to external debt or capital flows for example), transmission's channels of contagion.[19]
- Eventually, a comparison with the set of theoretical expected determinants, according to models previously discussed, shows that even though many vari-

depreciation might simply reflect the repercussion of high inflationary episodes and not the occurrence of large speculative attacks, many empirical studies correct this bias by either defining the behaviour of the exchange rate in real terms or by dividing the sample into "normal" and high inflationary periods with corresponding different estimations.

[17]Those countries have benefited from international (and domestic) financial liberalization in the late 80s. In our opinion, the latter constituted a major structural change for these economies. Therefore we only surveyed empirical studies whose sample's starting date is 1988 at least. A monthly analysis enables a more precise description of financial turbulences that generally last few months for each country such as currency crises. One article analyses separately Latin American Countries and South East Asian countries (Eliasson and Kreuter (2001)) whereas another one used two different methodologies (Schardax (2003)), which explains the higher number of studies.

[18]The concept of overvaluation reflects a deviation (towards a real appreciation of the domestic currency) from an equilibrium value of the real exchange rate here. This equilibrium can be either treated and calculated as an endogenous variable linked to several economic and financial determinants, or simply assimilated to the value of a trend.

[19]The fact these variables are less employed in our selection is due to lack of data availability for the required monthly frequency or country sample, an intrinsic qualitative nature, or the very recent links with underlying theory.

ables are consistent with these theories, some have been less used or have proved less significant than expected. This is especially true for the loss of official external reserves concerning the first generation, the increase in real wages, the level of unemployment, the burden of public debt, regarding the second generation, and proxies for the degree of official guarantees' credibility in terms of moral hazard concerning the moral hazard view of recent crises in the late 90's. Since each new generation of models is built after having drawn lessons from the previous ones and our selective survey focuses on the 90s, this is hardly surprising.[20]

An Early Warning System of currency crises based on volatility regimes

In our opinion, any early warning system of currency crises should be characterized by the precise empirical definition of the currency crisis (the dependent variable), the choice of crisis potential determinants (the explanatory variables), and the econometric methodology. As we have already mentioned, econometric methodologies using probit/logit models or the non parametric signalling approach are the most commonly used approaches in this related empirical literature. Even though probit/logit models have the advantages of greater flexibility, the direct interpretation of results in terms of probabilities and the possibility to run more formal statistical tests than the signalling approach, they still exhibit some important drawbacks. Apart from hypotheses imposed on the statistical distribution of the error terms, the transformation of a continuous and observable dependent variable into a discrete one, and the subsequent sequential regression of explanatory variables on the former imply not only some arbitrary definition for the associated threshold (with the risk of misclassifying crisis/no crisis episodes), but also a necessary loss of information.

Markov-switching models (MS) impose less hypotheses on the statistical distributions of variables and enable a simultaneous estimation of changes in dependent and independent variables, with the state in which the economy is located at each point in time being defined endogenously. They are also able to derive the statistical significance of crisis' potential determinants and probabilities of crisis. As a result, they have been recently applied in this empirical literature. Eventually, the empirical methodology of regime-switching seems also to fit better to the theoretical concept of multiple equilibria (Jeanne and Masson (2000)).

This paper will use the following definition of the dependent variable, denoted

[20] The fact that many theoretical variables are "transformed" in different ways to be empirically tested (ratios, growth, logarithmic transformations with varying lags for example), the observation that not all crises are alike, the restricted choice of studies with developing and emerging countries on a monthly basis frequency and the structural change represented by the financial liberalization of the late 80's are potential explanations for these differences between theoretical and empirical determinants of currency crises.

Index of Speculative Pressures (ISP): [21]

$$\mathrm{ISP}_t = \alpha_1 \Delta\mathrm{REX}_t - \alpha_2 \Delta\mathrm{IR}_t \tag{1}$$

where REX denotes the real (dollar) exchange rate, IR denotes the foreign exchange reserves at the domestic Central Bank and Δ denotes percentage growth. The (standard deviation) normalizing factors α are defined as

$$\alpha_1 = \left[\sqrt{\sum_{i=1}^{T} \left(\Delta\mathrm{REX}_i - \overline{\Delta\mathrm{REX}} \right)^2} \right]^{-1}$$

and

$$\alpha_2 = \left[\sqrt{\sum_{i=1}^{T} \left(\Delta\mathrm{IR}_i - \overline{\Delta\mathrm{IR}} \right)^2} \right]^{-1}$$

so that both variables give arise to an equal amount of variation in ISP.[22]

The following model will be used for extracting information about crises in the data:

$$\mathrm{ISP}_t = \mu_{R_t} + \phi \mathrm{ISP}_{t-1} + \epsilon_t \tag{2}$$

where the error term

$$\epsilon_t \sim \text{Student } t\left(0, \sigma^2_{S_t}, \nu\right)$$

where in turn ν denotes the number of degrees of freedom. Hence, we allow for two unobserved first order Markov regime switching processes S_t and R_t, where the former governs switches in levels through changes in the intercept and the latter switches in volatility (σ^2_t). We also allow for a regime independent auto-regressive term ϕ where significant auto-correlation is detected.

The transition matrix associated with the volatility regime process $\mathbf{S}$[23] is defined

[21] We use exchange rates in real terms to consider any potential inflationary bias that would have not distinguished depreciations due to high inflation or to speculative attacks. Apart from the fact that the effect of a rise in interest rates on foreign exchange speculation might not be univoqual, we did not include interest rates in our index because data were missing for some emerging countries in our sample. Preliminary tests indicating that an alternative transformation based on a moving average with decreasing weights on the index as in Bussiere and Fratzscher (2002) did not improve our results, we kept our initial definition.

[22] An interesting alternative could be to consider time-varying weights for the index ISP, that would be based on a moving variance over a past period, or on a GARCH specification. However, such options remain largely ad hoc and are still subject to specification problems. Furthermore, our empirical definition here has been guided by comparability motivations (Kaminsky et al. (1998)) and the fact that global movements in speculative pressures do not seem to be very sensitive to the precise choice of weights (Nitithanprapas and Willet (2000)).

[23] $\mathbf{X}$ denotes the $(Tx1)$ matrix of individual observations x_t, $t = 1...T$.

as (with states ordered so that $\sigma_1^2 < \sigma_2^2$):

$$\mathbf{P}_t = \begin{bmatrix} f(\lambda_1 \mathbf{Z}_t) & 1 - f(\lambda_1 \mathbf{Z}_t) \\ 1 - f(\lambda_2) & f(\lambda_2) \end{bmatrix} \tag{3}$$

where $f(x) = \frac{\exp(x)}{1+\exp x} \in [0,1]$ is the logistic function, λ_1 is a $(1xN)$ vector of parameter values and $\mathbf{Z}$ is a (NxT) matrix of independent variables with the first column being a vector of ones. For the high volatility state (σ_2^2), the transition probability is constant and λ_2 is consequently $(1x1)$.

Our first observation of this model is that if $\mathbf{R} = \mathbf{S}$, the structure of the regime switching process is exactly that of an ordinary regime switching process. In this case, the process $\mathbf{R}$ will be associated with the transition matrix of the process $\mathbf{S}$. In the case where $\mathbf{R} \neq \mathbf{S}$, the level regime switching process evolves with the transition matrix

$$\mathbf{Q} = \begin{bmatrix} f(\gamma_1) & 1 - f(\gamma_1) \\ 1 - f(\gamma_2) & f(\gamma_2) \end{bmatrix} \tag{4}$$

Hence, the most general model with $\mathbf{R} \neq \mathbf{S}$ entails two separate regime switching process as in, for example, Bollen et al.(2000). We order the process so that the first state corresponds to a low volatility "tranquil" state, and the second to a high volatility "crisis" state. The probability to switch from the tranquil to the crisis state at time t is represented by the upper right element of the transition matrix $\mathbf{P}_t$. We see that this probability is dependent upon the time period in the general case where $\mathbf{Z}$ is time-varying.[24] A model with this property will be denoted with "TVP". In the crisis state, we assume that the probability to exit the state, as identified by the lower left element of $\mathbf{P}_t$. In general notation, we have for the stay/transition probabilities that $\Pr(S_t = j | S_{t-1} = i) = \mathbf{P}_t^{ij}$.

A few notes on the choice of this structure are at place. To start with, we focus mainly on the volatility parameters, and only have a very simple parameterization of the level effects. It has been noted in several instances of the literature, e.g. Abiad (2003), that volatility effects are much stronger than level effects in actual data. For real exchange rates and frequencies higher than quarterly, this is concluded in Cheung and Erlandsson (2004). It is likely that we see the same effect in the data which we are to investigate. One objective will be to investigate whether the hypothesis $\mathbf{R} = \mathbf{S}$. If this is not done, and the true data generating process actually is governed under $\mathbf{R} \neq \mathbf{S}$, the estimates of both level and variance equations would be biased.

The main interest in the forthcoming investigation will be how to choose the set of variables to be included in $\mathbf{Z}$, since these will be the determinant of the probability to enter a crisis. If the data does not support time-varying transition probabilities, $\mathbf{Z}$ will be a $(Tx1)$ row vector of ones, and we will denote the model as having Constant Transition Probabilities (CTP). Any hypothesis testing involving whether to include a variable in $\mathbf{Z}$ or not can be easily tested using a standard

[24] Henceforth, we will call the probabilities along the principal diagonal of $\mathbf{P}_t$ "stay probabilities" and the off diagonal elements for "transition probabilities".

likelihood ratio statistic. The motivation behind this rather specific structure in transition probabilities is the fact that the dimensionality of the problem once more time-varying transition probabilities are allowed gets very high. In order to retain as many degrees of freedom as possible, we chose to focus on the factor of interest, and to apply the constancy assumption on the others.

Our estimation procedure is based on that of Hamilton (1994), eqs. 22.4.5-8. Consider a collection of unconditional densities for each regime in the (TxN) matrix η_t:

$$\eta_t' = \begin{bmatrix} \frac{1}{\sqrt{2\pi}\sigma_1} \exp\left\{\frac{-(\mathrm{ISP}_t - \mu_1 - \phi\mathrm{ISP}_{t-1})^2}{2\sigma_1^2}\right\} \\ \frac{1}{\sqrt{2\pi}\sigma_2} \exp\left\{\frac{-(\mathrm{ISP}_t - \mu_1 - \phi\mathrm{ISP}_{t-1})^2}{2\sigma_2^2}\right\} \\ \frac{1}{\sqrt{2\pi}\sigma_1} \exp\left\{\frac{-(\mathrm{ISP}_t - \mu_2 - \phi\mathrm{ISP}_{t-1})^2}{2\sigma_1^2}\right\} \\ \frac{1}{\sqrt{2\pi}\sigma_2} \exp\left\{\frac{-(\mathrm{ISP}_t - \mu_2 - \phi\mathrm{ISP}_{t-1})^2}{2\sigma_2^2}\right\} \end{bmatrix} \tag{5}$$

We can then iterate on the following equations[25]

$$\xi_{\mathbf{t|t-1}} = (\mathbf{Q} \otimes \mathbf{P}_t)' \cdot \xi_{\mathbf{t-1|t-1}} \tag{6}$$

$$\xi_{\mathbf{t|t}} = \frac{\xi_{\mathbf{t|t-1}} \odot \eta_{\mathbf{t}}}{\mathbf{1}'\left(\xi_{\mathbf{t|t-1}} \odot \eta_{\mathbf{t}}\right)} \tag{7}$$

given some initial value for $\xi_{\mathbf{0|0}}$.[26] The probabilities in (7) are the *filtered* probabilities that can be used to derive $\Pr(S_t = i|\Omega_t)$, where Ω_t denotes the information set at time t. The expression in (6) shows the forecasted probabilities, that is $\Pr(S_{t+1} = i|\Omega_t)$. A third measure of our inference on the state at time t can be useful; namely the *smoothed* probabilities that assign probabilities of each regime using full sample information, $\Pr(S_t = i|\Omega_T)$. They are given by the algorithm developed by Kim (1994):

$$\xi_{t|T} = \xi_{t|t} \odot \left\{[\mathbf{Q} \otimes \mathbf{P}_t]' \left[\xi_{t+1|T} \div \xi_{t+1|t}\right]\right\} \tag{8}$$

which is iterated from time $T-1, T-2...1$. Equations (5) and (6) form the basis of the log likelihood function:

$$L(\theta) = \sum_{t=1}^{T} \log \mathbf{1}'\left(\xi_{t|t-1} \odot \eta_{\mathbf{t}}\right) \tag{9}$$

We use the Berndt-Hall-Hall-Hausmann (BHHH) optimisation algorithm in Gauss 3.2.31 Constrained Maximum Likelihood (CML) library to maximize the function in equation (9) with respect to the parameter vector $\theta \in \left[\mu, \sigma^2, \lambda, \gamma\right]$. In order to

[25] $\otimes$ denotes the Kronecker product, $\odot$ element-by-element multiplication.

[26] This intial value will be set to the ergodic (long-run) transition probabilities of the corresponding CTP transition matrix.

increase the probability that we reach the global maximum of the likelihood function, we randomize a number of different starting values[27] and use the estimates of θ associated with the highest likelihood value.

A recently noted problem with using time varying transition probabilities in the Markov switching model is the apparent bias in the estimation procedure when selecting between different variables to include. Erlandsson (2004) notes that this bias will lead to the selection of short term predictors of regime switches rather than long term ones. When constructing an early warning system, this characteristic is especially damaging. In general, one will find short term variables, such as contagion, overtaking long term imbalances. As a consequence, it may not correspond to the information needed by a policy maker using such an early warning system. The proposed remedy of this problem is to introduce a penalty term in likelihood function. The suggested functional form is:

$$L(\theta)^* = \sum_{t=1}^{T} \left\{ \log \mathbf{1'} \left(\xi_{t|t-1} \odot \eta_{\mathbf{t}} \right) - \mathrm{e}^{\psi} \sum_{i=1}^{2} \left[\mathbf{P}_t^{ii} - \mathbf{P}_{t-1}^{ii} \right]^2 \right\} \tag{10}$$

The parameter ψ is set as the weight assigned to reduce the bias of the short run variables. The higher ψ is, the smoother the transition probability projection will be. With simulation evidence, it is shown that not only does the penalty increases the correlation between the projected and the true (data-generating) transition probability, but it is also reduces a spuriousity problem inherent the time varying probability setup. In small effective samples, the non-penalized model is more likely to find significant combinations of exogenous variables that perfectly predicts the exact timing of regime switches than is justified by the chosen significance level. In the currency crisis context, this issue is relevant since we have very small effective sample with only one or at most a handful of switches between tranquil and volatile periods.

Empirical results

Our sample covers the period 1989-2002 on a monthly basis for a panel of six emerging South-East Asian countries.[28] The signs affecting the weights are chosen so that an increase in the real exchange rate (real appreciation of the domestic currency) and/or a decrease in reserves (reflecting the defence of the implicitly or explicitly targeted parity) raises the index of speculative pressure. While the level equation is treated in a univariate framework for reasons mentioned above, an initial set of

[27]Due to the computational complexity of the model, this number has been set to 25. The effect of not finding a global maximum would be in the conservative direction, so that the model exhibits worse performance than possible. In general, 25 re-estimations seem to suffice for the data under study, especially when the the penalized likelihood function (see below) is applied.

[28]These countries are : Indonesia, Malaysia, Philippines, Singapore, South Korea and Thailand.

		P-values		Power at 10%	
	Emp. LR	$H_0: N = 1$	$H_0: N = 2$	$H_0: N = 1$	$H_0: N = 2$
Thailand	158.87	0.002	0.715	0.77	0.44
Singapore	51.51	0.002	0.617	0.96	0.99
Indonesia	112.83	0.002	0.497	0.99	1.00
Malaysia	108.04	0.002	0.579	1.00	1.00
Philippines	72.85	0.002	0.699	0.94	1.00
South Korea	174.26	0.002	0.834	0.88	0.90

Table 1: Testing for Markov switching dynamics.

explanatory variables belonging to various economic categories is chosen to enter the transition probability equation.

An essential issue for any applied work with Markov switching model is how to determine the number of states in the model. As already discussed in the original Hamilton (1989) paper, testing for the number of states is complicated due to the fact that parameters of the (N+1) state model are not identified under the null of (N) states. Consequently, a computed likelihood ratio statistic will not have a standard χ^2 distribution. A range of alternative tests for the number of states have been proposed, see e.g. Hansen (1992, 1996) In this paper, we will use the approach suggested in Cheung and Erlandsson (2004), which is based on the Rydén, Teräsvirta and Åsbrink (1998) procedure.

The test can be summarized as follows: the econometrician estimates the (N) and $(N + 1)$ state models and computes the corresponding empirical likelihood ratio statistic. Then, for the case of testing H_0 : (N) states versus the alternative of $(N + 1)$ states, one generates M number of data series as if H_0 were true. On these simulated data, the (N) and $(N+1)$ state models are estimated and the corresponding simulated likelihood ratio statistics are computed. To obtain the p-value of the test, one observes the number of simulated statistics that exceed the empirical (denoted m) and calculates the statistic as $(m + 1)/(M + 1)$.

Since this approach relies on the empirical data set, it is quite flexible in terms of specification. The main advantage, however, is the capability of testing for higher order $(N > 2)$ Markov switching. Moreover, if one switches the null hypothesis with the alternative, so that H_0 : $(N + 1)$ states, and uses the related estimated parameter vector to generate another set of artificial data, one can reach even further conclusions. A case where we are unable to reject H_0 : (N) states does not necessarily mean that we may reject H_0 : $(N + 1)$ states. As illustrated in Cheung and Erlandsson (2004), the data may not be informative enough for inference to be drawn on the exact number of states, in which case the testing procedure also reflects this. Other criteria have to be used to determine the structure.

Table 1 indicates that we are able to reject the null of no regime switching in

	$H_0: \mu_1 = \mu_2$	$H_0: \sigma_1^2 = \sigma_2^2$
Thailand	0.402	0.000
Singapore	0.011	0.011
Indonesia	0.959	0.000
Malaysia	0.735	0.001
Philippines	0.494	0.000
South Korea	0.728	0.000

Table 2: Testing for Markov switching dynamics.

		P-values		Power at 10%	
	Emp. LR	$H_0: N = 2$	$H_0: N = 4^*$	$H_0: N = 2$	$H_0: N = 4^*$
Thailand	12.76	0.064	0.956	0.09	0.03
Singapore	10.33	0.124	0.881	0.10	0.16
Indonesia	3.72	0.717	0.283	0.34	0.20
Malaysia	8.24	0.100	0.602	0.40	0.32
Philippines	9.54	0.068	0.474	0.64	0.58
South Korea	10.74	0.100	0.602	0.40	0.32

Table 3: Testing for dissociated regimes: $\mathbf{R} \neq \mathbf{S}$.

all cases. Moreover, we are unable to reject the null of 2 states. The conclusion one should draw from this is that the data generating process is regime switching. It is also illustrative to take a closer look at the best regime switching specifications. According to table 2, for all countries except Singapore, we are unable to reject that intercept parameters are equal across states, whereas we always reject the equality of the variance parameters. This leads us to conclude that there is regime switching in the volatility process. The question whether there is such dynamics in the level process or not remains open, since our tests of intercepts assume that the level regime coincides with the variance regime. To test whether there is regime switching in the level process under the assumption that the level regime possibly does not coincide with the volatility one, we conduct a new series of simulation with the results presented in table 3.

When testing for Markov switching (MS) against Extended Markov switching (EXTMS)- that is, testing for dissociated regimes - the results are much more ambiguous than in the first case. For Singapore, Malaysia and South Korea, the null of 2 states is on the threshold of being rejected with 10% significance. We produce no conclusive evidence against the EXTMS hypothesis for any country. It should come as no surprise that the power of the test in this setting is quite low considering the short data sample. Both these factors indicate that we will have to make a selection on other criteria for the countries that are not within the 10% significance criterion.

Given the flexibility of the EXTMS structure in front of the ambiguous results above, we have chosen this specification for Singapore, Malaysia, South Korea and the Philippines. Other diagnostics, such as the ability of models to correctly reproduce crises, regime durations, residual and squared residual autocorrelation, confirmed our choice. The ordinary MS was applied for the other countries. The remaining empirical work will be conducted using the concluded regime switching dynamics, defined as "optimal" model for each country.

To obtain final candidates for further specification step, we tested candidate variables for their individual significance for each country. Given the lessons from the theoretical and empirical literature, the data availability at the monthly frequency, and the desire to limit the correlation risk, we selected determinants related to the budgetary (public deficit and central bank's credit to the public sector), real (production, inflation, stock prices), financial ("banking fragility")[29] sectors, as well as measures linked to the current (trade balance, overvaluation of the real exchange rate) and capital accounts (vulnerability to capital outflows, and official external reserves), a proxy for contagion in the same region,[30] and the 3-month US LIBOR as an exogenous external shock.[31] Moreover, all these variables were subjected to a number of different time transformations as detailed in table 4.

From table 4, we can infer determinants of currency crisis that are statistically "significant" for the panel of Asian countries, namely : stock index, international reserves, overvaluation of the real effective exchange rate (Reer), banking fragility, central bank credit to the public sector, trade balance and contagion in increasing order of significance. These preliminary results seem to show that the probability of a coming currency crisis in South-East Asia was globally explained by a set of determinants belonging to all three theoretical generation models rather than just one. We also note that time transformations are important: in all cases except for contagion, all time transformations but one yield insignificant median results.

The next step is to specify each country's set of variables that enters the time-varying transition equation based on the candidates obtained from the panel significance. We note that the duration of the individual candidates are quite different; from the lagged first difference movements in the stock index to the level variables of e.g. the trade balance. Since the estimation procedures from here on will apply the previously discussed penalized likelihood function, the discrepancy between these different aggregates that normally would inhibit joint estimation is resolved.

[29]As detailed in appendix, this measure combines credit to the private sector, bank deposits and foreign debt of banks. This justifies the absence of a supplementary variables related to credit in our selection to avoid redundancy.

[30]We abstain from debates on the theoretical meaning of "contagion" and applied a broad definition. For each country, we used the average of filtered crisis probabilities in the remaining 5 countries derives from simple fixed transition probability models. This contrasts with usual practice of using the mean of the ISP levels and is consistent with our dating scheme based on probabilities.

[31]Other categories like political variables or measures of non financial firms' fragilities could not be included due to lack of data availability for emerging markets on a monthly basis. We also did not weight our measure of contagion by various trade and financial transmission channels contrary to Fratzscher [2002] since they do not represent the focus of our study. See appendix for details on the construction of these variables.

Var. / Trans.	FD(1)	FD(2)	MA(3)	MA(6)	MA(12)	MA(24)	Level	Median
Public deficit	0.573	0.616	0.679	0.667	0.845	0.848	0.423	0.667
CBCPS	0.856	0.506	0.081*	0.259	0.385	0.519	0.255	0.385
IBF	0.759	0.770	0.602	0.556	0.259	0.209	0.114*	0.556
VCO	0.349	0.471	0.453	0.318	0.318	0.466	0.787	0.453
IPr	0.525	0.200	0.429	0.389	0.252	0.361	0.262	0.361
Stock index	0.140*	0.352	0.226	0.195	0.457	0.346	0.311	0.311
Trade balance	0.388	0.488	0.671	0.379	0.251	0.272	0.013*	0.379
Inflation	0.754	0.480	0.769	0.552	0.733	0.377	0.505	0.552
IntR	0.285	0.185	0.304	0.394	0.260	0.577	0.134*	0.285
Terms of trade	0.854	0.874	0.903	0.907	0.828	0.756	0.828	0.854
LIBOR	0.605	0.696	0.593	0.615	0.572	0.714	0.214	0.605
Contagion	0.082	0.014	0.007	0.004*	0.026	0.178	0.112	0.026
Reer	0.627	0.242	0.530	0.131*	0.397	0.592	0.324	0.397
Mean	0.545	0.478	0.459	0.533	0.548	0.547	0.363	

Table 4: Panel of median significance values.

Through the rest of this study, ψ is set to 5. Still a number of conditions are imposed a priori so as to minimize the possibilities of individual overfitting. First, when candidate variables have correlation exceeding 0.9, the candidate among the two with the highest correlation with a third variable is removed from the set, so as to remove the most severe cases of multicollinearity. Second, once highly correlated variables are removed, the model is estimated and the least significant variable with an incorrect sign is removed. The procedure is repeated until no incorrectly signed variables are left in the model. The results of this procedure for each country is presented in table 5.

This table confirms the view that South-East Asian economies were not behaving similarly in crisis and tranquil regimes respectively given the different signs (Thailand) or degree of statistical significance (Indonesia) for models with coinciding states when looking at the constant parameters μ_1 and μ_2 initially. In those two cases, the expected and measured hierarchy is respected since $\mu_1 < \mu_2$ with the associated condition $\sigma_1^2 < \sigma_2^2$. For all countries irrespective or Markov switching structure, volatility in the crisis regime is of clearly greater magnitude than that of the tranquil regime. The ratio σ_2/σ_1 ranges between 3.04 (Singapore) and 8.44 (South Korea) with precise measurement.[32] Turning to the determinants of the probability to stay in the tranquil regime/the probability to enter the crisis regime, each final model contains between two (Philippines) and four (all other countries) economic variables. The finding that only one model exhibits three significant determinants at standard levels (trade deficit, overvaluation of the real exchange rate, and contagion in the South Korean case), as opposed to two (contagion and overval-

[32]The corresponding standard errors are available upon request.

uation for Indonesia, trade deficit and overvaluation for Thailand and Singapore), one (trade deficit for Philippines) or even none (Malaysia) for the other countries might appear worrying at first sight.

First of all, we started with an initial set of 13 determinants and retained a maximum of 4 variables in individual final models, whereas corresponding figures are respectively 22 and 6 for the study of Abiad (2003) which is comparable to ours in terms of empirical methodology and sample. Then, given that some variables have been taken out due to high correlation, it is fairly safe to assume the determinants appearing in our final models summarize the information content of a broader set. The different set of variables retained for each country confirms also the view that no theoretical generation models provides a relative superior explanation of exchange rate crises, even if some traditional common factors seem to be significant such as trade deficit and overvaluation of the real exchange rate.

Some other observations are worth underlining. As theory suggests, the direction of the effects of stock price rises is not clear cut. On one hand, it could be interpreted as good news (Singapore, Philippines, Indonesia) when it reflects positive investment's prospects, especially in economies where stock markets are sufficiently developed. On the other hand, it could reflect over-optimism translating into a financial bubble and be considered as bad news (Thailand, South Korea, Malaysia). The fact contagion is significant in few countries and banking fragilities are absent in the final models seem also paradoxical given lessons from third generation models and stylized facts. Apart from the corresponding information being partly contained in other retained variables, we believe this may be related to a short sample bias and the fact contagion, as well as banking difficulties, played a crucial role in the turbulence of 1997-98 only. Being relatively less affected than others (Singapore) or very early by the crises (Thailand and Malaysia) may well complement the explanation of weak or absent contagion effects in our final models. Eventually, if our contagion measure based on filtered probabilities, reflected more adequately private anticipations than the behavior of speculative pressures alone (ISP), the numerous comments pointing to the unexpected dimension of the Asian crises would back our findings of weak statistical significance.

Country	Thailand		Singapore		Indonesia		Malaysia		Philippines		South Korea	
Parameter	Value	p	Value	p	Value	p	Value	p	Value	p	Value	p
μ_1	-0.252	(0.001)	-0.014	(0.935)	-0.187	(0.000)	-0.307	(0.167)	0.594	(0.161)	0.860	(0.172)
μ_2	0.616	(0.539)	-1.156	(0.000)	-0.239	(0.506)	0.309	(0.431)	-0.557	(0.002)	-0.470	(0.000)
ϕ	-0.269	(0.003)					0.541	(0.286)				
σ_1	0.733	(0.000)	1.176	(0.000)	0.461	(0.000)	0.413	(0.000)	0.636	(0.000)	0.670	(0.000)
σ_2	4.249	(0.000)	3.571	(0.000)	1.879	(0.000)	1.657	(0.000)	2.513	(0.000)	5.650	(0.000)
Level states :												
λ_1			25	n.a.			2.087	(0.317)	0.888	(0.379)	0.915	(0.609)
γ_2			4.231	(0.000)			2.029	(0.024)	1.825	(0.002)	2.688	(0.000)
Volatility states:												
λ_{22}	2.754	(0.001)	2.627	(0.001)	2.266	(0.000)	2.850	(0.009)	2.424	(0.000)	2.098	(0.099)
λ_{11}	25	n.a.	25	n.a.	25	n.a.	8.872	(0.458)	22.781	(0.001)	25	n.a.
λ_{11}^{CBPS}					0.032	(0.326)						
λ_{11}^{TB}	3.180	(0.000)	2.001	(0.000)			4.990	(0.806)	2.050	(0.003)	3.609	(0.046)
λ_{11}^{STOC}	0.003	(0.068)	-0.019	(0.204)	-0.006	(0.634)	0.007	(0.879)	-0.010	(0.266)	0.001	(0.976)
λ_{11}^{IR}							0.591	(0.545)				
λ_{11}^{CONT}	0.027	(0.736)	0.191	(0.268)	0.392	(0.071)					0.716	(0.130)
λ_{11}^{REER}	0.115	(0.011)	0.418	(0.009)	0.550	(0.000)	0.437	(0.540)			0.418	(0.009)
ν	30	n.a.	7.614	(0.097)	4.325	(0.028)	3.066	(0.070)	30	n.a.	23.974	(0.615)
LogL LogL*	-220.18	-220.02	-301.62	-301.58	-219.99	-219.66	-228.78	-228.39	-251.99	-251.93	-217.89	-217.56
LogLreal	-219.44		-298.91		-218.15		-226.22		-247.10		-213.99	
R^2	0.012		0.161		0.020		0.138		0.208		0.178	
LB Q(4)*	2.346	(0.672)	2.817	(0.589)	3.558	(0.395)	4.084	(0.395)	2.136	(0.712)	3.034	(0.552)
ARCH(4)	4.435	(0.350)	2.236	(0.692)	4.178	(0.383)	15.808	(0.003)	6.605	(0.158)	3.591	(0.464)
LRreal	6.535	(0.163)	7.106	(0.069)	6.329	(0.176)	9.372	(0.052)	10.984	(0.004)	13.160	(0.011)
LR	5.056	(0.282)	1.695	(0.638)	2.644	(0.619)	4.251	(0.373)	1.202	(0.548)	5.359	(0.252)
LR*	5.381	(0.250)	1.784	(0.618)	3.310	(0.507)	5.021	(0.285)	1.320	(0.517)	6.023	(0.197)

Table 5: LRreal, LRp and LR* are likelihood ratio statistics respectively calculated from the likelihood functions: non penalized, penalized and non penalized using the parameter vector from the penalized estimation procedure. These ratios are deducted from the values of LogL(* or real) and the corresponding FTP probabilities. LB Q reflects the Ljung Box Q-statistics with the null of no autocorrelation; while LM ARCH refers to Engle's Lagrange multiplier test with the null of no ARCH effects. Parameters' P-values have been calculated using a heteroskedastic consistent Wald test based on the matrix of variances/covariances. Bounded values have been fixed at the absolute value of 25 for the crisis determinants and 30 for (degree of freedom of the Student-t law). All TVP variables have been transformed so that a positive coefficient indicates a rising probability of exiting the tranquil state.

In order to estimate the forecasting performance of our model in tracking speculative attacks, we need to derive dates of crises. Remembering that figures 1 and 2 respectively stand for tranquil and crisis states in terms of volatility regimes, we operate this dating scheme by choosing moments when smoothed probabilities $\mathrm{PrSmooth}(S_t = 2|\Omega_T)$ switch from below to above 50% as a standard procedure in regime-switching applications to business cycle turning points and currency crises.[33] Formally : if $\mathrm{PrSmooth}(S_t = 2|\Omega_T) > 0.5$ then date t is defined as a crisis period.[34] This empirical strategy enables to classify regimes over the whole sample. The next step consists in comparing the effective dates of crises with predictions of our models. For the $k = 1$ month ahead forecast, the prediction is simply:

$$\mathrm{PrFor}\left(S_{t+1} = 2|\Omega_t\right) = p_{22,t} \cdot \mathrm{PrFilt}\left(S_t = 2|\Omega_t\right) + \left[p_{12,t} \cdot \mathrm{PrFilt}\left(S_t = 1|\Omega_t\right)\right] \quad (11)$$

For the $k > 1$ step ahead forecast, we focus on the probability that we will observe at least one crisis period within the time interval $t+1, ..., t+k+1$. Obviously, this equals the complementary probability of having no crisis within the same time interval:

$$\mathrm{PrFor}\left[\min\left(S_{t+1,...,t+k+1}\right) = 2|\Omega_t\right] = 1 - \left\{\mathrm{PrFor}\left[\left(S_{t+1,...,t+k+1}\right) = 1|\Omega_t\right]\right\} \quad (12)$$
$$= 1 - \left[p_{21,t}p_{11,t}^{k-1}\mathrm{PrFilt}\left(S_t = 2|\Omega_t\right) + p_{11,t}^{k}\mathrm{PrFilt}\left(S_t = 1|\Omega_t\right)\right]$$

Expression 12 reflects that, given we are uncertain about the state we are initially in, the possibility of being in state 1 or 2, before remaining in state 1 (since we need here to derive $\mathrm{PrFor}\left(S_{t+1,...,t+k+1} = 1|\Omega_t\right)$), must be considered when building the forecast probability $\mathrm{PrFor}\left[\min\left(S_{t+1,...,t+k+1}\right) = 2|\Omega_t\right]$. In the rest of the paper we will consider a forecast horizon of 12 months. Apart from comparability purpose with alternative studies, this reflects a compromise between most accurate forecasts being shortly before effective dates of crises on one hand, and the fact early warning system's users would like to observe crisis signals as soon as possible.

Besides statistical diagnostics, a graphical and qualitative analysis of the fit of these models is useful. First, we plot crises states according to the definition above together with the probabilities to stay within the tranquil regime ($p_{11,t}$) according to our notations). It is clear from the resulting graphs that the Asian crises are well captured and chronologically ordered (see figure 1 below).[35] In order to further check the reliability of our dating scheme, the difference between filtered and

[33]The use of smoothed probabilities is simply due to the fact those inferred probabilities consider the whole set of information within the sample, consequently providing the most accurate idea on the unobservable state we are in at each date.

[34]This contrasts with a standard practice in alternative empirical methodologies where an arbitrary threshold is applied to the continuous index of speculative pressure either in terms of the distance of the standard deviation from the mean or a given percentage (often between 10% and 25%).

[35]The length of crises is also taken into account, since the latter last 3 months at least, and no arbitrary exclusion windows were needed contrary to common practice in related empirical work. This reinforces

smoothed probabilities can provide us with the amount of revisions on the regime inference that is needed when new information becomes available. Considering the number of observations and the maximum distance between those two probability types, the sum of such differences (in absolute terms) over the whole sample is bounded between 0 and 160, and we expect to observe the lowest values possible to consider the dating scheme as reliable to that extent. Corresponding estimated figures between 3.08 (South Korea) and 14.52 (Malaysia) fulfil our expectations in a satisfying way.

An even clearer view of the in-sample forecasting performance of our models concerning the major crises of 1997-98 can be seen when one compares the time t probability of having a crisis over the next 12 months (i.e. $k = 12$ in equation 12 above) with the effective dates of those crisis episodes as we reproduced in table 6 below.

In order to analyse the goodness of fit of our model more formally, one can calculate the number of correctly predicted crises (CPC) and tranquil periods (CPT), as well as the number of non correctly predicted crises (NCPC) and tranquil periods (NCPT). However one needs to define the optimal threshold to discriminate between correct and incorrect predictions in a preliminary step, before comparing those forecasts with effective dates of observations (as derived from our dating scheme). In related empirical work, most authors arbitrarily impose one or two thresholds between 20% and 50%. The reason behind these choices being simply that the higher the threshold, the higher the proportion of observations considered as tranquil to the detriment of those of crises and vice-versa. In the first case (in the second case), the risk of emitting false signals of future tranquil periods (crises) will rise. This shows that a trade-off necessarily exists between having a maximum of good signals and a minimum of false signals. Accordingly, we initially looked at the "optimal" threshold of our models according to 3 reference criteria proposed in empirical literature, when potential thresholds are between 20% and 50%:

- the minimum of the Noise-to-Signal ratio [NCPC/(NCPC+CPT)]/ [CPC/(CPC+NCPT)] reflecting the ratio of false signals of a coming crisis (over the number of tranquil periods) to good crisis signals (over the number of crisis periods) as suggested by Kaminsky et al. (1998) for example,
- the optimal combination of the percentage of correctly predicted observations [(CPC+CPT)/T] and the share of correctly predicted crises in total crisis signals [CPC/(CPC+NCPC)] (Esquivel and Larrain (1998))
- the "optimal" respect of at least 2 criteria out of the following 3: the percentage of correctly predicted crises [CPC/(CPC+NCPT)], and/or tranquil

further our choice of the Markov switching model. However, we recognize the imperfection of such dating schemes since a few crisis episodes seem to be apparent according to the behavior of smoothed probabilities in 1999-2000, contrary to stylized facts. This imperfection could simply result from a short sample bias or the better adequacy of time-varying weighting schemes for the index of speculative pressure for example.

periods [CPT/(CPT+NCPC)], and/or the minimum of the Noise-to-Signal ratio (Burkart and Coudert (2002)).

This exercise suggested to use a common threshold of 40% as a good compromise for all countries.[36] However, as suggested by Bussiere and Fratzscher (2002), such criteria do not take into account the preferences of domestic authorities that would use an early warning system of currency crises ; and particularly the degree of risk aversion towards missing a crisis (ρ). Reflecting the fact missing a crisis can be very costly in welfare terms on one hand, while receiving an early warning signal of a future crisis should motivate the implementation of preventive policy measures that are also costly (whether the crisis occur or not eventually) on the other hand, we built the following loss function LF(ρ) in order to derive optimal thresholds of correct previsions between 20% and 50%:

$$\mathrm{LF}(\rho) = \{\rho \cdot [\mathrm{NCPT}/(\mathrm{NCPT} + \mathrm{CPC})]\} + [(1-\rho) \cdot (\mathrm{CPC} + \mathrm{NCPC})/T] \qquad (13)$$

Results here were much more heterogeneous than with the previous 3 criteria since optimal thresholds of 40%, 25% and 20% seem to offer the best global compromise for degrees of risk aversion of respectively 0.2, 0.5 and 0.8. Generally speaking the higher the latter, the lower the optimal threshold will be, even if values of the loss function are quite close between 20% and 25%. Even if our preliminary estimates show that "optimal" thresholds of correctly predicted observations vary between countries and degrees of risk aversion towards missing a crisis, suggesting to implement individual optimal thresholds, we believe a restricted number of thresholds should be used to simplify the application of an early warning system. Given comments above, we chose trade-off thresholds of 25% and 40% for that purpose to present reference results concerning the forecasting performance of our models.
Table 7 below exhibits clearly the good predicting capacity of our models since the minimum percentage of correctly forecasted observations is 77% (Philippines), reaching 95% in Thailand and South Korea for example. Besides, even if the small proportion of crises in Thailand and Korea over the whole sample (14% and 20% respectively) could partly explain the individual performance of those two countries, not only the corresponding percentage is over 80% and the Noise-to-Signal ratio is below 0.3 in panel for both thresholds, but also forecasts seem to be precise and well calibrated according to QPS and GSB statistics.[37]

[36]The latter appeared to be optimal in 80% of the cases for all countries except for Thailand where it is rather close to 35%.

[37]The Quadratic Probability Score (QPS) and Global Score Bias (GSB) are analogue to Mean Squared Error criteria and have been used in the empirical literature on exchange rate crises by Berg and Patillo (1999) among others. These statistics measure the precision and calibration of forecasts respectively and are both bounded between 0 and 2, with lowest values indicating the highest performance. They can be formally written as: $\mathrm{QPS} = (1/T)\sum_{t=1}^{T} 2 \cdot \left\{\mathrm{PrFor}\left[\min\left(S_{t+1,\dots,t+k+1}\right) = 2|\Omega_t\right] - C_{t+1,\dots,t+k+1}\right\}^2$ with $C_{t+1,\dots,t+k+1} = 1$ if there is at least one crisis between $t+1$ and $t+k+1$ and 0 otherwise. $\mathrm{GSB} = 2 \cdot \left(\overline{\mathrm{PrFor}} - \overline{C}\right)^2$ with $\overline{\mathrm{PrFor}} = (1/T)\sum_{t=1}^{T}\left\{\mathrm{PrFor}\left[\min\left(S_{t+1,\dots,t+k+1}\right) = 2|\Omega_t\right]\right\}$ and $\overline{C} = (1/T)\sum_{t=1}^{T} C_{t+1,\dots,t+k+1}$.

Figure 1: Thailand, Singapore and Indonesia: crises (bars) and probability to stay within the tranquil state.

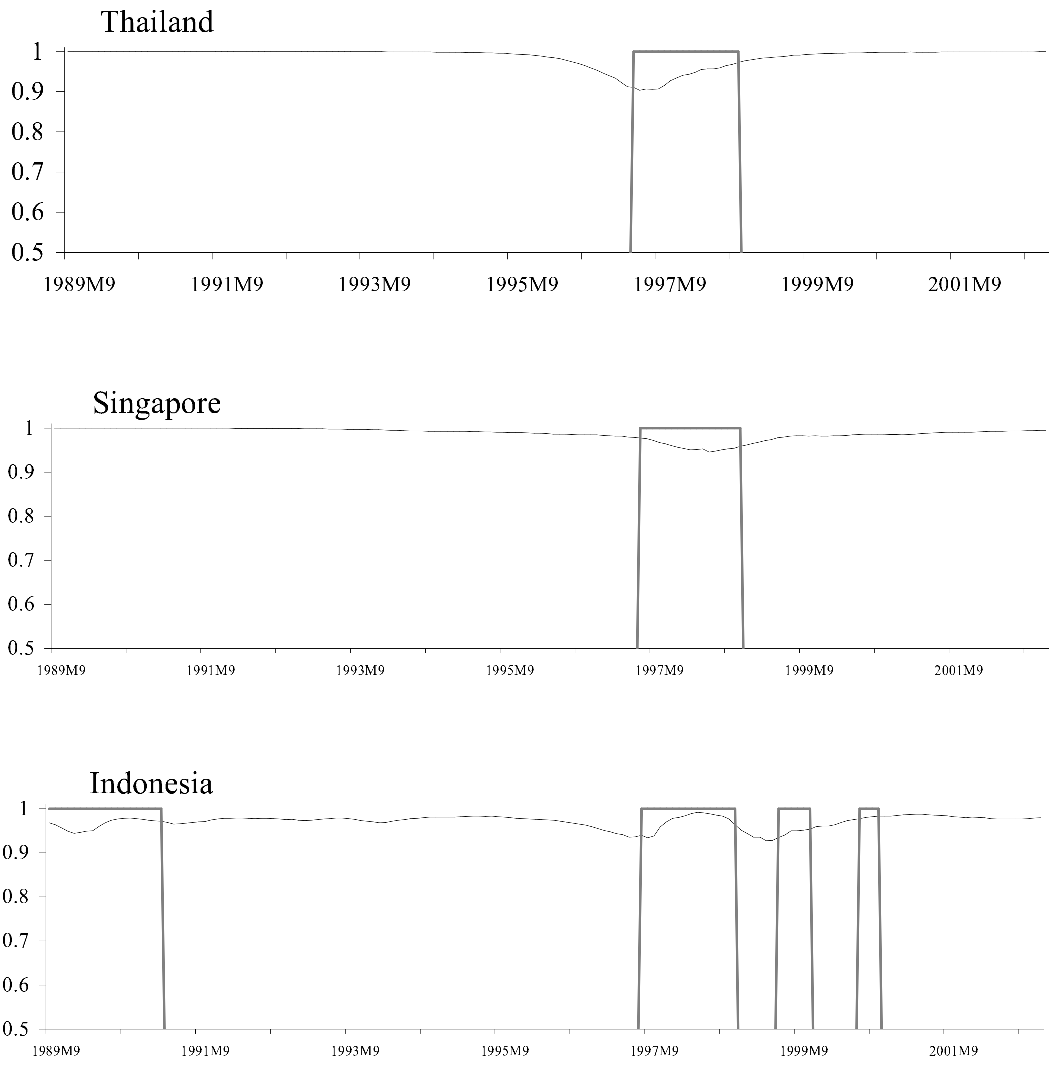
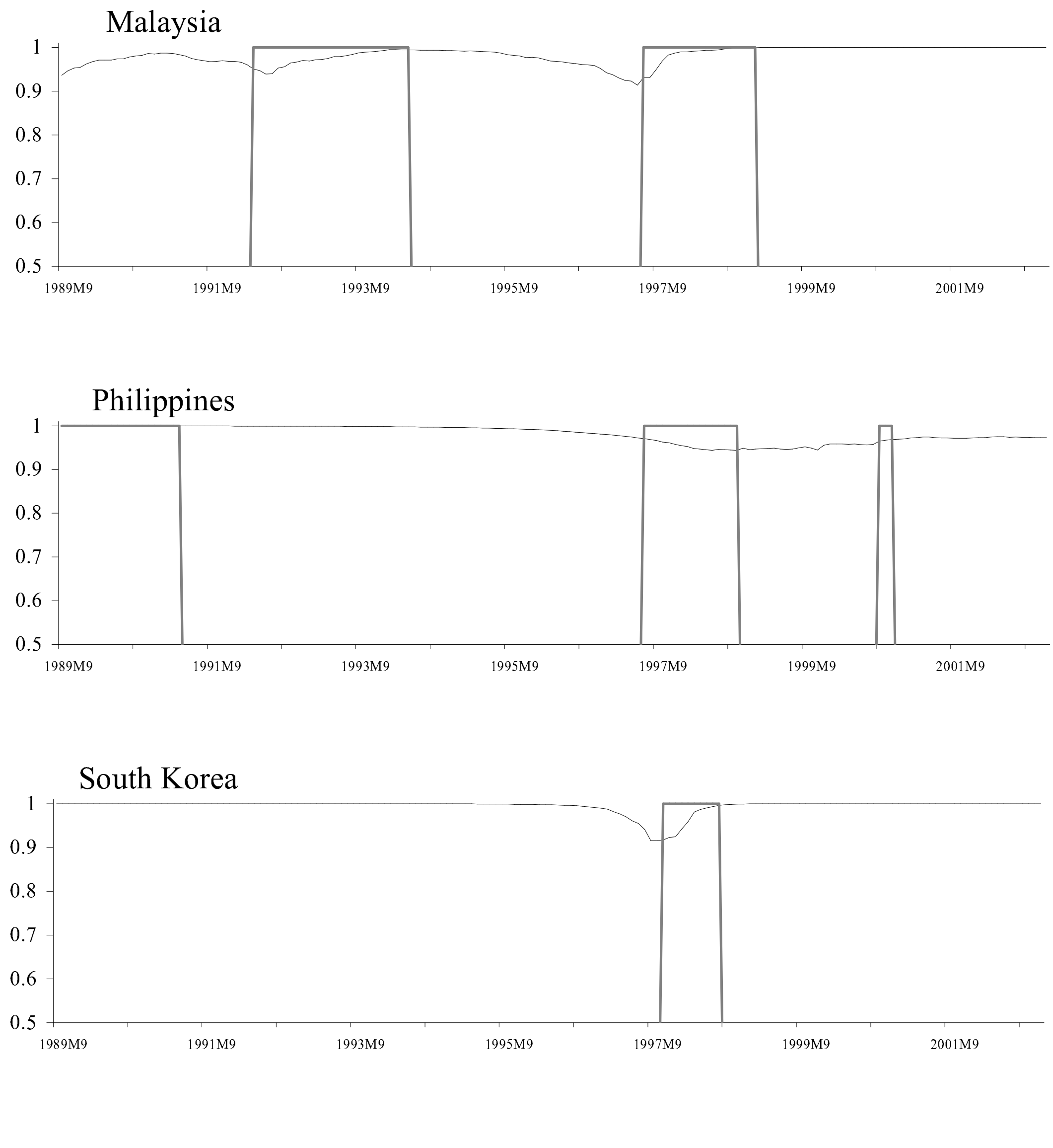


Figure 2: Malaysia, the Philippines and South Korea: crises (bars) and probability to stay within the tranquil state.



	Thailand	Singapore	Indonesia	Malaysia	Philippines	Korea	Panel(average)
1996M1	0.111	0.129	0.244	0.308	0.102	0.017	0.152
1996M2	0.127	0.135	0.352	0.358	0.106	0.019	0.183
1996M3	0.152	0.144	0.293	0.328	0.113	0.026	0.176
1996M4	0.169	0.149	0.272	0.383	0.120	0.032	0.188
1996M5	0.196	0.157	0.276	0.380	0.130	0.030	0.195
1996M6	0.236	0.158	0.290	0.359	0.144	0.037	0.204
1996M7	0.272	0.163	0.300	0.367	0.154	0.042	0.216
1996M8	0.306	0.169	0.318	0.377	0.165	0.043	0.230
1996M9	0.349	0.176	0.334	0.398	0.181	0.055	0.249
1996M10	0.396	0.174	0.353	0.399	0.192	0.073	0.264
1996M11	0.438	0.176	0.446	0.413	0.200	0.084	0.293
1996M12	0.489	0.180	0.609	0.459	0.212	0.100	0.342
1997M1	0.528	0.192	0.572	0.525	0.223	0.137	0.363
1997M2	0.592	0.201	0.502	0.551	0.234	0.141	0.370
1997M3	0.630	0.206	0.494	0.591	0.249	0.199	0.395
1997M4	0.677	0.208	0.516	0.679	0.264	0.251	0.432
1997M5	**0.975**	0.233	0.535	0.653	0.276	0.310	**0.497**
1997M6	**0.897**	0.234	0.559	0.680	0.295	0.384	**0.508**
1997M7	**0.947**	**0.280**	0.576	**0.916**	**0.940**	0.430	**0.682**
1997M8	**0.980**	**0.496**	**0.858**	**0.972**	**0.846**	0.546	**0.783**
1997M9	**0.980**	**0.384**	**0.723**	**0.967**	**0.943**	0.658	**0.776**
1997M10	**0.940**	**0.748**	**0.939**	**0.958**	**0.914**	0.660	**0.860**
1997M11	**0.974**	**0.576**	**0.778**	**0.906**	**0.792**	**0.958**	**0.831**
1997M12	**0.971**	**0.921**	**0.929**	**0.949**	**0.949**	**0.955**	0.946
1998M1	**0.969**	**0.956**	**0.926**	**0.950**	**0.933**	**0.954**	**0.948**
1998M2	**0.968**	**0.960**	**0.853**	**0.950**	**0.950**	**0.894**	**0.929**
1998M3	**0.967**	**0.876**	**0.836**	**0.845**	**0.954**	**0.931**	**0.901**
1998M4	**0.962**	**0.827**	**0.908**	**0.792**	**0.909**	**0.912**	**0.885**
1998M5	**0.963**	**0.957**	**0.901**	**0.866**	**0.856**	**0.557**	**0.850**
1998M6	**0.945**	**0.927**	**0.914**	**0.933**	**0.949**	**0.379**	**0.841**

Table 6: In-sample predicted probabilities of a crisis between $t+1$ and $t+13$ versus crisis dates between January 1996 and June 1998. **Bold** type indicates crisis dates as derived from smoothed probabilities (if at least one of of the 6 countries was affected by a crisis in the "panel" column); while italic type shows values of predicted probabilities over the minimum threshold of correct predictions of 20% before the first crises occurred.

	Thailand		Singapore		Indonesia		Malaysia		Philippines		S. Korea	
Threshold	25%	40%	25%	40%	25%	40%	25%	40%	25%	40%	25%	40%
CPCE	27	23	16	14	68	60	67	53	49	44	16	12
CPNE	6	4	13	8	48	8	37	18	30	18	3	1
NPCE	2	6	12	14	0	8	0	14	11	16	5	9
NPNE	113	115	107	112	32	72	44	63	58	70	124	126
Total T	148	148	148	148	148	148	148	148	148	148	148	148
%correctC	0.93	0.79	0.57	0.50	1	0.88	1	0.79	0.82	0.73	0.76	0.57
%correctT	0.95	0.97	0.89	0.93	0.40	0.90	0.54	0.78	0.66	0.80	0.98	0.99
%correctC&T	0.95	0.93	0.83	0.85	0.68	0.89	0.75	0.78	0.72	0.77	0.95	0.93
NtS	0.05	0.04	0.19	0.13	0.60	0.11	0.46	0.28	0.42	0.28	0.03	0.02
QPS	0.10		0.20		0.23		0.26		0.33		0.1	
GSB$\cdot 10^{-3}$	0.020		1.607		0.784		0.005		2.994		4.094	
LF(0.2)	0.19	0.19	0.24	0.22	0.63	0.39	0.56	0.43	0.46	0.39	0.15	0.16
LF(0.5)	0.15	0.20	0.31	0.32	0.39	0.29	0.35	0.34	0.35	0.34	0.18	0.26
LF(0.8)	0.10	0.20	0.38	0.43	0.16	0.19	0.14	0.26	0.25	0.30	0.22	0.36

Table 7: Goodness of fit of Markov Switching models. %correctC&T, %correctC, and %correctT respectively refer to the percentage of correctly predicted observations, crises, and tranquil periods, and NtS is the Noise-to-signal ratio. For remaining measures, see text.

Eventually, we conducted a series of complementary analysis. As we previously mentioned, values of the likelihood ratio statistics are not easily interpretable since we applied a penalized log-likelihood function. This implies that no conclusive evidence in favor of the utility of endogenizing the transition probabilities (by a set of economic determinants) could be drawn so far. For that purpose, we proceed an indirect way by comparing the forecasting performance of our reference models above with that of their Fixed Transition Probability counterparts. Our findings were here definitely in favor of the Transition Variable Probability framework only 4 statistics out a total of 66 were (only slightly) better with FTP-models.[38]

Since one might believe that the short period following a currency crisis reflects an adjustment phase that could still be considered as part as the crisis regime, we tested the impact of increasing the length of estimated crisis periods by a quarter. Contrary to the preceding sensitivity analysis, we found here an improvement of the forecasting performance since only 7 statistics were better with our reference models out of the previous total of 66. Even though these results pave the way to further analysis concerning the duration of crisis regimes, we still believe that lengthening the crisis period in such an arbitrary way is quite risky for any reliable interpretation, especially since the forecasting capacity of models was only slightly improved and almost only for South Korea.[39]

The former complementary exercise concerned the sensitivity of the forecasting performance to changes in the dating scheme. We also tested the sensitivity of our results to the empirical definition of forecast probabilities. If one considers the case where the regime of the first monthly observation to be predicted is known and refers to a state of "tranquillity" (regime 1) before the economy remains at this calm state, the predicted probability of having no crisis over the next $k = 12$ months corresponds to a simpler annualisation as in Abiad (2003). Expression (12) above would then be rewritten as (14) below:

$$\mathrm{PrFor}\left[\min\left(S_{t+1,\ldots,t+13}\right) = 2|\Omega_t\right] = 1 - \left[1 - \mathrm{PrFor}\left(S_{t+1} = 2|\Omega_t\right)\right]^{12} \qquad (14)$$

Using this formula and comparing results with the forecasting performance of our reference models, we found only 10 out of 66 cases where such simpler definition led to improved estimates. Besides, all former concerned the percentage of correctly called crises only. Since overall forecasting performance deals with much more criteria such as the percentage of correctly predicted observations, the Noise-to-Signal ratio, or the precision and calibration of forecasts, we believe our reference empirical definition (12) should be maintained.

[38]This figure corresponds to individual measures (for each of the 6 countries analysed) %correctC&T, %correctC, %correctT, NtS at 25% and 40% thresholds of "correct" predictions, and the QPS and GSB statistics as well as the "reliability" measure (sum of differences between smoothed and filtered probabilities in absolute terms).

[39]Testing Markov Switching models with 3 volatility regimes to take account of this post-crisis adjustment period, in the spirit of Bussiere and Fratzscher (2002) who implemented this with in a logit framework, seems to be a more promising alternative even though it would imply more parameters to be estimated and, consequently, even more burdensome calculations.

Eventually, the out-of-sample performance has also been tested as it represents a recent standard practice in the field of currency crisis empirical applications (Berg and Patillo (1999)). However, given the size of our sample, and the low proportion of crises in-sample, we rather focused on the period following the 1997-98 Asian crises. More precisely, we re-estimated our models on the new in-sample window 1989-1999 and used 2000-2002 as the out-of-sample forecasting period, expecting to observe almost no crisis episodes given stylized facts and the few estimated crisis dates over that period. Even though such exercise is interesting, we want to insist on the fact that one has to be cautious in interpreting corresponding estimates since not only the potential short sample bias will be increased, but also the dating scheme is still applied on the whole sample 1989-2002 as reflected in table 8 below.[40] On one hand, our findings suggest that Thailand, Malaysia, South Korea (whatever the threshold of "correct" predictions) and Singapore (at the 40% threshold) were not affected by any significant speculative attacks after 1999, as expected. On the other hand, the out-of-sample forecasting performance for Indonesia and Singapore is less satisfying because of false signals of a coming crisis or tranquil period respectively, even though Noise-to-Signal ratios remained below unity. Apart from a short sample bias (that could have also affected the dating scheme), a late rebound of speculative attacks in early Spring 1998 might have wrongly resulted in out-of-sample higher probability of a crisis in Indonesia, while other economic determinants of transition probabilities, not included in the Philippines model, might have improved the forecasting capacity for this country.[41] For example unemployment was still close to 10% in early 2000, while the widening budget deficit and rising interest rates that same year or the non performing loan ratio of commercial banks around 14.7% in June could have raised the time varying transition probability from tranquil to crisis states if included in the model, given their impact on investors' concerns according to various crisis generation models for example.

Conclusion

Based on a preliminary discussion on theoretical and empirical models of currency crisis, this paper built a regime-switching model within the framework of Early Warning Systems. After specifying individual optimal Markov switching models, and deriving panel significant determinants of currency crisis, we constructed and estimated final country-by-country specifications. The diversity of crisis determinants reinforced the view that country-specific models, though based on a preliminary set of "regional" variables, might be more appropriate than panel specifications, in the case of South East Asia at least. The existence of regime-switching in foreign spec-

[40] Consequently, a complete out-of-sample estimation would have required to use forecasts of crises dates instead of ex-post known dates.

[41] This comment is specific to the Philippines case since only one out of two TVP variables is statistically significant in-sample as table 5 exhibited.

	Thailand	Singapore	Indonesia	Malaysia	Philippines	South Korea
2000M1	0.0213	0.3236	**0.6683**	0.0083	**0.0045**	0.0005
2000M2	0.012	0.2805	**0.5014**	0.0039	**0.0066**	0.0002
2000M3	0.0056	0.2524	**0.3923**	0.0026	**0.0111**	0.0005
2000M4	0.0043	0.2361	**0.3626**	0.002	**0.0216**	0.0002
2000M5	0.0031	0.2149	**0.407**1	0.002	**0.0529**	0.0002
2000M6	0.0026	0.2089	**0.2946**	0.0022	**0.087**	0.0003
2000M7	0.002	0.2024	**0.2615**	0.0033	**0.2125**	0.0002
2000M8	0.0024	0.2059	**0.7326**	0.0025	**0.3431**	0.0002
2000M9	0.0014	0.1985	**0.9347**	0.0025	**0.6161**	0.0003
2000M10	0.0014	0.1736	0.9324	0.0041	**0.9759**	0.0005
2000M11	0.0013	0.1517	0.7824	0.0027	0.6544	0.0012
2000M12	0.0009	0.1393	0.5241	0.003	0.2226	0.0004
2001M1	0.0008	0.1265	0.2991	0.0027	0.0849	0.0004
2001M2	0.0006	0.1212	0.2653	0.0038	0.041	0.0006
2001M3	0.0008	0.2466	0.2989	0.008	0.0219	0.0019
2001M4	0.001	0.1859	0.4724	0.0047	0.0197	0.0005
2001M5	0.0008	0.1361	0.2822	0.004	0.0114	0.0002
2001M6	0.0007	0.1113	0.247	0.0048	0.0083	0.0002
2001M7	0.0007	0.1043	0.4932	0.0095	0.0077	0.0002
2001M8	0.0006	0.171	0.3365	0.0068	0.0102	0.0002
2001M9	0.0006	0.2024	0.3404	0.0103	0.0053	0.0004
2001M10	0.0005	0.1403	0.4205	0.0039	0.004	0.0002
2001M11	0.0005	0.1133	0.3648	0.0027	0.0025	0.0002
2001M12	0.0005	0.0828	0.3053	0.0016	0.0025	0.0003

Table 8: Out-of-sample predicted probabilities between $t+1$ and $t+13$ compared to crisis dates. Bold type indicates crisis dates according to the dating scheme based on smoothed probabilities.

ulative pressures, with dissociated shifts in the level and volatility of the underlying process, confirmed empirically our choice. Furthermore, it seems that reducing the excessive impacts of significant movements in potential crisis determinants, shortly before the regime switches actually occur, embeds such model into a more realistic framework. Eventually, the good in-sample and out-of-sample forecasting performance of our models and their robustness to some sensitivity analyses make us believe Markov switching models are all the more adequate to build reliable early warning systems of currency crises.

We must however be cautious in interpreting our results, especially concerning the way such models could be used. On one hand, we showed that the choice of the optimal threshold of "correct" forecasts is crucial since it varies between countries, especially depending on the degree of risk aversion towards missing crises of early warning system users such as domestic authorities. On the other hand, we believe that the reporting of such models' results should be only realized after some comparisons with alternative methodologies to seek convergence in the potential crisis signals attributed to Markov switching models. Authorities should also be cautious in the way such information would be made available to the private sector given the potential panic they might trigger. Besides, the intervention of policymakers themselves might well contradict former signals derived from early warning systems, with the paradoxical conclusion that a poor forecasting performance would not come from inherent econometric deficiencies.

References

Abiad, A. (2003). Early-Warning Systems: A Survey and a Regime-Switching Approach. IMF Working Paper 03/32.

Agenor, P.-R., Bhandari, J., and Flood, R. (1992). Speculative attacks and models of balance of payments crises. IMF Staff Paper 39/92.

Ahlumawïa, P. (2000). Discriminating contagion : An alternative explanation of currency crises in emerging markets. IMF Working Paper 00/14.

Berg, A. and Patillo, C. (1999). Are Currency Crises Predictable? A Test. *Journal of International Money and Finance*, 18:561–586. IMF Working Paper 98/154.

Bisignano, J. (1999). Precarious Credit Equilibria: Reflections on the Asian Financial Crisis. BIS Working Paper 64/99.

Bollen, P., Gray, S., and Whaley, R. (2000). Regime-switching in foreign exchange rates : Evidence from currency option prices. *Journal of Econometrics*, 94:239–276.

Brüggemann, A. and Linne, T. (2002). Are the central and eastern european transition countries still vulnerable to a financial crisis? results from the signals approach. Bank of Finland Discussion Papers 5/02.

Burkart, O. and Coudert, V. (2002). Leading Indicators of Currency Crises for Emerging Economies. *Emerging Market Review*, 3:107–133.

Bussiere, M. and Fratzcher, M. (2002). Towards a new early warning system of financial crises. European Central Bank Working Paper.

Bussiere, M. and Mulder, C. (1999). External vulnerability in emerging market economies : How high liquidity can offset weak fundamentals and the effects of contagion. IMF Working Paper 98/99.

Bussiere, M. and Mulder, C. (2000). Political Instability and Economic Vulnerability. *International Journal of Finance and Economics*, 5:309–330.

Bustelo, P. (2000). Novelties on financial crises in the 1990s and the search for new indicators. *Emerging Markets Review*, 1:229–251.

Calvo, G. and Mendoza, E. (2000). Rational contagion and the globalization of securities markets. *Journal of International Economics*, 51:79–113.

Cheung, Y. W. and Erlandsson, U. G. (2004). Real Exchange Rate Dynamics: An Alternative Approach. In Lardic, S. and Mignon, V., editors, *Recent Developments on Exchange Rates*. Applied Econometrics Association, Palgrave Macmillan.

Corsetti, G., Pesenti, P., and Roubini, N. (1999). Paper Tigers? A Model of the Asian Crisis. *European Economic Review*, 1211-1236:43:7.

Corsetti, G., P. P. R. N. (1998). Fundamental determinants of the Asian crisis : A preliminary empirical assessment. Mimeo.

Dooley, M. (2000). A model of crises in emerging markets. *The Economic Journal*, 110:256–272.

Dornbusch, R., Park, Y.-C., and Claessens, S. (2000). Contagion : Understanding how it spreads. *The World Bank Research Observer*, 15:2:177–197.

Edison, H. and Reinhart, C. (2000). Capital Controls During Financial Crises: The Case of Malaysia and Thailand. Board of Governors of the Federal Reserve System, International Finance Discussion Papers 662.

Eliasson, A.-C. and Kreuter, C. (2001). On crisis models: An alternative crisis definition. Research Notes in Economics and Statistics, Quantitative Analysis Economics, Deutsche Bank Research.

Erlandsson, U. G. (2004). Reconnecting the Markov switching model with economic fundamentals. Working Paper 04:4, Department of Economics, Lund University.

Esquivel, G. and Larrain, F. (1998). Explaining currency crises. *Harvard Institute for International Development Discussion Paper No. 666.*

Flood, R. and Garber, P. (1984). Collapsing exchange rate regimes: Some linear examples. *Journal of International Economics*, 17:1–13.

Flood, R. and Marion, N. (1996). Speculative attacks: Fundamentals and self-fulfilling prophecies. NBER Working Paper 5789.

Flood, R. and Marion, N. (2000). Self-fulfilling predictions: An application to speculative attacks. *Journal of International Economics*, 50:245–268.

Flood, R. P., Garber, P. M., and Kramer, C. (1996). Collapsing Exchange Rate Regimes: Another Linear Example. *Journal of International Economics*, 41:223–234.

Glick, R. and Moreno, R. (1999). Money and credit, competitiveness, and currency crises in asia and latin america. *Pacific Basin Working Paper Series, No. PB99-01, Center for Pacific Basin Monetary and Economic Studies, Federal Reserve Bank of San Francisco.*

Hamilton, J. D. (1989). A New Approach to the Economic Analysis of Nonstationary Time Series and the Business Cycle. *Econometrica*, 57:357–384.

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

Hansen, B. E. (1992). The Likelihood Ratio Test under Non-Standard Conditions: Testing the Markov Switching Model of GNP. *Journal of Applied Econometrics*, 7:S61–S82.

Hansen, B. E. (1996). Inference when a nuisance parameter is not identified under the null hypothesis. *Econometrica*, 64:413–430.

Hawkins, J. and Klau, M. (2000). Measuring potential vulnerabilities in emerging market economies. BIS Working Papers 91/00.

Hermalin, B. and Rose, A. (1999). Risks to lenders and borrowers in international capital markets. *NBER Working Paper 6886.*

Hutchison, M. and Neuberger, I. (2002). How bad are twins? output costs of currency and banking crises. EPRU Working Paper 2002-09.

Jeanne, O. and Masson, P. (2000). Currency crises, sunspots and markov-switching regimes. *Journal of International Economics*, 350:327.

Kaminsky, G. L., Lizondo, S., and Reinhart, C. (1998). Leading indicators of currency crises. IMF Staff Paper Vol. 5, No. 1.

Karmann, A., Greßmann, O., and Hott, C. (2002). Contagion of currency crises - some theoretical and empirical analysis. Deutsche Bank Research, Quantitative Analysis Economics, Research Notes in Economics and Statistics, No. 02-2.

Kim, C.-J. (1994). Dynamic Linear Models with Markov–Switching. *Journal of Econometrics*, 60:1–22.

Krkoska, L. (2001). Assessing macroeconomic vulnerability in central europe. European Bank for Reconstruction and Development, Working Paper No. 52.

Krugman, P. (1979). A model of balance-of-payments crises. *Journal of Money, Credit and Banking*, 11:311–325.

Krugman, P. (1996). Are currency crises self-fulfilling? NBER Macroeconomic Annual, Vol. 2, pp 345-378.

Krugman, P. (1999). Balance sheets, the transfer problem, and financial crises. *International Tax and Public Finance*, 6:459–472.

Kumar, M., Moorthy, U., and Perraudin, W. (2003). Predicting emerging market crashes. *Journal of Empirical Finance*, 10:4:427–454.

Kwack, S. Y. (2000). An Empirical Analysis of the Factors Determining the Financial Crisis in Asia. *Journal of Asian Economics*, 11:195–206.

Masson, P. R. (1999). Multiple equilibria, contagion and the emerging market crises. IMF Working Paper, No. 99/64.

Miotti, L. and Plihon, D. (2001). Libéralisation financière, spéculation et crises bancaires. *Economie Internationale, la Revue du CEPII*, 85:1:3–36.

Mishkin, F. (1999). Lessons from the East Asian crisis. NBER Working Paper 7102.

Miyakoshi, T. (2000). The causes of the asian currency crisis : Empirical observations. *Japan and the World Economy*, 12:243–253.

Morris, S. and Shin, H. (1998). Unique equilibrium in a model of self-fulfilling currency attacks. *American Economic Review*, 88:587–597.

Mulder, C., Perrelli, R., and Rocha, M. (2002). The role of corporate, legal and macroeconomic balance sheet indicators in crisis detection and prevention. IMF Working Paper 02/59.

Nitithanprapas, E. and Willett, T. D. (2000). A Currency Crises Model that Works : A Payments Disequilibrium Approach. Claremont Colleges Working Papers in Economics, No. 2000-25.

Peltonen, T. (2002). Are currency crises predictable? Manuscript, European University Institute.

Radelet, S. and Sachs, J. (1998). The East Asian Financial Crisis: Diagnosis, Remedies, Prospects. Brookings Papers on Economic Activity, No. 1., pp. 1-74, 88-90.

Rangvid, J. (2001). Second generation models of currency crises. *Journal of Economic Surveys*, 15:5:613–641.

Reagle, D. and Salvatore, D. (2000). Forecasting financial crises in emerging market economies. *Open Economies Review*, 11:247–259.

Rodrick, D. and Velasco, A. (1999). Short term capital flows. Working Paper No. 7364, Harvard University.

Rydén, T., Teräsvirta, T., and Åsbrink, S. (1998). Stylized facts of daily return series and the hidden Markov model. *Journal of Applied Econometrics*, 13:217–244.

Schardax, F. (2003). An early warning model for currency crises in Central and Eastern Europe. Manuscript, Capital Invest, Austria.

Subbaraman, R., Jones, R., and Shiraishi, H. (2003). Financial crises : An early warning system. Global Economics, Lehman Brothers.

Vlaar, P. J. (2000). Currency crisis models for emerging markets. De Nederlandsche Bank, Research Paper.

Zhang, Z. (2001). Speculative attacks in the asian crisis. IMF Working Paper 01/189.

Zulkhibri, M., Majid, A., and Yusoff, M. (2000). ASEAN currency crises and contagion effects : Further evidence. Faculty of Economics and Management, Universiti Putra Malaysia, Working Paper No. 8/2000.

Data description

All data come from the April 2003 International Financial Statistics (IFS) CD, International Monetary Fund (IMF), Bloomberg for stock indexes, and National sources (Central Banks, Governments, National Statistics Institute) via the IMF web site. The whole monthly data sample covers the period 1989M1-2002M12. Since Gross Domestic Product data were only available on an annual basis and represent a flow variable, we interpolated the corresponding data using the Quadratic Match Sum routine of the software EViews so as to construct monthly series. Eventually when (few) data were missing we derived the corresponding unobservable values by seasonally adjusted interpolation. When gaps were located either at the beginning or the end of the sample, we simply dropped those observations from it. Explanatory variables enter the transition probability equations with lags corresponding to their frequency of data reporting to reflect the fact that the private sector should only be aware of the true data once they are published (Vlaar (2000)). Accordingly, the following lags were applied : (t-1) for all variables apart from monetary aggregate M2, domestic credit (to the public or private sector), exports and imports, and gross domestic product (t-2). When a variable combined measures with different frequencies, the lowest was applied.

Dependent variable:	Data definitions and sources
Index of exchange market speculative pressure	Nominal exchange rate (NER) : IFS line ae, Price indexes (PI) : IFS line 64 (CPI) International reserves of the central bank except gold (R): IFS line .1L
Independent variables by sector:	
Fiscal sector: -Fiscal balance as a share of Gross Domestic Product -Growth of Central Bank credit to the public sector	 Deficit (-) or surplus (+): IFS line 80 Gross Domestic Product (GDP): IFS line 99b Central Bank credit to the public sector : IFS line 12a
Financial/monetary domestic sector: -Index of banking fragility (IBF)[42] $\mathrm{IBF}_t = \Delta\mathrm{BCpriv}^*_t + \Delta\mathrm{BFL}^*_t + \Delta\mathrm{BD}^*_t$ *Real sector* - Growth of industrial production - Growth of stock prices - Inflation	 Banking credit to the private sector (BCpriv) : IFS line 22d, Banks' foreign liabilities (BFL) : IFS line 26c, Banks' deposits (BD) : sum of IFS lines 24 and 25. Industrial production : IFS line 66 Stock indices: Bloomberg Consumer Price Index (CPI): IFS line 64
Current account Overvaluation of the real effective exchange rate: deviation from Hodrick-Prescott trend, penalty 14400 -Trade balance as a percentage of GDP ($mathrmTB$): $\mathrm{TB} = (\mathrm{X} - \mathrm{M})/\mathrm{GDP}$	 J.P. Morgan Exports (X): IFS line 70, Imports (M): IFS line 71
Capital account - Growth of International reserves (except gold) - Ratio of the domestic liquidity (that could be used to speculate against the domestic currency) (M2 − M1) and the international reserves of the Central Bank (R)(M21R): $\mathrm{M21R} = (\mathrm{M2} - \mathrm{M1})/\mathrm{R}$	 Int. reserves of the dom. central bank except gold (R) : IFS line .1L
External shock Off-shore short term interest rate (LIBOR)	 3-months London Inter-Bank Offer Rate (LIBOR) : IFS line 11160Lddzf
Contagion Mean of filtered probabilities in other countries (see text)	

Table 9: Data sources and definitions.

	(a)	(b)	(c)
POLITICAL VARIABLES			
Degree of Effective Government's Majority (-)		1/0	
Effective Number of Political Parties (+)		1/0	
FOREIGN SECTOR			
Current account:			
Trade Balance (-)	4/2	3/-2	3/-2
Exports (-)	3/2	13/2	10/2
Imports (+)	2/1	2/0	2/0
Terms of Trade (-)	2/1	1/0	1/0
Price of Exports (+/-)	1/0		
National Investment/GDP (+)	1/0		
National Savings/GDP (-)	1/0		
Current Account Deficit (+)	7/2	15/9	11/8
Current Account Deficit/Exports (+)		1/1	
FDI - Current Account Deficit (+)		4/3	1/1
Decrease/Overvaluation of the RER (+)	13/11	24/(19,-2)	17/(12,-2)
Anticipated Depreciation (Surveys) (+)	1/0		
Capital account:			
Reserves (-)	5/4	10/-5	9/-5
Past Volatility of Official External Reserves (+)		1/1	1/1
Reserves Adequacy to Trade Flows (-)	2/-2	5/-2	4/-2
Capital Account Balance (+/-)	1/0		
Capital Inflows (+/-)		2/1	2/1
Capital Flight (+)		1/0	1/0
Short Term Capital Inflows (+)	2/1		
FDI (-)	1/1	4/0	3/0
Portfolio Investments (+/-)		2/-1	2/-1
Short Term Interest Rate Differential (+/-)	2/1	1/0	1/0
External Debt Profile:			
Total Foreign Debt (+)	1/0	6/4	4/3
Public Foreign Debt (+)	1/1	3/2	3/2
Banking Foreign Debt (+)	1/0		
Concessional Foreign Debt (-)	1/1		
Foreign Debt at Variable Rate (+/-)	1/0		
Short Term Foreign Debt (+)	2/0	6/3	4/3
Foreign Debt With Multilateral Institutions (+)	1/0		
Foreign Aid (-)	1/0		
Participation to an IMF Program (-)	1/-1		

	(a)	(b)	(c)
Other foreign factors			
Financial Variables:			
(M2/R or (M2-M1])/R)(+)	2/2	13/(5,-1)	10/(4,-1)
R Adequacy to Narrow/Reserve Money (-)	4/-4	3/0	1/0
R/Foreign Debt (-)		3/-1	3/-1
R/Short Term External Debt (-)		12/-9	9/-8
R/Middle-Long Term Foreign Debt (-/+)	1/1	1/1	
Banking External Assets/Banking External Debt (-)		2/0	2/0
Exports/External Debt (-)		3/-1	3/-1
Exports/External Debt's Service (-)		1/0	1/0
Banking External Debt/Domestic Credit (+)	1/0		
R/Domestic Credit to the Private Sector (-)		1/0	
R/Domestic Credit to the Public Sector] (-)		1/0	
Upper Bound of the ERM Fluctuation Margin (-)	1/1		
Closeness to Central Exchange Rate Parity (-)	1/1		
Parallel Exchange Market Premium (+)	1/1		
Other Exogenous Factors:			
Foreign Economic Growth or GDP (-)	1/0	2/-1	1/0
Foreign Prices (-)	2/1	2/0	2/0
World Petroleum Price (+/-)		1/0	1/0
((-) for Exporters and (+) for Importers)			
International Stock Indexes (+)		2/0	2/0
Indicator of Global Liquidity (+)		1/-1	1/-1
Foreign Interest Rate (+)	3/1	3/1	2/0
Causes of- or Vulnerability to- Contagion:			
Occurrence of a Currency Crisis Elsewhere (+)	1/1	6/6	5/5
Vulnerability via Real Integration (+)	1/1	4/2	3/2
(via bilateral trade/competition on third markets)			
Vulnerability via Financial Interdependence (+)		2/1	1/1
Vulnerability via Macroeconomic Similarities (+)	1/0	1/1	
"Common Creditor" Effect (+)		1/0	
Occurrence of a crisis in the past (+)	1/1	6/6	4/4
Past Volatility of the exchange rate (+)	1/1	3/2	3/2
Past Exchange Market Event (except crisis) (+)	1/0		
Time Spent in Fixed Exchange Rate Regime (-)	1/1	1/-1	1/-1

Table 10: Significance results in surveys (theoretically expected sign in relation to the crisis probability).

Notes:

(1) case (a) refers to "KLR98 (survey)"; (b) to a "Selection of studies" and (c) to "Without studies using regressions."

(2) We have only selected "in sample" studies dealing with episodes of depreciation/devaluation (on speculative pressure in the same direction) of the domestic currency. Some articles may exhibit more than one "study" when different econometric methodologies are used (Schardax (2003)) or different emerging regions are covered (South East Asia and Latin America in Eliasson and Kreuter (2001)). Notice that explanatory variables are generally treated with lags due to the predictive aspect of most studies (except in the case of exogenous shocks sometimes). Apart from the survey of Kaminsky et al.(1998) (denoted KLR98), the corresponding articles for our selection of studies are : Corsetti et al. (1998), Radelet and Sachs (1998), Bussiere and Mulder (1999 and 2000)), Glick and Moreno (1999), Rodrick and Velasco (1999), Tornell (1999), Ahlumalia (2000), Hawkins and Klau (2000), Kwack (2000), Miyakoshi (2000), Nitithanprapas and Willett (2000)), Reagle and Salvatore (2000), Vlaar (2000), Zulkhibri and al. (2000), Eliasson and Kreuter (2001), Krkoska (2001), Zhang (2001), Bussiere and Fratzscher (2002), Brüggemann and Linne (2002), Karmann et al. (2002), Kumar et al. (2003), Mulder et al. (2002), Peltonen (2002), Schardax (2003). Most studies in our selection use the following econometric methodologies : standard linear regressions, non parametric "signalling" approach, or probit/logit, sometimes combined with other more specific approach (autoregressive conditional hazard model in Zhang (2001), scoring analysis in Hawkins and Klau (2000), or Artificial Neural Network in Peltonen (2002)).

(3) The statistical significance is here determined by the critical values of the standard corresponding statistical tests. Concerning studies using the "signalling" methodology, we have considered as "statistically significant" the variables whose "noise-to-signal" ratio was not above 0.55. For other kind of methodologies, we chose a statistical significance between 1% and 10% according to usual tests such as t-tests (Student). Given this discriminating methodology, the value 1 (-1) is attributed to a variable that "significantly" increase in the probability of- or the index of- speculative pressure (decrease in), and 0 otherwise.

(4) Variables that might influence speculative pressure are classified according to the economic category to which they belong in the spirit of Kaminsky et al. (1998). The theoretically expected sign of this influence is given in brackets. FDI, R, RER, GDP respectively stand for Foreign Direct Investments, External Official Reserves, Real Exchange Rate, and Gross Domestic Product. Concerning the article of Kumar et al (2003), we only reported results with the model using the most standard index of speculative pressure (not ajusted from the Interest Rate Parity).