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Visual Predictions of Currency Crises: A Comparison of Self-Organizing Maps with Probit Models

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Abstract

Throughout the 1990s, four global waves of financial turmoil occurred. The beginning of the 21st century has also suffered from several crisis episodes, including the severe subprime crisis. However, to date, the forecasting results are still disappointing. This paper examines whether new insights can be gained from the application of the Self-Organizing Map (SOM) – a non-parametric neural network-based visualization tool. In this paper, we develop a SOM model for prediction of currency crises, and compare it with a probit model. The results indicate that the SOM model is a feasible tool for predicting currency crises. Moreover, its visual capabilities facilitate the understanding of the factors and conditions that contribute to the emergence of currency crises in various parts of the world.

Keywords: Currency crisis, early warning, financial instability, Self-Organizing Maps, prediction

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1. Introduction

In the 1990s, the world economy was struck by four global waves of financial turmoil: the European ERM crisis from 1992–1993, the Mexican Peso crisis from 1994–1995, the Asian crises from 1997–1998 and the Russian crisis in 1998. Consequently, the repeated occurrence of financial distress has stimulated research on this particular phenomenon. However, the results of crisis forecasting, for example in the Asian and Argentinean crises, are disappointing for most of the models (Berg et al., 2004). Additionally, the more recent subprime crisis did not receive adequate forecasting results since it surprised not only financial market participants, but also policy decision-makers. This being the case, finding an effective early warning system (EWS), i.e., an empirical tool for predicting financial distress, remains an important issue and needs further research.

To date, empirical studies have mainly focused on conventional statistical methods, such as simplified probit/logit analyses and the so-called signals approach, and neural network-based methods to construct EWSs. In this paper, we investigate whether new insights can be gained from the application of the Self-Organizing Map (SOM) to the prediction of currency crises. Currency crises are a variety of economic crises characterized by a sudden depreciation of the exchange rate, often also having severe effects on the country's real economy.

The SOM technique is a special type of neural network that uses unsupervised learning to find similarities between data vectors (Kohonen, 2001). Its output is a mapping of the data onto a two-dimensional topological grid, which makes this tool particularly useful for visualizing large amounts of multidimensional data. We choose the SOM as the data analysis tool because of its visualization capabilities and efficiency, measured by computational cost.

The research question addressed in this study is to find out to what extent a visual model, developed by employing the SOM method, is capable of predicting currency crises. To answer this question, we develop a SOM-based EWS and discuss its capabilities in showing countries' economic conditions prior to currency crises. Moreover, the constructed model is used to visually monitor the evolution of a country over time and to benchmark countries based on their vulnerability to an imminent crisis. In order to evaluate the SOM-based model, we compare it with a replica of the probit model described in Berg and Pattillo (1999b). The comparison regards the prediction accuracy and explanatory power of the two models. We train both models with the exactly same data, thus, being fully comparable. In addition, we evaluate and discuss the SOM model as to its prediction performance for each country in part.

This paper is structured as follows. In Section 2, we provide relevant background knowledge on theoretical models of currency crises. Section 3 presents current methods for constructing EWSs and summarizes the main results from the empirical literature. Section 4 introduces the SOM. Section 5 presents the data, the training process and the SOM model for predicting currency crises. Section 6 evaluates the performance of the SOM model in comparison with a probit model, in terms of accuracy and other related measures. Moreover, the prediction accuracy for individual countries is described. Section 7 illustrates two types of analyses that can be conducted using the SOM model, monitoring the evolution of individual economies and benchmarking several countries as to their vulnerability to an imminent crisis. Section 8 concludes the paper by presenting our key findings and recommendations for future research.

2. Currency Crises

A currency crisis refers to a situation in which massive capital outflows force a country to either devalue or float its fixed exchange rate. A balance-of-payments crisis, on the other hand, is a broader concept which refers to a shortage of reserves to cover balance-of-payments needs, often also including a sharp devaluation. However, in this paper, both concepts are used with an identical meaning. The recent frequent occurrence of currency crises has influenced the number of modeling attempts on the phenomenon. Although the models are mainly ex-post explanations of past crises, the studies often concentrate on the determinants and early warning signals of the crises (Chowdhry and Goyal, 2000).

There are three generations of crisis models. In Krugman's (1979) seminal model on balance-of-payments crises, he describes a small open economy with a fixed exchange rate. The economy's fixed exchange rate is maintained with the country's foreign exchange reserves. In this model, the well-informed rational speculators understand when fundamental macroeconomic variables show unfavorable values. They attack the currency when the floating of the fixed exchange rate yields the required return. Thus, even though there is no change in the central bank's policies, the reserves will eventually run out. The unfavorable values of the fundamentals of an economy are, for example, large and growing current account deficits, a rapidly growing budget deficit, and a loss in exports. Even though the first-generation models reveal some aspects of currency crises, their main deficiency is that they assume that speculators have perfect foresight. In reality, speculators are unsure about both the exact timing of a crisis and the size of the exchange rate fluctuation.

After the collapse of the exchange rate agreement ERM (European Exchange Rate Mechanism) in 1993 and the Mexican crisis in 1994, the existing economic literature on currency crisis prediction was reconsidered. Traditional first-generation models had problems anticipating crises due to two factors. First, Obstfeld and Rogoff (1995) insisted that the reason for floating fixed exchange rates – particularly during the ERM crisis – was not the depleted foreign exchange reserves, but rather the governments' reluctance to combat speculative attacks with high interest rates. In other words, these models explain, by taking into account the costs and benefits of floating their fixed exchange rates, government behavior during speculative attacks. Second, the ERM crises were in nature both unexpected and unexplained, and therefore, several researchers suggested that self-fulfilling expectations may have played a significant role in the timing of the crises.

According to Obstfeld (1986; 1994), these so-called self-fulfilled crises are mainly characterized by the relationship between the governments' valuation of the cost of maintaining the fixed exchange rate and private sector expectations. If the private investors expect that the country in question will either devalue or float its currency, the governments' costs to maintain the fixed exchange rate increases. Simultaneously, higher costs for maintaining the fixed exchange rate will cause increased expectations of devaluation or floating of a fixed currency, leading to a vicious circle. Thus, the second-generation models suggest that currency crises are caused by expectations and that the exact timing of the crisis is very difficult to anticipate. These models should, for example, include unemployment, the quantity of manufactured goods, short-term debt and domestic interest rates as explanatory variables. However, even if the second-generation models use a number of additional variables, they do not clearly differ from the first-generation models. Hence, the first two generations of models do not exclude each other – they are often considered as complements of each other.

According to many scholars, the Asian crises from 1997–1998 were not caused by monetary deficits, as in first-generation models, or the governments' reluctance to combat speculative

attacks with high interest rates, as in second-generation models. They are explained by a new, third generation of theoretical models, linking currency crises with the financial sector's vulnerability. The third-generation models emphasize financial institutions' and asset prices' importance during the pre-crisis period. In other words, the models stress the effect of balance-sheet problems on the occurrence of currency crises. (Aghion et al., 2001)

A property shared by all generations of currency crises of the 1990s − the ERM crisis, the Mexican peso crisis, the Asian crises and the Russian crisis − is that they have been worsened by contagion on the global financial markets. In the literature, this contagion is explained by several factors. One cause is a so-called "monsoonal effect" caused by a rise in world interest rates, which may lead to a crisis in countries that are vulnerable to high interest rates (Masson, 1998). Moreover, crises may also be triggered by spillover effects to neighboring countries from another country's devaluation – a loss of competitiveness and weak external demand for countries that either trade with each other or compete for third markets (Gerlach and Smets, 1995). The empirical studies on contagion concentrate on analyzing how speculative attacks elsewhere affect macroeconomic variables in the analyzed country, and thus also the likelihood of an oncoming crisis episode (see, for example, Eichengreen et al., 1996).

3. Early Warning Systems

Studies of EWSs for financial crises have, until recently, been divided into two different types of analysis methods: logit or probit models and the signals approach. Lately, a third group of computational analyses based on artificial intelligence have evolved.

A logit/probit model is a regression which estimates the probability of a crisis occurring on lagged values of early warning indicators. A renowned paper using a probit/logit regression is Frankel and Rose (1996)[1]. In their study, they examined how external factors and international debt structure affect the probability of an oncoming crisis period. They used a multivariate probit model on annual data of 105 developing countries from 1971−1992. They constructed a dummy crisis variable according to the following crisis definition: at least a 25 percent depreciation of the nominal exchange rate which exceeds the previous year's depreciation by at least 10 percent. However, their findings show that the general explanatory power of the model is comparatively low.

Kaminsky, Lizondo and Reinhart (1998) (KLR) and Kaminsky and Reinhart (1999) introduced the so-called signals approach. In order to obtain a direct measure of the importance of each explanatory variable, the signals approach monitors prior to a crisis episode the evolution of a set of economic variables separately. Similarly as previously, a crisis is identified by the movements of an index of exchange market pressure. The variables are compared, one at a time, with the crisis index. When one of these variables deviates beyond a specific threshold value the model issues binary signals of a possible crisis episode. The number and strength of these binary signals will indicate the probability of an imminent currency crisis. Moreover, for exemplary goodness-of-fit, the signals approach optimizes the signal-to-noise ratio for the various potential indicators of a crisis, meaning that the ratio of the success rate of crisis predictions in relation to the false alarm rate is maximized.

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[1] For studies using probit/logit models, see Berg and Pattillo (1998), Eichengreen and Rose (1998), Frankel and Rose (1996) and Sachs et al. (1996)

KLR tested monthly data of 20 countries from 1970−1995 and estimated 15 variables with optimal thresholds for each country. In their study, the thresholds are optimized in relation to the observations of the indicator, thereby, maximizing the correct signals and minimizing the false. Their signal horizon is 24 months and the crisis index is defined as the weighted average of monthly percentage depreciation in the exchange rate and monthly percentage decline in reserves exceeding its mean by more than three standard deviations. The accuracy of each indicator is measured according to the percentage of correct signals to the percentage of false signals. Their findings show that most indicators send the first signals between 1−1.5 years before a crisis period. In their study, the best indicators for a currency crisis are the real exchange rate, exports, a banking crisis dummy, stock prices and the domestic money stock as a percentage of international reserves. Later, Kaminsky and Reinhart (1999) extended the KLR approach by combining information from several indicators into a single composite indicator of crises; a weighted sum of the indicators, where each indicator is weighted by the signal-to-noise ratio. However, the precision is not significantly better in comparison with KLR.

Since the publication of KLR, numerous authors have applied modified versions of the KLR approach on various other sets of currency crises. In comparison with KLR, the other models have presented both positive[2] and negative[3] results. Many of these studies focus on the currency crises in Asia during 1997. For example, Edison (2003) applied the KLR method to analyze the Asian crises in 1997. The KLR model shows some success in identifying zones of vulnerability, signaling a crisis some months before the Asian crises in July 1997. However, the model misses some of the actual crisis episodes and predicts crises that did not occur, thus the author himself concluded that the model, in general, performs poorly. Moreover, Edison suggested that EWSs must be supplemented by surveillance of individual countries. Lestano and Kuper (2003) show, using four groups of indicators for currency, banking and debt crises, better results on predicting the Asian crises.

Berg and Pattillo (1999a) tested the KLR approach on 23 countries, using data from January 1970 to April 1995, confirming that the approach can indeed be useful. However, the model predicts correctly most of the tranquil periods while the majority of crises are still missed. Moreover, Berg and Pattillo (1999a) also compared the KLR approach with a probit regression model, the latter model achieving slightly better results. However, Berg and Pattillo concluded that, although these methods enable identification of countries that are vulnerable to an impending crisis, they generally do not enable the prediction of the exact timing of a currency crisis.

A third approach for predicting financial crises uses artificial neural networks (ANN). The first publication on predicting financial instability using an ANN-based EWS was by Nag and Mitra (1999). Their results on predicting the Asian crises, in particular the Malaysian, Thai and Indonesian currency crises, suggest that their recurrent ANN performs better in comparison with the signals approach. Likewise, Franck and Schmied's (2004) application of a multilayer perceptron network to predicting the highly contagious speculative attacks in Russia in 1998 and Brazil in 1999 outperforms a logit model. Peltonen (2006) compares an ANN-based EWS for predicting currency crises in emerging markets with a probit model, however, showing poor results for both models. Lately, Fioramanti (2008) showed that an ANN approach, when applied to predicting debt crises, outperforms a random effect probit estimator.

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[2] Examples of models that outperformed the KLR model: Berg and Pattillo (1999a), Edison (2003) and Lestano and Kuper (2003).
[3] Examples of models that were outperformed by the KLR model: Furman and Stiglitz (1998), Alvarez-Plata and Schrooten (2004).

In previous research, the first author of this paper has employed an unsupervised neural network method, namely the Self-Organizing Map (SOM) in two exploratory studies of currency crises (Liu et al., 2010; Sarlin, 2010). Liu et al. (2010) introduced a visualization of early warning signals for currency crises; they use the SOM to visualize the evolution of economic indicators for the 1992–93 currency crisis in Finland. However, the SOM is not implemented as a general EWS for predicting currency crises. Furthermore, Sarlin (2010) proposes a generalized model for visualizing early warning signals of currency crises using the SOM; multidimensional panel data for a large set of countries are visualized on a two-dimensional grid.

Although the studies using ANN-based EWSs are few in number and at a preliminary stage, they seem to outperform the conventional statistical methods. However, direct comparisons between ANNs and statistical analyses, e.g. logit/probit models, are rare and seldom come to any crucial conclusions on superiority.

4. Self-Organizing Maps

The SOM is a non-parametric artificial neural network using an unsupervised learning method developed by Kohonen in 1980s. The network consists of two layers: the input layer and the output layer. The number of neurons in the input layer equals the number of data dimensions (variables). The output layer is a two-dimensional topologic grid (map) which is composed of a specified number of neurons (also called nodes or units). During the unsupervised learning, each neuron learns to attract data with similar characteristics, while also all neighboring neurons learn, with diminishing weight, to attract similar data. Hence, the areas on the map are organized according to some specific characteristics of data, and thus neurons can be divided into clusters of neurons.

The scope of application for the SOM is broad. The method has most commonly been applied in engineering and medicine (Oja et al., 2003), while it recently has increasingly been used in financial applications (e.g., Deboeck and Kohonen, 1998). The financial applications include credit assessment (Tan et al., 2002), bankruptcy analysis (Martín-del-Brío and Serrano-Cinca, 1993; Kiviluoto, 1998; Back et al., 1995) and financial benchmarking (Back et al., 1998; Eklund et al., 2003). Except Arciniegas Rueda and Arciniegas' (2009) study on speculative attacks' real effects and the visualization of early warning signals by Liu et al. (2010) and Sarlin (2010), the additional applications of the SOM in economic time-series analysis consists primarily of two analyses: classifications of countries according to socio-economic data (Kaski and Kohonen, 1996) and clustering of countries according to welfare and poverty (Collan et al., 2007).

Kohonen's training model serves as a foundation for all variants of the SOM algorithm. In this paper, the model will be explained in brief (for further details, see Kohonen (2001)). The training begins with an initialization phase in which the size of the map (number of neurons) is specified. Each neuron i on the map is allocated a parametric reference vector denoted by m_i. This vector is composed of the same dimensions (the amount of variables) as the actual dataset and its initial values are determined randomly.

The SOM algorithm has two steps: (1) finding the best-matching unit (BMU), i.e. the node whose reference vector is most similar to an input data vector, and (2) adjusting the reference vectors in a specified neighborhood of BMU so that they resemble even closer the input data vector. These two steps are repeated a specified number of times (iterations). The duration or length of the training process is set so that all data points are fed into the network a sufficient number of times, which enables the reference vectors to learn the input data patterns.

In the first step, the algorithm compares, using the Euclidean distance, each input data vector, x, with each of the network's reference vectors, m_i, to find the best match, m_c, i.e.

$$\forall i, \left\| x(t) - m_c(t) \right\| \leq \left\| x(t) - m_i(t) \right\|, (1)$$

where, at time t, the distance between the input data vector x and the winning reference vector m_c is less than the distance between input x and any other reference vector m_i. In the second step, the BMU and the neurons in a specified neighborhood of BMU learn from the input data vector x. The learning is controlled by a learning rate $\alpha(t)$ and a neighborhood function $N_c(t)$, where t denotes the time or step in the learning process, i.e.

$$m_i(t+1) = \begin{cases} m_i(t) + \alpha(t)[x(t) - m_i(t)], \text{if } i \in N_c(t) \\ m_i(t), \text{otherwise} \end{cases} . (2)$$

The learning coefficient $\alpha(t) \in [0,1]$ defines the relative pace of the learning and $N_c(t)$ denotes the size of the area around the winning neuron that is affected by the learning coefficient. In other words, the reference vector m_i learns from the input data vector x, if i is one of the neurons within $N_c(t)$. The learning rate is multiplied by the difference between the input data vector and the reference vector. Additionally, both $\alpha(t)$ and $N_c(t)$ are monotonically decreasing functions of time.

After the training is completed, the data points are arranged on the map based on their similarities. A node in the map can represent none, one or more data points, and in this sense the SOM method is considered a clustering method; it groups in the same node similar data points. Nevertheless, the SOM method projects the multidimensional data onto a two-dimensional grid, which makes the visualization of these data easy. The reference vectors obtained after training can further be used in clustering, the result being a partition of the map into higher-level clusters that group the similar nodes.

For this study, we have used the software Viscovery SOMine, which employs the batch training algorithm; a slightly different version of the earlier presented SOM algorithm. The batch algorithm (Vesanto et al., 2000) operates iteratively, similarly as the basic SOM algorithm. However, it differs by not processing the data vectors one by one (sequentially), instead the data vectors are processed simultaneously. It presents the whole amount of data to the map and each input data vector x_j is paired with a BMU, namely $c(j)$. Then each reference vector m_i is adjusted using the equation (3) instead of (2). That is,

$$m_i(t+1) = \frac{\sum_{j=1}^{n} h_{ic(j)}(t) x_j}{\sum_{j=1}^{n} h_{ic(j)}(t)}, (3)$$

where $h_{ic(j)}(t)$ is a weight that represents the value of the neighborhood function defined for the node i in the BMU $c(j)$ at time t. The index j indicates the input data vectors that belong to the neuron c, and n is the number of these vectors.

The most important advantage of the SOM batch algorithm is the reduction of computational cost. In the second step, the reference vectors are adjusted to averages of the attracted data vectors, including the input vectors located in the neighborhood. In Viscovery SOMine, the user specifies a so-called tension parameter as a measure of $N_c(t)$. The parameter describes the size of the neighborhood around the BMU that will affect the learning process. If a high tension is chosen, the training rounds off the results, while smaller values produce a detailed map. The tension can take values in the interval [0,2]. The neighborhood function is defined as being the Gaussian function.

Other parameters that can be set are the map size, the map format (square or rectangular), and the length of training (fast, normal or accurate). The length of training (number of training cycles) is related to the accuracy of the mapping measured in terms of quantization error: the longer the training time, the more accurate the mapping. The quantization error represents an average of the distances between the input vectors (x_j) and their corresponding best matching reference vectors ($m_{c(j)}$).

The output of the SOM algorithm, i.e. the mapping of the data points onto the two-dimensional grid, can be visualized in multiple ways, each having its own merit for increasing the understanding of the data (Vesanto, 1999). A useful visualization is provided by the feature planes. They are produced for individual columns of data and they represent graphically how different values of the variables are distributed over the map. Different color schemes can be used for this purpose (e.g. colored, grayscale and black and white). In this paper, we chose to use feature planes in color, where warm colors (red and yellow) represent high values and cold colors (blue and green) represent low values.

5. The SOM Model for Predicting Currency Crises

5.1 The Data

The data used in this paper are a replica of the dataset analyzed by Berg and Pattillo (1999b) (henceforth BP). The dataset consists of monthly data of the following five variables: the foreign exchange reserve growth (RESG), the export growth (EXPG), the real exchange rate overvaluation relative to trend (RDEV), the current account deficit relative to GDP (CANE), and the short-term debt in relation to reserves (STDR2). The dataset includes data for 23 developing countries for the period from 1970:1−1997:12. Table 1 presents the statistics for the data.

As the SOM is insensitive to missing data, small amounts of missing values are not considered a problem (Bigus, 1996). However, to have a comparable model with the one described in BP, we did not include the months which contain missing values in the training set. In addition, when calculating the model performance, all rows with missing data in the test sets are excluded. The splitting of the dataset into training and test sets is also done so that it enables direct comparison of results with those in BP. Thus, the training set includes the time frame 1986:1−1995:4 (shown in Table 1a), whereas the test set is divided into two subsets. First test set covers 1995:5−1996:12 (shown in Table 1b), and the second test set covers the year 1997. The variables in the datasets are transformed into percentile form, using the same procedure as BP, i.e. the raw data are converted into percentiles of the country's distribution for a variable over the whole in-sample period (1970:1–1995:4). The countries and crisis episodes are shown in Table 2.

The predicted variable is a dummy variable that indicates whether or not a currency crisis occurs within 24 months, and is defined in a similar way as in BP[4]. A crisis is defined to occur when the sum of a weighted average of monthly percentage depreciation in the exchange rate and monthly percentage declines in reserves exceeds its mean by more than three standard deviations[5]. Moreover, to avoid that crises are associated with high inflation, the sample is split into periods with low and high inflation, whereafter separate indices are constructed for each of the samples[6]. The pre-crisis period is defined to start 24 months before the crisis episode measured by the earlier definition. This variable is denoted in the dataset by C24 and is henceforth referred to by this name.

Table 1a: Statistics for data from 1986:1–1995:4 (training set)

VARIABLE	*ABBREVIATION*	*OBS*	*MEAN*	*STD.DEV*	*MIN*	*MAX*
Reserve loss	RESG	2474	-0.31	0.73	-13.12	0.83
Export loss	EXPG	2474	-0.12	0.21	-1.53	0.51
Real exchange rate deviation	RDEV	2474	-0.01	0.19	-0.78	1.23
Current account deficit to GDP	CANE	2474	1.41	4.55	-22.53	19.27
Short-term debt to reserves	STDR2	2474	2.17	3.71	0	41.76

Table 1b: Statistics for data from 1995:5–1996:12 (test set 1)

VARIABLE	*ABBREVIATION*	*OBS*	*MEAN*	*STD.DEV*	*MIN*	*MAX*
Reserve loss	RESG	441	-0.18	0.42	-3.2	0.68
Export loss	EXPG	441	-0.13	0.16	-1.2	0.25
Real exchange rate deviation	RDEV	441	0.15	0.19	-0.22	0.69
Current account deficit to GDP	CANE	441	2.88	3.57	-13.44	8.86
Short-term debt to reserves	STDR2	441	1.14	1.33	0.21	8.47

Table 1c: Statistics for data from 1997:1–12 (test set 2)

VARIABLE	*ABBREVIATION*	*OBS*	*MEAN*	*STD.DEV*	*MIN*	*MAX*
Reserve loss	RESG	262	-0.28	0.69	-4.30	0.58
Export loss	EXPG	262	-0.08	0.12	-0.50	0.30
Real exchange rate deviation	RDEV	262	0.15	0.20	-0.37	0.63
Current account deficit to GDP	CANE	262	2.80	3.94	-13.44	7.99
Short-term debt to reserves	STDR2	262	1.26	1.85	0.15	11.57

The foreign exchange reserve growth and export growth are on a given month defined as the percentage change in the level of the variable with respect to its level a year earlier. The real exchange rate is defined with respect to the US dollar on a bilateral basis and the overvaluation measured as the percentual deviation from a deterministic time trend. The current account deficit in relation to GDP is the ratio of a moving average of the current account deficit over the previous twelve-months in relation to a moving average of the GDP over the same period. The data for short-term debt is measured in relation to foreign exchange reserves. The export growth and reserve growth have been multiplied by -1. Thus, the EXPG and RESG actually represent export loss and reserve loss rates, respectively. This is particularly helpful when interpreting the models, because as we will see, in both the probit and the SOM model, high values of all variables will be associated with high probabilities of currency crises.

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[4] The definition of a crisis is originally from Kaminsky et al. (1998).
[5] Weighted so that the variances of the two components are equal.
[6] A further discussion on the optimal transformations of variables can be found in Berg and Pattillo (1999a) and Kaminsky et al. (1998).

Table 2: Countries and crisis episodes in the currency crisis model

Country	Crisis episodes	In-sample crisis episodes	Out-of-sample crisis episodes	Total number of crises
Argentina	1975, 1982, 1989-'90	1989-'90		4
Bolivia	1982-'83, 1985	-	-	3
Brazil	1979,1982-'83, 1990-'91	1990-'91	-	5
Chile	1972-'74	-	-	3
Colombia	1985, 1995, 1997	-	1995:8; 1997	3
India	1991, 1993	1991, 1993		2
Indonesia	1978, 1983, 1986, 1997	1986	1997	4
Israel	1974, 1977, 1983-'84	-	-	4
Jordan	1988-'89	1988-'89		2
Korea	1980, 1997	-	1997	2
Malaysia	1997		1997	1
Mexico	1976, 1982, 1994	1994		3
Pakistan	1972	-	-	1
Peru	1976, 1987	1987		2
Philippines	1983-'84,1986, 1997	1986	1997	4
South Africa	1975, 1984-'85,	-	-	3
Sri Lanka	1977	-	-	1
Taiwan	1970, 1987, 1997	1987	1997	3
Thailand	1981, 1997	-	1997	2
Turkey	1980, 1994	1994		2
Uruguay	1971-'72, 1982	-		3
Venezuela	1984, 1986, 1989, 1994-'96	1986, 1989, 1994	1995:12, 1996	6
Zimbabwe	1982, 1991, 1994, 1997	1991, 1994	1997	4
Total				67

The first four variables (i.e., reserve growth, export growth, real exchange rate overvaluation and current account deficit) represent macroeconomic fundamentals that according to the first-generation models indicate the occurrence of a currency crisis. The fifth variable (short-term debt in relation to reserves) is a measure of countries' vulnerability to an economic panic (Radelet and Sachs, 1998), which is an important factor in the second-generation models of currency crises.

5.2 Training the SOM Model

The training is done using the training set shown in Table 1a. The dataset is further pre-processed using the column-wise normalization by variance. The predicted variable C24 defining the pre-crisis periods and the CRISIS variable defining the crisis episodes are used as *associated attributes* in training, i.e. their priority is set to 0, meaning that they do not have any impact on the ordering process.[7] This operation enables us to visualize the areas on the maps that correspond to pre-crisis or crisis periods.

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[7] For further information on associating variables, see Deboeck (1998).

During the training process, several maps have been trained by tuning different parameters (map size, tension, cycles of training and number of clusters). After many experiments, we select for analysis a map with 67 nodes on an 8x9 lattice. Other parameters for training are accurate schedule (i.e., 4 training cycles) and a tension of 1.0. The average quantization error of this map is 1.59. We choose this map based upon both its interpretability and its in-sample accuracy.

In order to distinguish the early warning nodes from the tranquil nodes, the map is clustered using the Ward's (1963) hierarchical clustering with respect to the C24 variable. The map is partitioned into two clusters, thus generating an early warning cluster and a tranquil cluster. The map and its clusters are described in the next section.

5.3 The SOM Model

The SOM model of currency crises is a mapping of the time series multidimensional data on a two-dimensional grid. In addition, this grid is partitioned into two clusters, one representing the early warning signals or pre-crisis periods, and the other, the tranquil periods. The model is best interpreted by using visual means, for example, the feature planes. Figure 1 presents the feature planes of the five input variables, as well as of the associated C24 and CRISIS variables. The line that splits the maps into two parts shows the clustering of the map nodes based on the C24 variable. The left cluster represents the early warning cluster or crash cluster (henceforth CC), while the right represents the tranquil cluster (TC).

Each feature plane has its own color scale, which shows the correspondence between the variables values and colors[8], thus warm colors indicate high values of the variables, while cold colors, low values. The warm-colored nodes in the C24 map correspond to pre-crisis periods. Similarly, in the CRISIS map, red and yellow nodes indicate a higher proportion of crisis periods in those nodes.

For determining the nodes in the model that signal warnings of a currency crisis, we set a threshold value for the C24 associated variable. If this value is exceeded, then the node is classified as an early warning node (EWN). We set the threshold to 0.30 for the same reason stated in BP, namely that it generates false alarms in only 10 percent of the tranquil periods.

The feature planes for the input variables (RESG, EXPG, RDEV, CANE, and STDR2) facilitate the understanding of the characteristics of the pre-crisis periods. The pre-crisis periods can be divided into two sub-clusters of the CC: the lower and upper halves of the cluster. The lower half area is characterized by extremely high values for the real exchange rate overvaluation relative to trend. In addition, the reserve loss, export loss and current account deficit to GDP are average, while the short-term debt to reserves is low. The area in the upper half is characterized by high losses of reserve and export, a large current account deficit to GDP, and average values for the short-term debt to reserves and the exchange rate overvaluation.

The method applied to understanding the pre-crisis periods can also be applied to understanding the main characteristics of the crisis episodes. The crisis episodes are mainly mapped in the upper half of the CC. Consequently, the crises mapped into the upper left corner are characterized by high current account deficit and reserve loss, and low values for the exchange

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[8] The nodes representing export growth and reserve growth represent data that have been multiplied by -1, thus high values indicate a loss, while low values indicate growth. Moreover, all variables have been further transformed into percentile form, leading to a range [1, 100].

rate overvaluation. This agrees with the commonly accepted view that the collapse of a fixed exchange rate regime is often combined with an overvalued exchange rate, a current account deficit and a depletion of the foreign exchange reserves. Furthermore, the collapse of a fixed exchange rate regime causes depreciation in the exchange rate, thus justifying the low values for the exchange rate overvaluation.
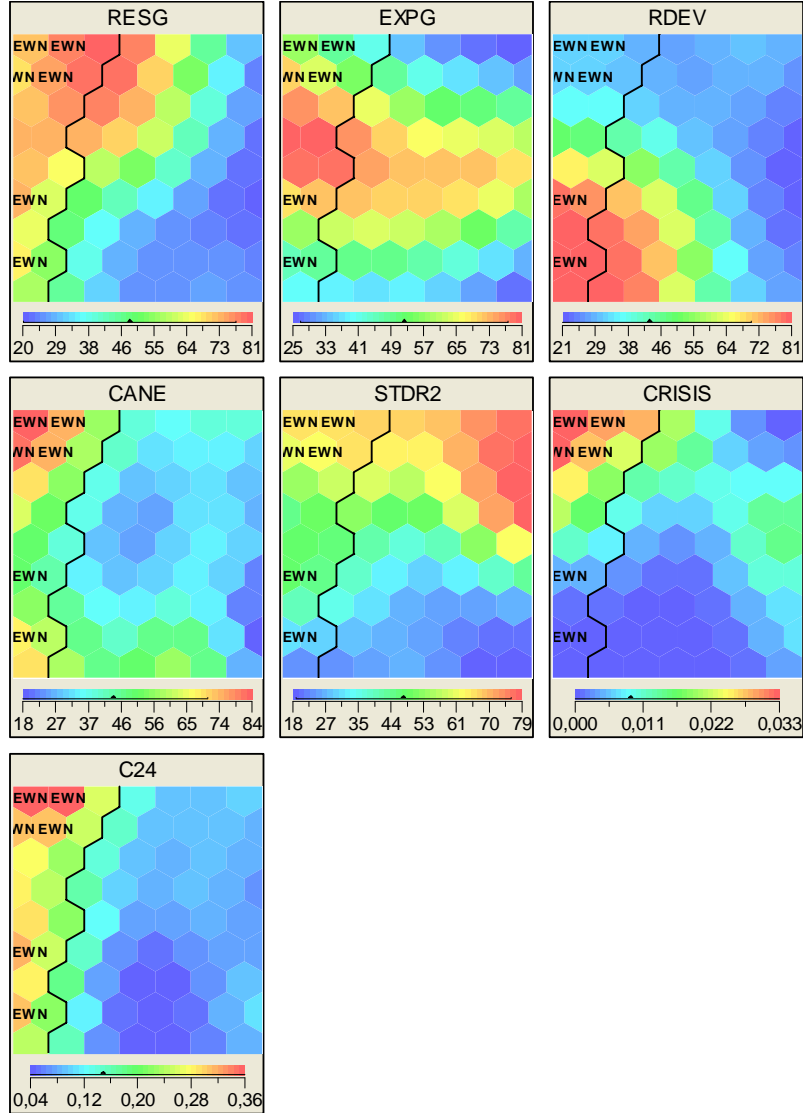

Figure 1: The feature planes for the SOM model

The model can be applied to new data (e.g., the test sets) and thus be used in prediction of currency crises. If the test data are mapped into an EWN, the respective month is considered an early warning signal, otherwise it is considered as a tranquil period.

6. Evaluation of the SOM Model

The performance of the model is measured in terms of accuracy, precision, recall, and type I and II error rates for predicting crash (pre-crisis) and tranquil periods. The accuracy measures the

overall accuracy of the model, i.e. the total number of correctly classified crash and tranquil periods in relation to the total number of periods. The precision measures the number of correctly classified crashes relative to the total number of predicted crashes, while the recall measures the number of correctly classified crashes relative to the total number of actual crashes. Likewise, precision and recall are also calculated for the tranquil months. Moreover, the percentage of type I errors measures the number of wrongly classified crashes relative to the total number of actual crashes, i.e. false negatives, while the type II error measures the number of wrongly classified tranquil periods relative to the total number of actual tranquil periods, i.e. false positives (or false alarms). These measures are calculated separately for the training and test sets.

6.1 Comparison with a Probit Model

We compare the SOM model with a replica of the probit model in Berg and Pattillo (1999b) (BP). The BP model is precisely reproduced and is thus fully comparable with our SOM model. The probit analysis is meant to identify the extent to which each explanatory variable is related to the dependent variable, namely the C24. Moreover, the model generates a prediction of the early warning signals. The estimates of the model are presented in Table 3.

Table 3: The BP probit model (replica)

Parameter	Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Intercept	-2.4749	.132	-18.715	.000	-2.607	-2.343
RESG	.0069	.001	5.608	.000	.004	.009
EXPG	.0019	.001	1.485	.138	-.001	.004
RDEV	.0050	.001	3.964	.000	.003	.007
CANE	.0109	.001	8.903	.000	.009	.013
STDR2	.0043	.001	3.541	.000	.002	.007

Table 3 shows that all variables, except export loss, are significantly related to the dependent dummy variable C24. The estimates show that the strongest relationships are between C24 and the current account deficit to GDP, reserve growth and the exchange rate overvaluation, respectively. These findings are also observed in the SOM model. The features planes of these attributes display patterns that confirm these relationships. On the one hand, in the upper half of the CC, the four EWNs display very high values for the current account deficit to GDP and the reserve loss. On the other hand, the two distinct EWNs in the lower half of the CC, show relationships with high values for exchange rate overvaluation and average reserve loss and current account deficit. This means that a high exchange rate overvaluation, if accompanied by a loss in reserves and a current account deficit, is likely to indicate an imminent currency crisis.

The prediction of the C24 variable is based on the estimates of the probit model and expressed in terms of a probability value. To be able to determine which values of the predicted C24 signify a pre-crisis period, and to assess the model fitness, a threshold for the probability has to be chosen. Berg and Pattillo specify the cut-off value to be 26.2 percent because it generates false alarms of an imminent crisis (false positives) in only 10 percent of the tranquil periods. The classification into crash (pre-crisis) and tranquil periods for the training set and the predictions for the test sets are summarized in Table 4.

Table 4: Performance measures of the probit model

| Dataset | TP | FP | TN | FN | Crash periods | | Tranquil periods | | Accuracy | FP rate |
					Precision	Recall	Precision	Recall		
Train set	126	211	1893	244	37.4 %	34.1 %	88.6 %	90.0 %	81.6 %	10.0 %
Test set 1	87	54	267	33	61.7 %	72.5 %	89.0 %	83.2 %	80.3 %	16.8 %
Test set 2	55	22	168	17	71.4 %	76.4 %	90.8 %	88.4 %	85.1 %	11.6 %

The performance of the SOM model is calculated in a similar manner as for the probit model. We used the values of the associated attribute C24 as the indicator for crash and tranquil periods. For a threshold value of 0.30, Table 5 presents the classification, prediction and the performance measures of the SOM model.

Table 5: Performance measures of the SOM model

| Dataset | TP | FP | TN | FN | Crash periods | | Tranquil periods | | Accuracy | FP rate |
					Precision	Recall	Precision	Recall		
Train set	125	208	1896	245	37.5%	33.8%	88.6%	90.1%	81.69%	9.9 %
Test set 1	89	40	281	31	69.0%	74.2%	90.1%	87.5%	83.9%	12.5 %
Test set 2	39	16	174	33	70.9%	54.2%	84.1%	91.6%	81.3%	8.4%

For the selected threshold, except for the second test set, the SOM model's performance is generally better than the performance of the probit model. In the training set, only one misclassification of a pre-crisis period is recorded. If the threshold value is chosen at a level that would include an additional node, namely 0.288, the accuracy rate in the in-sample data will be 81.33 percent, while the recall of pre-crises periods will be higher, namely 36.48 percent, accounting for 135 crash periods. Moreover, for the first test set, the change in the threshold value will result in predicting in total 93 crash periods, representing 77.5 percent of the total crash periods, and having an overall accuracy rate of 84.35 percent. This indicates that the SOM model would also perform accurately using a lower threshold.

Figure 2 shows how the in-sample accuracy, recall and false positives vary with different threshold values of the associated variable C24. In the picture, the C24 shows the probability of an imminent crisis for each node. The chosen threshold (0.30) is shown by the vertical line. The graph shows that when more nodes are defined as EWNs, i.e. the threshold is lowered, the accuracy decreases, while recall and false positive rates increase. The values on the horizontal axis represent the indices of the nodes in the SOM grid. In the Appendix, similar figures for both test sets are included (Figures A and B).
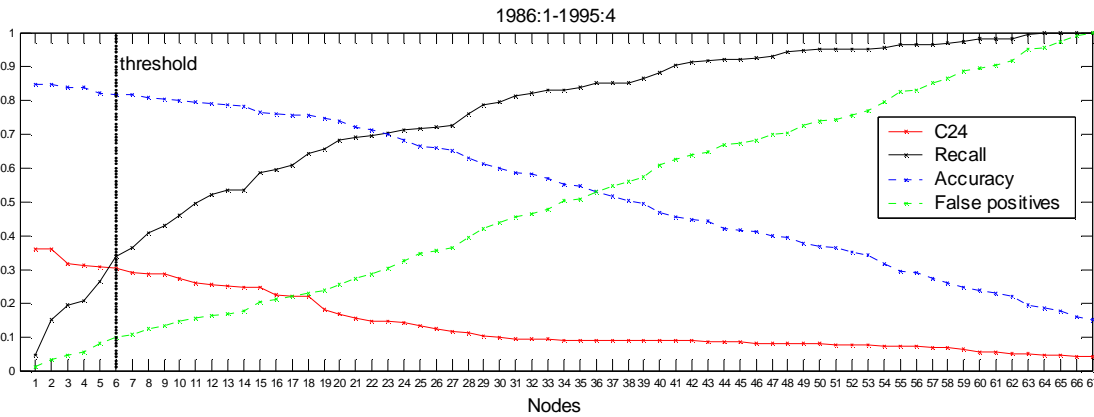

Figure 2: Ratios of accuracy, recall of crash periods and false positives for in-sample data. The threshold chosen (C24=0.30) includes six nodes in the SOM model.

13

In the second test set, the overall accuracy and the precision of the crash periods in the SOM model are high, but lower than in the BP model. The model identifies 54.2 percent of the actual crash periods, i.e. 39 out of 72 months. The lower recall rate on this set is mainly due to the failure in predicting the crises in two Asian countries that will be discussed in Section 7.

In addition to the goodness-of-fit based on a chosen threshold, we have used receiver operating characteristic (ROC) curves (Witten and Frank, 2005) to compare the performance of the two models on the training and test sets (Figures 3–5). In order to normalize the probabilities between the models, we have used the rate of false positives (FP) as a threshold. The accuracy is measured by the rate of true positives (TP). The ROC curves show the trade-off between the benefits and costs of choosing a certain threshold. When two models are compared, the best one has a higher benefit, expressed in terms of TPs on the vertical axis, at the same cost, expressed in terms of FPs on the horizontal axis.

As shown in Figure 3, for FP rates under 0.4, the ROC curves corresponding to the two models on the in-sample data are similar. For higher FP rates, the SOM model is more accurate. When the threshold is set to a false positive rate of 10 percent (see the vertical line), the models are equally accurate.

For the first test set, the ROC curves show that the probit model is superior for low FP rates, while the SOM model is more accurate for average FP rates (Figure 4). On the other hand, for the second test set, the ROC curves show that the SOM model is more accurate for low FPs, while the probit model is more accurate for average FP rates (Figure 5). For higher FP rates, both models are approximately equally accurate. To sum up, the probit model performs better on the first test set, while the SOM model performs better on the second. Thus, the ROC curves illustrate that the models show similar performance, varying as to the chosen dataset and threshold.
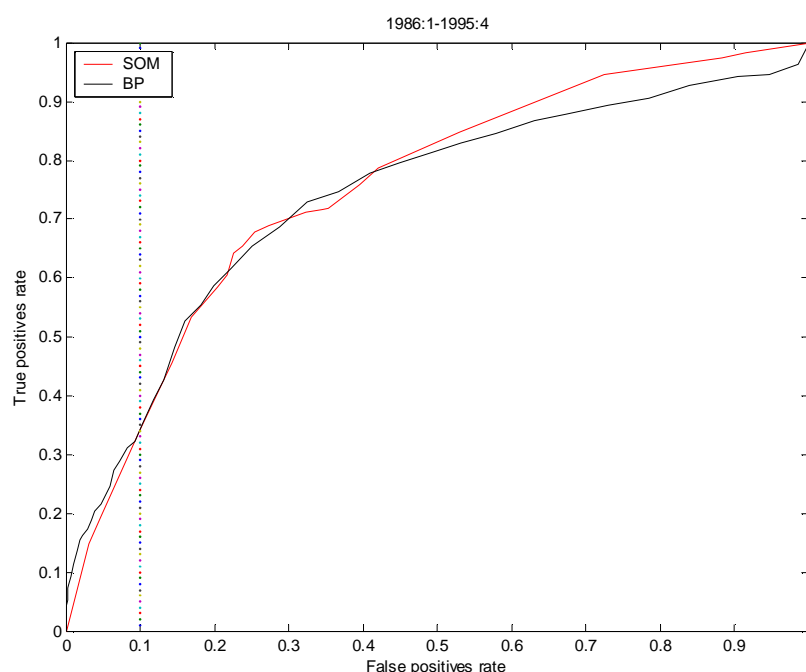

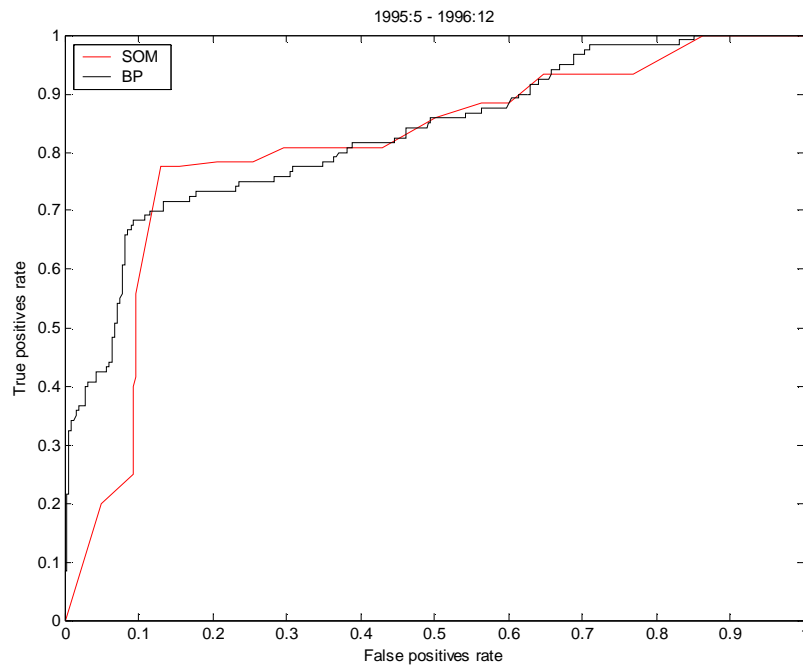*Figure 3: ROC curves for assessing the performance of the models on the training set*

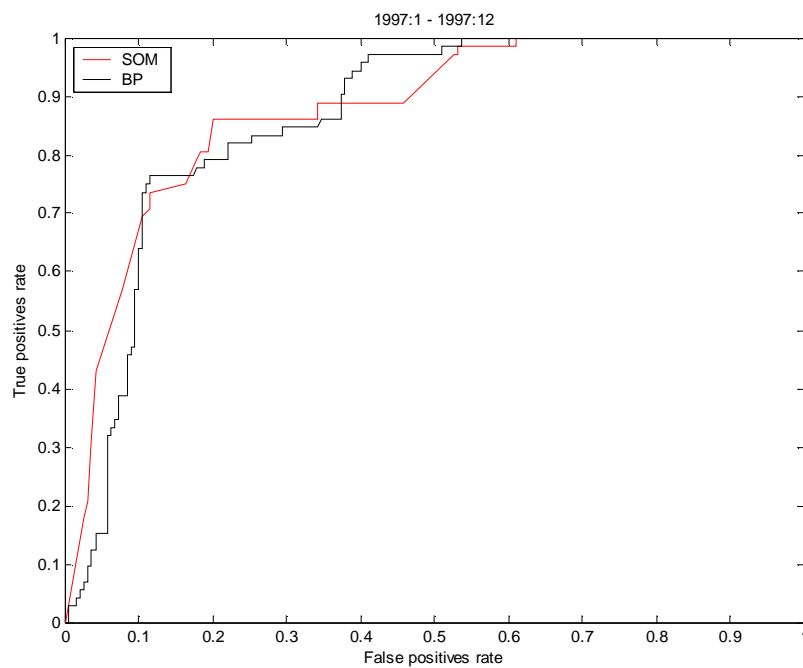*Figure 4: ROC curves for assessing the performance of the models on first test set.*

Figure 5: ROC curves for assessing the performance of the models on the second test set.

6.2 Country-Specific Evaluation of the Currency Crises

In this section, we present to which extent the currency crises have been predicted for each country. We discuss also some of the most extreme countries when measured by prediction

accuracy, with a special emphasis on the Asian countries. Table 6 presents the overall accuracy and recall rates for the whole sample (both in-sample and out-of-sample). The last three columns in the table show the average values of the C24, when the months belong to pre-crisis periods, tranquil periods, and for months with missing data, respectively. It is observed that, in most of the cases, high values of the C24 node correlate with the presence of pre-crisis months, while low values, with the presence of tranquil months.

In Table 6, there are a few remarkable differences between countries. The number of experienced crises explains to some extent the observed differences in performance. For example, countries not experiencing any crises (see Table 2) have in general the accuracy above 90 percent. Individual line graphs that show the value of the associated attribute C24 over the entire period are shown in Figure C in the Appendix.

Table 6: Individual in-sample and out-of-sample accuracies for the SOM model

Country	Overall accuracy	Recall (accuracy rate for predicting crises) *	Average value of the C24 nodes ** before crises *	Average value of the C24 nodes during tranquil periods	Average of the C24 nodes when missing data ***
Argentina	83.3%	47.1%	0.22	0.15	
Bolivia	89.4 %			0.12	0.15
Brazil	77.1 %	5.7 %	0.18	0.13	
Chile	98.6%			0.12	
Colombia	93.7 %	86.7 %	0.30	0.11	0.30
India	75.0 %	70.2 %	0.27	0.19	
Indonesia	77.1 %	71.9 %	0.33	0.17	
Israel	96.5 %			0.13	
Jordan	75.0 %	70.0 %	0.30	0.16	0.11
Korea	79.9 %	16.0 %	0.25	0.13	
Malaysia	89.6 %	89.7 %	0.31	0.11	
Mexico	82.6 %	33.3 %	0.26	0.12	
Pakistan	76.4 %			0.17	
Peru	80.6 %	17.4 %	0.23	0.17	
Philippines	83.3 %	16.0 %	0.16	0.11	
South Africa	94.4 %			0.14	
Sri Lanka	91.7 %			0.15	
Taiwan	56.6 %	54.5 %	0.23	0.26	0.31
Thailand	91.0 %	89.7 %	0.31	0.12	
Turkey	70.0 %	12.0 %	0.19	0.15	0.11
Uruguay	99.3 %			0.12	
Venezuela	57.6 %	34.1 %	0.25	0.11	
Zimbabwe	70.2 %	33.3 %	0.19	0.10	0.22
Average	82.13%	46.73%	0.25	0.14	-

* The empty cells correspond to countries for which no currency crises were encountered.
** The C24 node represents the associated attribute C24 (i.e., the predicted probability of a crisis).
*** The missing data regarding Bolivia and Turkey do not coincide with the crash periods. Jordan has missing values in 12 months: 2 pre-crises and 10 tranquil months. The missing data regarding Colombia and Zimbabwe do coincide with crash periods. These facts are successfully discovered by the SOM model despite the missing data values. However, Taiwan has one month (1997:12) with missing values which corresponds to a tranquil period, but which comes soon after the crisis in October.

The poor classification accuracy for the 1994 crisis in Turkey may be due to the fact that Turkey has many missing values in its data. Another cause may be the fact that the 1994 currency crisis in Turkey was partly explained by other factors than currency crises in general. Kibritcioglu et al. (1999) state that the currency crisis was explained by unobserved second-generation variables, besides fundamental variables. More precisely, due to forthcoming elections, the government was reluctant to increase the interest rates in order to avoid a devaluation of Turkish lira.

Table 7 presents the out-of-sample accuracies and the averages of the C24 associated attribute for the countries that experienced a currency crisis in the test period 1995:5–1997:12. The recall rates are very high for the crash periods. The only low values are encountered for Korea and the Philippines.

The tranquil months that are mapped onto the C24 nodes with high values are, in most of the cases, explained by the fact that these months were either before pre-crisis periods or immediately after the crisis episodes. Thus, in some of these countries, e.g. Indonesia, Malaysia and Taiwan, the economic conditions showed signs of an imminent currency crisis even before the 24-month period prior to the crisis. Moreover, both during and immediately after a currency crisis, it is likely that indicators still signal imbalances in the economy. That is, in some countries, e.g. Colombia, Indonesia, Malaysia, and Taiwan, either it takes a longer time for the economy to recover or the indicators signal a crisis before the 24-month period.

Table 7: Individual out-of-sample 1995:5–1997:12 accuracies for the SOM model. Only countries that experienced a crisis during this time are shown.

Country	Overall accuracy	Recall (accuracy rate for predicting a crises)	Average value of the C24 node before crises	Average value of the C24 node during tranquil periods	Average of the C24 node when missing data
Colombia*	83.9 %	92.3 %	0.31	0.30	0.30
Indonesia	81.3 %	95.8 %	0.34	0.28	
Korea	34.4 %	16.0 %	0.25	0.10	
Malaysia	81.3 %	89.7 %	0.31	0.31	
Philippines	37.5 %	16.7 %	0.16	0.19	
Taiwan**	77.4 %	100.0 %	0.33	0.36	0.31
Thailand	90.6 %	89.7 %	0.31	0.16	
Venezuela	90.6 %	72.7 %	0.25	0.07	
Zimbabwe ***	100.0 %			0.25	0.22
Average	75.22%	71.61%	0.28	0.22	

* Columbia has one pre-crisis month with missing data.
** Taiwan has one month (1997:12) with missing values which corresponds to a tranquil period after the crisis in October.
*** Zimbabwe experienced a crisis in 1997, but the months corresponding to the pre-crisis period contain missing values and therefore we did not use them in the calculation of accuracy. The last column shows that these months have generally a high value of the C24. Thus, most of them would, if they would be projected on the SOM grid, enter in the CC, although not in the EWNs.

7. Visual analyses of currency crises

7.1 Monitoring the evolution of a country

Using the SOM model described in Section 5, one can also monitor the evolution of a country over time. In this situation, only the labels for the country under analysis are displayed. Economic conditions mapped into the CC give weak signals of an imminent currency crisis. If the conditions are mapped into an EWN, a strong signal of an imminent currency crisis is given. This approach can be visualized using trajectories, i.e. lines that connect every consecutive data points that are labeled. Figure 6 shows trajectories for semi-annual labels from 1986:1−1996:12 for Colombia, Thailand and Uruguay.

Colombia experienced its first crisis in the end of 1995. The map shows that the macroeconomic conditions are mapped into the TC until mid-1993, thereafter the conditions move into the CC and, eventually, in early-1994, into an EWN. The second crisis episode was in 1997 and, in accordance with that, the variables move between two different EWNs, except in mid-1997, until the end of the sample period.

The trajectories for Thailand are shown in the middle map in Figure 6. Thailand experienced only one crisis episode in 1997. The macroeconomic conditions move into the CC already in 1993, thereafter they move back into the TC. The variable values move into an EWN in early-1996 and stay there until the end of 1997.
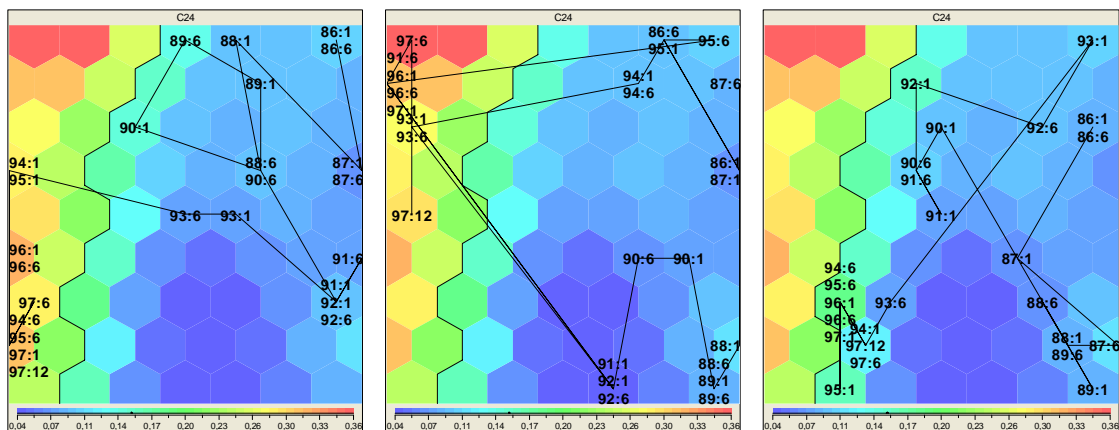
Figure 6: Trajectories for Colombia (left); Thailand (middle); Uruguay (right)

Uruguay did not experience any crisis. Figure 6 (right) displays the economic conditions in Uruguay for the selected path. The country approaches the CC in the end of the sample period. A possible explanation for the movement of the variables is the global impact of the Asian crises in 1997 and their effects on the imminent South American economic crises.

7.2 Benchmarking countries' vulnerability at a given time

Another use of the SOM model is in benchmarking a set of countries at a given point in time. This gives an overview of the countries' vulnerability to an imminent crisis episode. Figure 7

displays the countries in the dataset, projected as to their conditions in 1996:1 and 1997:12, in the left and right maps, respectively[9].
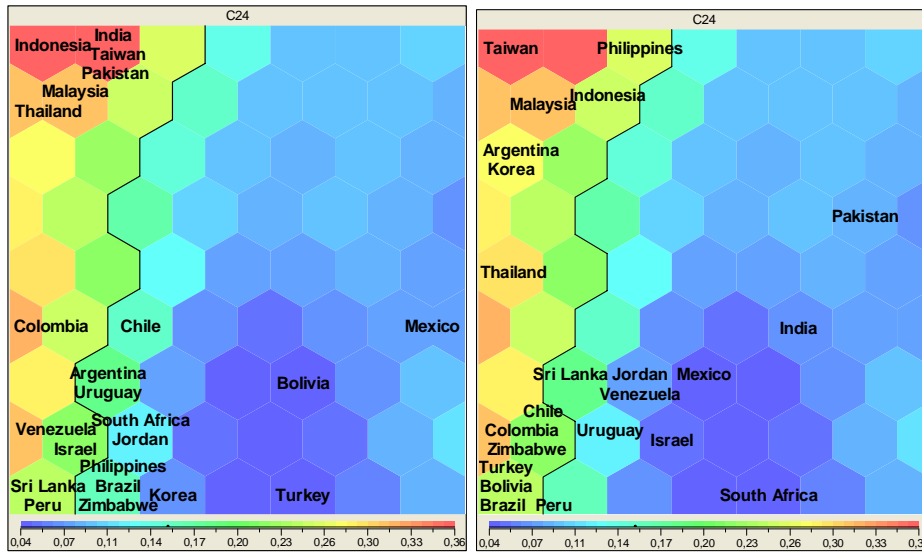

Figure 7: Mapping 1996:1 (left) and 1997:12 (right) for all countries in the dataset

In 1996:1, the upper left corner of the map represents most of the South Asia countries, while the lower left corner represents generally the rest of the countries. Two South Asian countries are not mapped in the upper left corner, namely the Philippines and Korea. Their crisis episodes in 1997 were also the two most poorly predicted. Eventually, in the end of 1997, both Korea and the Philippines have moved into the upper left corner. The feature planes show the changes in the macroeconomic conditions that are associated with this movement (e.g., exchange rate depreciation, high reserve loss).

The country monitoring and the benchmarking can be combined and used to understand further why the predictions for Korea and the Philippines have been quite inaccurate. Figure 8 shows the economies from South East Asia before the crisis in 1997. In the left map, Indonesia (IND), Malaysia (MAL) and Korea (KOR) are shown, while the right map shows the Philippines (PHI), Thailand (THA) and Taiwan (TAI).

The economic conditions in Korea move in the CC without entering the EWNs much before the collapse of the currency. The C24 nodes in the map in Figure 8 indicate that Korea's probability for an imminent crisis is, for a long period, only slightly under the chosen threshold. The economic conditions of Taiwan and Thailand are, except the first and last vector for Thailand, situated in the EWNs. An interesting remark is that although Taiwan was one of the last Asian economies to devalue their currency (October 1997), their macroeconomic variables were mapped into an EWN during the whole out-of-sample period. The economic conditions of the Philippines, on the other hand, are situated in the lower-left corner of the map until the crisis vector in December 1997. In other words, although having an overvalued exchange rate, the Philippines macroeconomic variables did not indicate an imminent crisis, since the warning signals given by other variables were not strong enough.

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[9] When the defined month had missing data, the preceding complete month was chosen. For Zimbabwe, as the earliest complete data vector was in 1995, the best predicted month in 1997, namely October, was chosen.
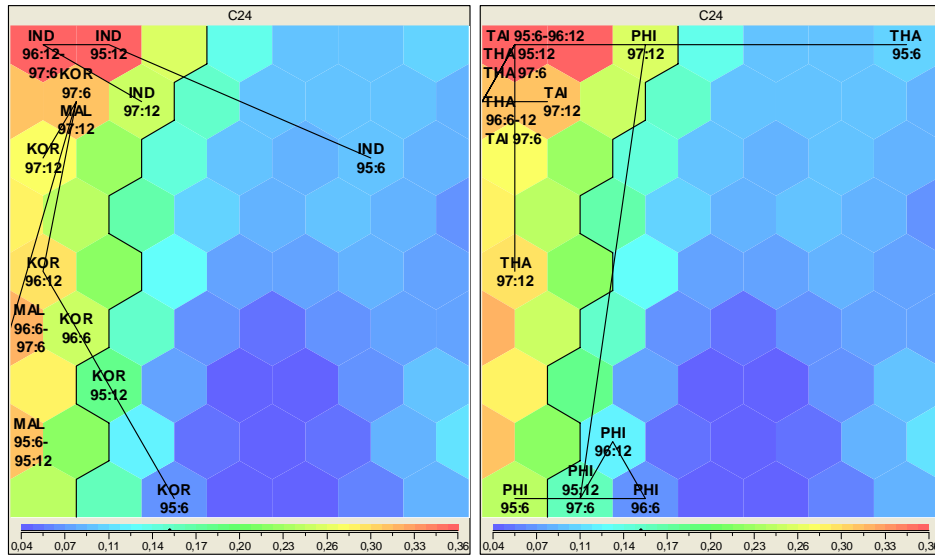
Figure 8: The trajectories for Indonesia, Malaysia and Korea (left), and the Philippines, Thailand and Taiwan (right)

The maps in Figure 8 show that most of the crisis episodes in Asia are predicted correctly by the SOM model. This means that the macroeconomic variables used in the model are able to capture the effects of contagion that affected the countries, thus giving early warning signals of an imminent crisis.[10]

8. Conclusions

Anticipating crisis episodes interests decision-makers in many fields; policymakers want to avoid economic fluctuations, financial market participants want to earn profits, and businesses want to set production to optimize profits. This paper contributes to the literature on crisis prediction with two main findings: the powerful visual presentation of early warning signals using the SOM and the good prediction accuracy of the model.

The first key finding is that the SOM is capable of classifying and describing macroeconomic time-series data according to vulnerability for an imminent crisis. For this task, the SOM was used in conjunction with the Ward-clustering algorithm. Moreover, the predicted variable was entered as an associated attribute and used to classify the nodes into early warning and tranquil nodes. To describe the economic conditions prior to currency crises, the visual features of the SOM, namely the feature planes, have been used for monitoring a large set of variables simultaneously. In addition, we demonstrated how the SOM model can be used for analyzing the evolution of individual countries, thereby signaling unfavorable conditions. Moreover, the SOM model has been used for benchmarking countries as to their vulnerability to an imminent crisis.

The second key finding is that the prediction accuracy of the SOM model is equally accurate and to some extent superior in comparison with a multivariate probit model. When comparing the two models' in-sample performance using an unbiased threshold, the models show almost

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[10] The crises in Asia are explained in the literature, e.g. Masson (2001), Park and Song (1999) and Schmukler et al. (2001), as crises triggered by contagion from neighboring countries.

identical accuracy, precision and recall when predicting both crisis episodes and tranquil periods. However, when predicting crises out-of-sample using the chosen threshold, the SOM model shows better accuracy, precision and recall for both types of periods.

For results that are independent from the chosen threshold, we compared the models' ROC curves. Although the models have slightly different performances, depending on the chosen dataset and threshold, the ROC curves for the in-sample and both out-of-sample models show that their performance is similar. Thereby, our conclusive finding is that the SOM model does not only visualize early warning signals intuitively, but performs equally well in comparison with a conventional statistical method, in terms of classification and prediction accuracy. Moreover, the missing data do not cause problems; the prediction accuracy is stable even when incomplete data are tested. This confirms that missing data is not considered a problem for the SOM.

An idea for future work is to add more variables to the model – variables that are extensively discussed in the theoretical models of currency crises. Moreover, this study focused on currency crises, but the same analysis could, using a different set of variables and crisis definitions, be conducted on other types of crises, e.g. banking and debt crises. However, for optimal results in monitoring financial stability and predicting crises, the SOM should be used in combination with other methods, all employing their respective advantages.

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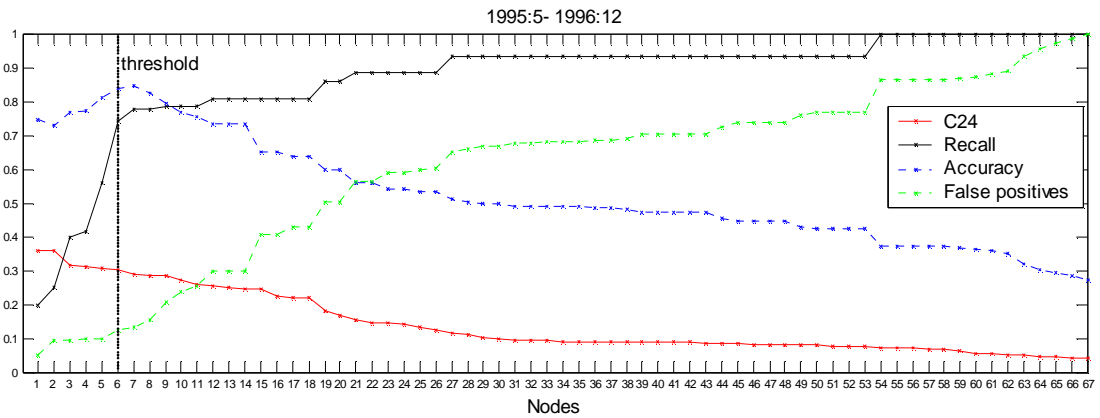
Appendix

Figure A: Ratios of accuracy, recall of crash periods and false positives for the 1995:5–1996:12 out-of-sample data. The threshold chosen (C24=0.30) corresponds to six nodes in the SOM.
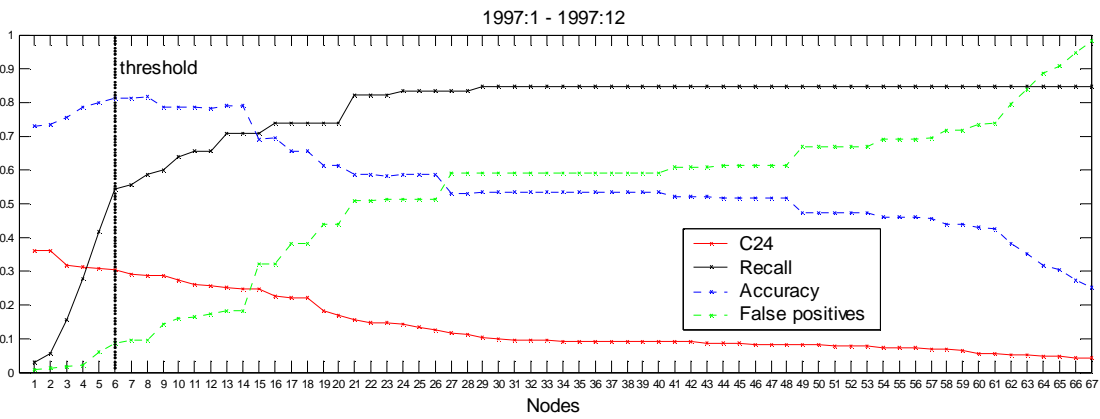

Figure B: Ratios of accuracy, recall of crash periods and false positives for the 1997 out-of-sample data. The threshold chosen (C24=0.30) corresponds to six nodes in the SOM.
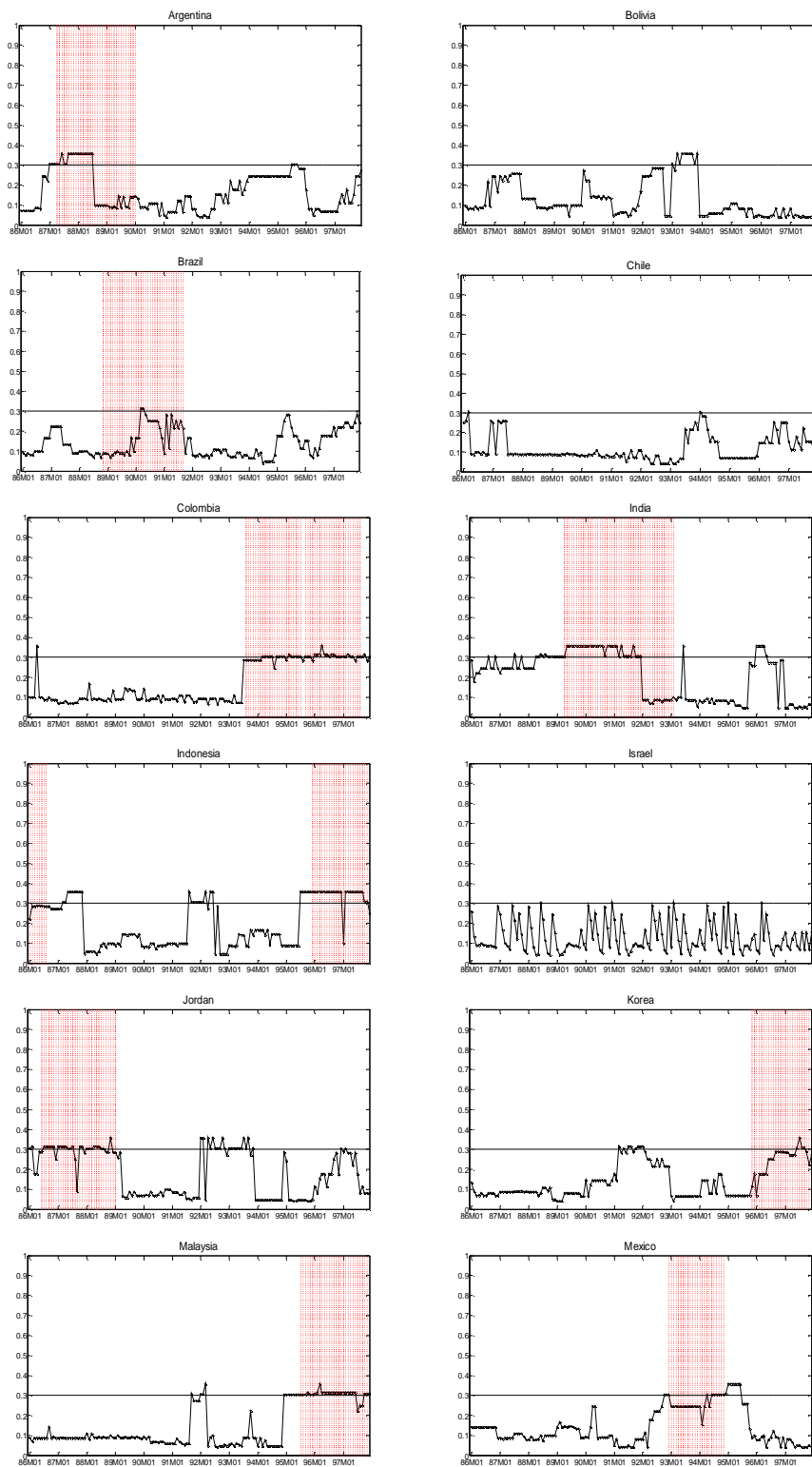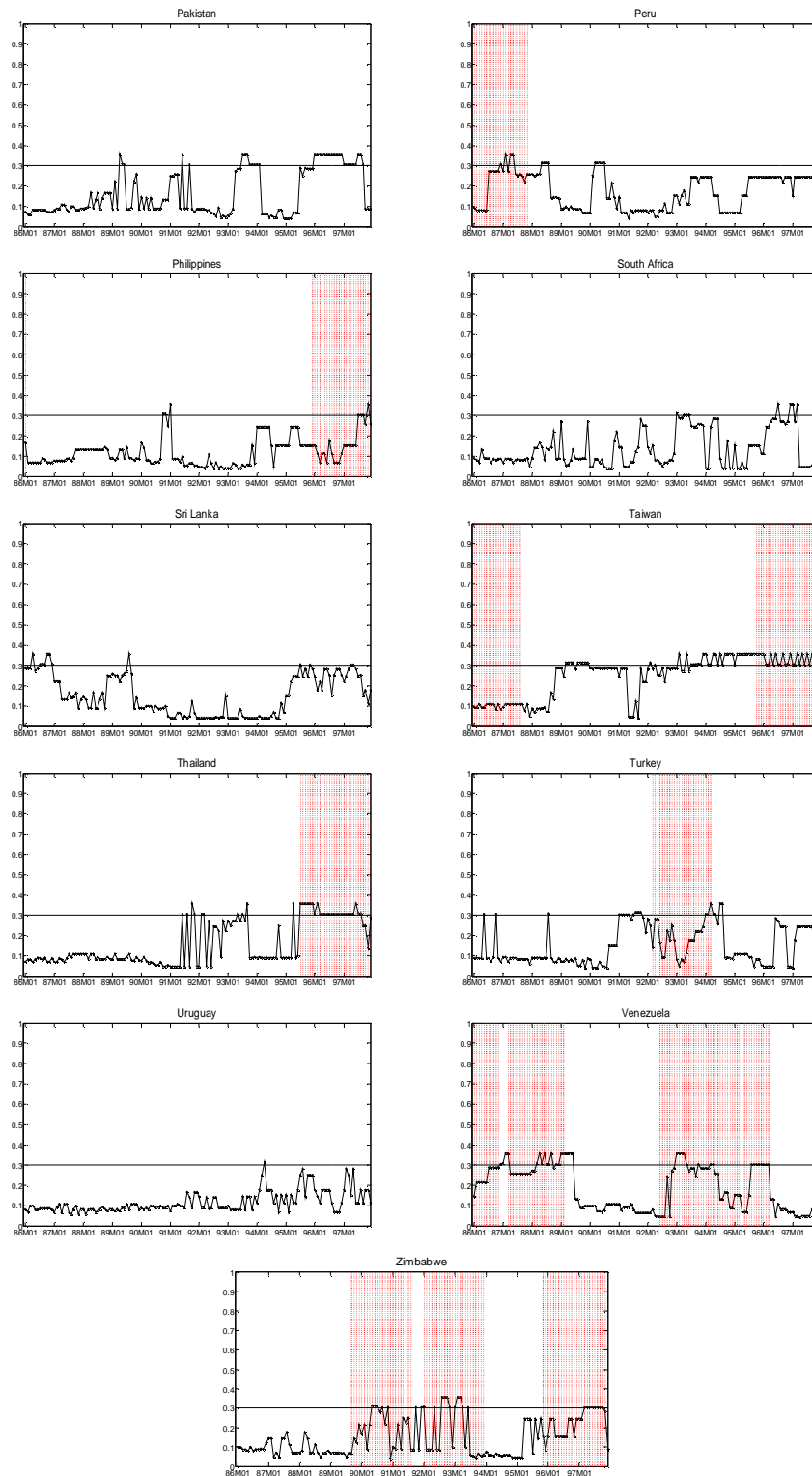
Figure C: The associated attribute C24 for each country during the entire time span. Values of C24 higher than the threshold 0.30 indicate the presence of crisis within 24 months. The shadows represent the actual pre-crisis periods.(Cont.)

Figure C: The associated attribute C24 for each country during the entire time span. Values of C24 higher than the threshold 0.30 indicate the presence of crisis within 24 months. The shadows represent the actual pre-crisis periods.(Cont'd)
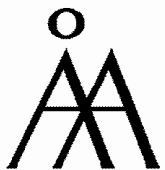
27

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