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Early Warning System for Currency Crises in Emerging Markets

Relatore: Prof. Guido Traficante

Correlatore: Prof. Marco Morelli

Candidato: Vincenzo Napoli

Matricola: 733951

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Introduction

The COVID-19 pandemic has had a profound impact on the global economy in recent years, leading to widespread inflation. A range of factors, including supply chain disruptions, a surge in demand for goods and services during the reopening phase after lockdowns, and massive monetary stimuli implemented by governments and central banks globally, have contributed to this inflation. The sustained increase in prices, particularly for essential items such as food and fuel, has raised public concern. To mitigate inflationary pressures, central banks worldwide have adopted monetary policies aimed at controlling inflation, including an increase in interest rates.

The United States have also experienced an inflation trend, with a peak of 9.1% in June 2022, the highest level in over four decades. In response, the Federal Reserve implemented a stringent monetary policy, leading to an increase in interest rates to 4.75%. The monetary policy of the United States exerts a significant impact on economies globally, particularly on emerging nations, as a significant portion of their debt is denominated in US dollars. The increase in interest rates causes the currency to appreciate, further exacerbating the already challenging economic conditions faced by these nations.

The likelihood of a drop in raw material prices, a crucial aspect for the economies of many developing countries, particularly in South America, due to the potential of a worldwide recession, coupled with these various factors, exposes the currencies of these emerging countries to the risk of devaluation. The objective of this research is to utilize an early warning system to assess if there are countries at risk of a currency crisis and, if so, establish a ranking to determine which countries are most susceptible to a currency crisis.

The first chapter of the thesis is devoted to a literature review of the early warning system. After a brief description of the first generation model introduced by Krugman (1979), and the second generation ones introduced by Ozkan and Sutherland (1995) and Obstfeld (1995, 1996), three models proposed prior to the 1997 Asian currency crisis will be described: the FR model, proposed by Frankel and Rose in 1996; the STV model, developed by Sachs, Tornell and Velasco in 1996; and the KLR model, also known as the "signal extraction", introduced by Kaminsky, Lizondo and Reinhart in 1998. In the second part, it will be shown why the KLR model is the best for the purposes of this work, and it will also be demonstrated, using the work of Andrew Berg and Catherine Pattillo (1999b) that it is also the model that provides the best out-of-sample results.

The second chapter will present the model that will be used to calculate the current probability of a currency crisis. This model will focus on 18 countries from three different regions: Asia (Indonesia, India, Malaysia, Pakistan, the Philippines, Singapore, and Thailand), South America (Argentina, Bolivia, Brazil, Chile, Colombia, Mexico, Peru, Uruguay, and Venezuela), and other countries (Turkey and South Africa). The historical data for the model covers the period from 1980 to 2002. I have chosen to exclude the 1970s from my study as many data points from that period are no longer available and it would not be relevant to include outdated information. Additionally, I have decided not to extend beyond 2002, as there have been relatively few currency crises in recent years.

The final chapter of the thesis will utilize a composite indicator approach to analyze the risk of a currency crisis in the selected countries. The methodology involves combining the results of individual indicators into a single index by assigning weights to each indicator based on its past performance. The composite index will be transformed into a probability, with a higher value of the index indicating a higher likelihood of a currency crisis.

Chapter 1: Historical literature of Early Warning System

Introduction

In the second half of the 20th century, a lot of researchers started to develop models that attempted to predict currency crises in countries that decided to peg their currencies. The peg is a practice in which a country ties the exchange rate to another currency that is relatively stable, such as the dollar or the euro. The primary reasons that lead a country to take this decision are: to reduce foreign exchange risk, to have a strong competitive position with other international trading partners, be more credible and reliable in the eyes of international investors and in general to improve the stability of the currency. In some cases, maintaining the peg could be dangerous. If a currency is pegged at an overly high rate, the domestic goods will be too much expensive in comparison with the foreign ones and so the consumers will buy too many imports and drive up the demand. This situation can create a chronic trade deficit that puts a lot of pressure on the home currency. Consequently, the Central Bank would be forced to sell its foreign exchange reserves through open market operations and interventions in the forward exchange market in order to defend the peg. When the government's reserves are completely depleted, the peg will collapse.

When a currency peg fails, imports become more expensive, inflation rises, and a country may have difficulty paying its debts. The problem is even more severe in emerging markets, where after a currency crisis the average cumulative loss of real output (relative to trend) is 8%, and it can cause a contagion effect that increases the likelihood of other economies experiencing spillover effects. This significant impact on the economy prompted a large number of researchers to attempt to develop models for preventing this type of crisis. If a model could accurately predict a currency crisis, policymakers would be able to take the necessary measures to prevent or at least mitigate its effects.

In the 1980s and early 1990s, the literature was divided into 2 schools of thought. The first-generation, prevalent in the 1980s, viewed the fundamental weaknesses of a country as the primary cause of the crisis; while the second-generation gave less importance to fundamental factors and emphasized the self-fulfilling nature of currency crises and the fact that crises are extremely difficult to predict. Now we will analyze the models of the pioneers of both generations, focusing on how they were developed and their most significant flaws.

First-generation models

Krugman's (1979)[1] work marked the beginning of the first-generation models; he focused on countries with shaky economic fundamentals resulting from expansive fiscal and credit policies. He observed that excessively expansive policies increased the demand for traded goods, causing relative price increases and a currency appreciation. Together with the increase in credit expansion, the real appreciation caused a significant and persistent decline in international reserves.

The gradual but consistent depletion of international reserves leads economic agents to rebalance their portfolios by decreasing the proportion of assets denominated in domestic currency. This change is caused by the lower returns of domestic assets and fears that the government will be unable to maintain the exchange rate system. This outflow of capital causes the demand for money to fall faster than the available reserves, resulting in a sudden speculative attack that wipes out the central bank's remaining foreign reserve stock and forces the government to abandon parity.

Krugman's analysis is based on a model that is highly simplified. It assumes a small open economy that produces a single tradable goods with a price determined by the global market, where domestic and foreign currencies are the only assets available to investors and nominal interest rates are zero.

[1] Krugman, Paul. 1979. A model of balance-of-payments crises. Journal of Money, Credit and Banking 11: 311–25.

Since in the model the only way a government can lock in the exchange rate is to sell international reserves, the assumption that only two assets are available restricts government actions in an unrealistic manner. In a more realistic model, alternative exchange rate stabilization policies should be accounted for. Even with this flaw, the analysis helps explain why trying to keep exchange rates fixed so often leads to crises.

Second-generation models

Scholars of the second generation have harshly challenged first-generation models that identify a fundamental crisis as the primary reason of the exchange rate's collapse. The models were developed in the wake of the 1992-1993 European Monetary System (EMS) crises, which saw a speculative attack on certain currencies despite the pegs being fundamentally sustainable. The crisis affected the exchange rates of countries, most notably England and Italy, whose economic fundamentals were safe and whose international reserves did not exceed critical thresholds.

One of the key characteristics of these models is that policymakers constantly monitor the sustainability of the peg. The parity is abandoned when the evolution of key economic variables, such as interest rates and unemployment rate, causes the costs associated with the peg to outweigh the benefits. For instance, in Ozkan and Sutherland (1995)[2], the maintenance of the peg is primarily connected to the evolution of foreign interest rates. To maintain parity, the authorities must raise the domestic interest rate in response to an increase in the foreign interest one. Higher interest rates result in higher financing costs and consequently banking system problems. When foreign interest rates rise above a certain threshold, the cost of maintaining the peg exceeds its benefits and the policymakers abandon it.

[2] Ozkan, F. Gulcin, Alan Sutherland, 1995, "Policy Measures to Avoid a Currency Crisis," Economic Journal, Vol. 105 8March), pp. 510-519

According to these models, a currency crisis could occur without a change in fundamentals, but rather as a result of a speculative attack driven by market participants' expectations. The attack of the speculators is motivated by the awareness that the authority will abandon the peg following the attack, allowing them to make a significant profit. One of the most prominent proponents of this theory, Obstfeld (1996)[3], outlines the mechanisms by which self-fulfilling currency crises emerge. Initially, the economy may be in equilibrium, but in countries with high public debt, the expectation of currency depreciation causes domestic interest rates to rise. The government will decide to end the peg out of concern for rising public spending and banking sector pressure. With these models, an economy can move from an equilibrium with no expectations of devaluation and a sustainable peg to one with high expectations of devaluation and a peg that becomes unsustainable, with no change in fundamentals. As a result, unlike Krugman's model, forecasting a currency crisis is extremely difficult for second-generation models.

The first- and second-generation models' early warning systems have several limitations. In their study, Eichengreen, Rose, and Wyplosz (1995)[4] proved that political issues and an increase in the interest rates on bonds denominated in the local currency are not typical precursors to currency crises. This study demonstrates that the principle underlying self-fulfilling crisis models lacks empirical support, as it is implausible that these crises were caused by economic agents who accurately foresee future policy deterioration. Eichengreen, Rose, and Wyplosz also demonstrated that crises were not due to the causes identified in the traditional approach (first-generation model), which was primarily based on budget deficits, paving the way for new models in which the devaluation of the currency is driven by a number of variables other than international reserves.

[3] Obstfeld, Maurice. 1996. Models of currency crises with self-fulfilling features. European Economic Review 40: 1037–47.

[4] Eichengreen, Barry, Andrew K. Rose, and Charles Wyplosz, 1995, "Exchange Market Mythem: The Antecedents and Aftermath of Speculative, Attacks" Economic Policy, Vol. 21 (October), pp., 239-312

Different methodologies of Early Warning System

In this section, I will evaluate the various methodologies that use different variables to predict currency crises. The studies can be grouped into four major methodological categories. The first group focuses solely on qualitative analysis, highlighting the evolution of some indicators. I will not review any research that falls into this category because, in these papers, the selection of key indicators is completely arbitrary, and no tests are done to see if they are statistically significant.

In the second group, the behavior of a variable during non-crisis periods is compared to its behavior during a crisis. To determine whether there are systematic differences between precrisis episodes and the control group, a nonlinear regression model is employed. These tests can be used to determine which variables exhibit anomalous behavior prior to a crisis. Frankel and Rose's Probit model[5] will be analyzed in relation to this group.

The third group is based on an estimate of the likelihood of devaluation one or more periods in the future. Individual country studies and multicounty panel studies are examples of this methology; the most important model in this category is the Sachs, Tornell, and Velasco (1996)[6] Tequila Crisis Model. It is a Cross-Country Regression model that attempts to identify macroeconomic variables that can assist in explaining which countries were vulnerable to the effects of the Mexican crisis in December 1994.

The final methodology is employed by Kaminsky, Lizondo, and Reinhart's (1998)[7] Signal Approach, which is based on the creation of a non-parametric model that tracks the evolution of a

[5] Frankel, Jeffrey A., and Andrew K. Rose, 1996. Currency Crashes in Emerging markets: An Empirical Treatment, Journal of International Economics, Vol. 41 (November): 351-66

[6] Sachs, Jeffrey, Aaron Tornell, and Andres Velasco, 1996. Financial Crises in Emerging Markets: The lesson from 1995. Brookings Papers on Economic Activity: 1, Brookings Institution: 147-215

[7] Kaminsky, Graciela, Saul Lizondo, and Carmen M. Reinhart. 1998. Leading indicators of currency crises. IMF Staff Papers 45: 1–48.

large number of economic variables. It is an extension of the second methodology, which compares the behavior of variables in periods preceding crises to that of the control group. The deviation of these variables from their norm is interpreted as an indication of a potential currency crisis. On the basis of the past performance of the various indicators, it is possible to evaluate their individual and combined capacity to forecast crises.

Frankel and Rose (1996) Probit Model

Frankel and Rose created the model using annual data from 105 countries from 1971 to 1992. The use of annual data restricts the applicability and implementation of the model as an early warning system, but it permits the use of extremely important variables, such as external debt, for which monthly or quarterly data are rarely available. The currency crisis is defined as "a minimum of 25% nominal depreciation that also exceeds the previous year's change in the exchange rate by at least 10%," excluding episodes of high inflation and speculative attacks successfully avoided by the authorities.

The analysis conducted by Frankel and Rose encompasses a vast array of economic variables classified as: domestic macroeconomic indicators, external variables, debt composition, and foreign variables. In order to identify the variables that can be used to predict a currency crisis, they compare the pre-crisis behavior of these variables with their behavior during non-crisis periods. The authors then combine the evolutions of the different variables from various countries and time periods and create a probit model with both present and lagged regressors. Frankel and Rose conclude, after examining the robustness of their model results, that the probability of a currency crisis increases with a decline in foreign direct investment (FDI), an increase in public sector debt, a low GDP growth rate, and high foreign interest rates.

Sachs, Tornell, and Velasco (1996) Tequila Crisis Model

Sachs, Tornell, and Velasco investigate the magnitude of the Mexican financial crisis in 1994 and its effect on emerging markets in 1995. The model attempts to identify the critical variables that make certain countries more vulnerable to the contagious effect of the crisis. Based on a sample of 20 countries, the study found out that countries affected by a crisis in 1995 had significant macroeconomic fundamental flaws. Rational investors fled countries with these issues because they feared a sudden decline in currency value. This resulted in a massive capital outflow and ultimately in the crisis.

They define the crisis index (Tequila Crisis Model) as the weighted average of the percentage decrease in reserves and the depreciation in exchange rates from November 1994 to April 1995. The real exchange rate, which indicates that the currency is overvalued, and the lending boom in the private sector, which is a good proxy for the banking system's vulnerability, are used as explanatory variables. Moreover, these factors are more significant for nations with extremely low international reserves, as indicated by a reserves/M2 ratio in the bottom quartile, and weak fundamentals, as indicated by a real exchange rate in the bottom three quartiles or a landing boom in the top three quartiles. With a regression R^2 of 0.69, the authors conclude that their model adequately explains the pattern of contagion in emerging markets during the examined time period.

The purpose of the STV model was not to serve as an early warning system, but rather to explain the 1995 attacks. However, in 1997 a number of researchers began to argue that the model could be used to predict crises such as the 1997 Asian Crisis. Similar to the Latin American crises that followed the Mexican crisis, the Asian crises that followed the Thai crisis were caused by contagion. The International Monetary Fund[8] asserts that the STV results are applicable to the

[8] International Monetary Fund, 1998, *World Economic Outlook* (Washington: International Monetary Fund, May).

Asian crisis and is developing a composite indicator capable of predicting future currency crises in emerging countries.

Considerations about these models and comparison with KLR

The probit Model and the Cross-Country Regression model have the advantage of considering all variables simultaneously and summing up all information regarding the probability of a crisis in terms of the probability of devaluation. However, they have some important limitations. First of all these approaches do not provide a criterion for evaluating indicators based on their propensity to predict crises and prevent false alarms. Measures of statistical significance can help us determine which indicators are the most accurate, but they cannot tell us whether an indicator's relative strength derives from correctly predicting a large number of crises at the cost of a large number of false alarms. Second, these methodologies do not provide a clear picture of the origins and causes of common macroeconomic issues. Consequently, it is less suitable for monitoring and preventative intervention.

The KLR model, of course, has also some important limitations. Since it is based on a quantitative process (study of macroeconomic factors), it cannot account for exogenous and political factors (such as the Danish referendum on the EUM) which frequently accelerate the timing of speculative attack.

Despite this limitation, the signal approach appears to be more appropriate for use as the base for designing an early warning system. Indeed, this model provides information on the origin and scope of problems, emphasizing the likelihood of a crisis. Furthermore, the signals emitted by the various indicators can be used to estimate the probability of a crisis. This method is described in detail in the section that follows.

The Kaminsky, Lizondo, and Reinhart (1996) Signal Approach model

Kaminsky, Lizardo, and Reihnart have developed a non-parametric method in which they observe the evolution of various economic indicators that have a propensity to behave differently prior to a crisis. When these variables deviate from their normal levels by more than a certain threshold, it is interpreted as a sign that a currency crisis is likely to occur. To better comprehend the model, it is necessary to discuss its various components.

Definition of crisis

First of all, we have to identify what is a crisis. A currency crisis is characterized by a significant depreciation of the currency, a significant decline in international reserves, or a combination of the two. Contrary to models of the first and second generations, this definition includes not only attacks involving currencies with a fixed exchange rate but also other exchange regimes. The crisis is identified through the behavior of an index of exchange market pressure developed by Girton, Lance and Don Roper (1977)[9] that is equal to:

$$\boldsymbol{emp_t = \%\Delta e_t - \alpha_1 \Delta r_t}$$

As we can see above, the exchange market pressure index is defined as the weighted average of monthly percentage changes in the exchange rate (e_t), which is the unit of domestic currency per U.S. dollar or Euro, and the monthly percentage change in international reserves (r_t). This final component is also weighted by the alpha, which is the ratio of the standard deviation of the rate of change of the exchange rate to the standard deviation of the rate of change of reserves, such that the sample volatility of the two components of the index is equal. The index rises with a currency's

[9] Girton, Lance and Don Roper, 1977, "A monetary model of exchange market pressure applied topostwar Canadian experience," *American Economic Review,* September, pp 537 - 548.

depreciation or a decline in international reserves; thus, a rise in the index means high selling pressure on the domestic currency. A currency crisis occurs when:

$$\boldsymbol{emp_t > 3\sigma_{emp} + \mu_{emp}}$$

where σ_{emp} represents the sample standard deviation and μ_{emp} represents the sample mean. As we can see, a currency crisis occurs when the exchange market pressure index at time t is more than three standard deviations above the This formula is based on the empirical rule, also known as the three-sigma rule. According to this statistical rule, 99.7% of data in a normal distribution fall within three standard deviations of the mean. Using three standard deviations above the mean as threshold, the authors identify as a currency crisis only the extreme value of the Exchange market pressure.

Indicators and signal horizon

KLR has identified fifteen key variables that can be used to predict a crisis. They are selected based on theoretical considerations as well as their monthly availability in all countries and time periods.

Category	Indicator	Tail	Comments
Current Account	deviation of the real exchange rate	lower	Real exchange rate over-valuations (-) are linked to currency crisis
	imports	upper	Weak external sector is part of currency crisis
	exports	lower	Weak external sector is part of currency crisis
Capital Account	foreign exchange reserves	lower	Loss of foreign reserve characteristic of currency crisis ala Krugman
	M2/foreign exchange reserves	upper	Expansionary monetary policy and/or sharp decline in reserves are associated with the onset of a crisis
	real interest rate differential	upper	High world interest rates may lead to reversal of capital flows
	short-term debt/reserves	upper	Increases in short term debt and/or sharp declines in reserves are associated with crises
Real Sector	industrial production	lower	Recessions often precede financial crises
	equity indices	lower	Burst of asset price bubbles often precede financial crises
Domestic Financial	M2 multiplier	upper	Rapid growth of credit
	domestic credit/GDP	upper	Credit expands prior to crisis and contracts after.
	domestic real interest rates	upper	High real interest rates could signal a liquidity crunch or have been increased to fend off a speculative attack
	excess real M1 balances	upper	Loose monetary policy can lead to currency crisis
	commercial bank deposits	lower	Loss of deposits occur as crisis unfolds
	lending/deposit interest rates	upper	Lending rates tend to rise prior to crisis, reflecting decline in loan quality

*Table 1: **Sources: Edison 2003:" Do indicators of financial crises work? An evaluation of an early warning system"***

In the table 1 above shows that the 15 indicators are divided into four categories: ***current account indicators, capital account indicators, real sector indicators, and financial indicators.*** The table shows whether the higher or lower values of each variable indicate the economy is vulnerability to a currency crisis. In addition, a brief economic rationale for the variable is reported as a comment.

The monthly value of these variables is expressed as a percentage change in the level of the variable compared to its level in the previous year. KLR argues that using the 12-month percentage changes ensures that the units are comparable across countries and that the transformed variables are stationary without any seasonal effects. Only the deviation of the real exchange rate from the trend, the “excess” of real M1 balances, and interest rate variables are not calculated with this filter.

Signal Extraction Method and definition of threshold

In the KLR method, each variable is analyzed separately, country by country, and an indicator produces a signal when it deviates from the mean by more than a predetermined threshold. If the signal is followed within 24 months by a crisis, it is considered a good signal; otherwise, it is considered a false signal or noise. We will use a two-by-two matrix like the one below to measure how well an indicator works:

Performance of an Indicator		
	crisis within 24 months	No crisis with 24 months
Signal issued	A	B
No signal issued	C	D

Table 2: The table provides a concise summary of a variable’s potential outcomes. We concentrate on entries A and B, which are considered a signal (cell A) and noise (Cell B). A perfect indicator would only contain entries in cells A and D.

Sources: Kaminsky 1998:” Leading indicators of currency crises”

In this matrix, cell A indicates the number of months in which the indicator issued a good signal, cell B indicates the number of months in which the indicator issued a bad signal, cell C indicates the number of months in which the indicator failed to issue a signal and a crisis followed (missed signal), and cell D indicates the number of months in which the indicator did not issue a signal and no crisis followed (good silent). Noise-to-signal ratio is a ratio that combines the indicator's capacity to issue positive signals and avoid negative ones. It is determined by dividing the proportion of false signals relative to the total number of months without a crisis by the proportion of good signals relative to the total number of months with a crisis: [B/(B+D)]/[A/(A+C)].

Choosing a threshold level that strikes a compromise between the risks of having many false signals and the risks of missing many crises is one of the most crucial aspects of the signal extraction method. KLR, in order to determine the "*optimal*" threshold level, conducted a grid search in which potential threshold values are evaluated to identify the one that minimizes the noise-to-signal ratio. The thresholds are determined relative to the percentile of the indicator's country-specific distribution. For example, the best threshold for the real exchange rate is the 10th percentile[10] of its distribution for each country; hence, the percentile for the indicators is the same in each country, but the country-specific thresholds are likely to vary. As an illustration, the table 2 below, drawn from Edison (2003)[11], shows the threshold values for reserve loss and export growth for South Korea, Mexico, and Thailand. Both variables send a signal if their values fall under the bottom 10 percentage of the distribution, but the threshold level varies.

[10] Goldstein Morris , Kaminsky and Reinhart. 2000. Assessing Financial Vulnerability: An Early Warning System for Emerging Markets: Introduction. Washington, DC: Institute for International Economics.

[11] Edison, Hali J. 2003. Do indicators of financial crises work? An evaluation of an early warning system. International Journal of Finance &Economics 8: 11–53

Example of country-specif thresholds		
Country	**Critical Value for Export Growth**	**Critical Value for Reserve Loss**
South Korea	-0,8	22,2
Mexico	-6,5	49,5
Thailand	-4,5	9,2

Table 3: Sources: Edison 2003:" Do indicators of financial crises work? An evaluation of an early warning system"

Construction of Composite Crisis Indicator

After defining the indicators and the method for calculating the optimal threshold, we must define the method for combining the different indicators to generate a composite indicator of currency crisis vulnerability. Initially, Kaminsky constructed an index that is equal to:

$$\boldsymbol{I_t^1 = \sum S_t^j}$$

Where St is equal to one if variable j crossed the threshold in period t and zero otherwise. So, this composite index is based on summing the number of the indicators that issued a signal at any point in time. For example, if at time t five indicators are above their optimal threshold, the index would be equal to 5. This methodology has the disadvantage of weighing the contribution of each variable in the same way; however, certain indicators are more accurate at anticipating crises. For this reason, Kaminsky chose to develop the composite crisis indicators using a weighted index. It employs weights that are inverses of the signal-to-noise. Variables having a low noise-to-signal ratio are given a greater weight than those with a high noise-to-signal ratio. The weighted composite indicator is defined as follows:

$$\boldsymbol{I_t^2 = \sum S_t^j / w^j}$$

Where w^j is the noise-to-signal ratio of variable j.

Even if the composite indicator gives valuable information about the macroeconomic health of a country, it is necessary to calculate the probability of a future crisis for each value of the composite index. KLR and the following researchers therefore use the following formula to calculate the odds:

$$\boldsymbol{P(C_{t,t+h} \,|\, I_i^2 < I_t^2 < I_J^2)} = \frac{\boldsymbol{\sum Months\ with\ I_i^2 < I_t^2 < I_j^2\ given\ a\ crisis\ occurs\ within\ h\ months}}{\boldsymbol{Months\ with\ I_i^2 < I_t^2 < I_j^2}} =$$

where P represents probability $C_{t,t+h}$ represents the occurrence of a crisis in the interval $[t, t + h]$, h is the crisis window (24 months), $I^2$is the weighted index, and the subscripts I and j indicate upper and lower intervals for the composite index indicator. $P(C_{t,t+h} \,|\, I_i^2 < I_t^2 < I_j^2)$ signifies the likelihood of a crisis occurring within h months at time t, given that the composite indicator I_t^2 falls within therange $I_i^2 and\ I_j^2$.

There are two ways to examine the results: a cross-country comparison, which compares probabilities between countries at two distinct times, and an intertemporal comparison, which compares probabilities over time for a group of countries. The highest estimated probability of the model is 50%. This is due to the fact that indicators frequently signal, but no crisis occurs. This result is consistent with the relevant literature, where it is common to find estimates of probabilities to be quite low.

Results of the models out-of-sample

The decision to use the KLR was also influenced by the empirical findings of Berg and Pattillo's studies[12]. In the 1999 study, the authors examine the three models KLR, FR, and STV and attempt to answer the question: "If we had been using these models in the late 1996, how well armed would we have been to predict the Asian crisis?". To answer this question Berg and Pattillo use a common country sample to compare the various models, rank countries based on the predicted probability and severity of a crisis in 1997, and then compare the predicted and actual rankings.

The study discovers that the KLR model was statistically significant for predicting the Asian financial crisis, while the FR and STV models provide forecasts that are no more accurate than random guessing. The researchers were, however, quite disappointed with the final outcome of the test: the KLR model is statistically significant, but with only a correct prediction of 37% of crises (with a 27% unconditional probability of a crisis) and an excessive number of false alarms and missed crises. As a result, they decided to create a new early warning system known as the Developing Country Studies Division (DCSD).[13]

The new model was developed with the same definition of a crisis and time horizon as the KLR model, with the main difference being the model's incorporation into a multivariate probit regression. The authors reached this conclusion due to their belief that the likelihood of a crisis increases linearly as the predictive variables change. The variables that are used are the real exchange rate deviations from the trend, the current account ratio to GDP, the growth of reserves and exports, and the growth of short-term debt.

[12] Berg, Andrew, and Catherine Pattillo. 1999c. Are currency crises predictable? A test. IMF Staff Papers 46: 107–38.

[13] Berg, Andrew, and Catherine Pattillo. 1999b. What caused the Asian crises: An early warning system approach. Economic Notes 28: 285–334.

They demonstrated that, in the prevention of Asian crisis, their model is superior to the KLR one, with a higher likelihood of correctly identifying crises (40% versus 38%), a reduction in false alarms (60% versus 62%), and a substantial reduction in missed crises (from 18% to 10%). In light of these results, it seems obvious that the DCSD model is better. However, we must remember that Berg and Pattillo's model was created in 1998, after the Asian financial crisis, and that it influenced the selection of certain variables. For this reason, we must test the DCSD and the KLR using a new set of observations that are not part of the estimation sample.

In a separate paper[14], Berg and Pattillo evaluated the various models utilized by the International Monetary Fund to forecast currency and balance of payments crises between January 1999 and December 2000. In addition to the DCSD and KLR models, they also examine models from the private sector, including Goldman Sachs' GS-WATCH, Credit Suisse First Boston's (CSFB), and Deutsche Bank's Alarm Clock (DBAC). Private models will not be considered because they were designed to be used in foreign exchange trading strategies with a very short-term orientation (from one to three months).

[14] Berg, A., E. Borensztein, and C. Pattillo. 2005. Assessing early warning systems: How have they worked in practice? IMF Staff Papers 52: 462–502.

	Asian crisis 1995:5 to 1996:12		Out-of-sample period 1999:1 to 2000:12	
	DCSD	**KLR**	**DCSD**	**KLR**
Percent of obs. correctly called	62	57	72	76
Percent of crisis in 24 mo. Correctly called	84	75	31	58
Percent of tranquil in 24 mo. Correctly called	53	49	80	79
False alarms as percent of total alarms	60	62	78	65
Probability of crisis given signal	40	38	22	35
Probability of crisis given no signal	10	18	14	9

*Table 4: **Sources: Berg 2005:" Assessing Early Warning System: How Have They Worked in Practice?"***

As shown in the table 3, the KLR model outperforms the DCSD by correctly identifying more crises (35% vs. 22%), generating fewer false alarms (65% vs. 78%), and demonstrating a significant reduction in missed crises. (9% vs. 14%). Every performance of the DCSD model deteriorated substantially in out of sample compared to the sample period. The conclusion of this study is that the KLR model was the only one whose results did not deteriorate out of sample. In addition, the overall performance of the model is enhanced by modifying the variables employed, including indicators such as the level of current account balance and M2/reserves.

Chapter 2: Measuring Indicator Efficiency in Forecasting Currency Crises

Introduction

In this chapter, I will present the model that will be utilized in the final chapter to calculate the current probability of a currency crisis. To begin, I will outline the country coverage and historical data horizon that will be used in the model. The model will focus on 18 countries from three different regions: Asia (Indonesia, India, Malaysia, Pakistan, the Philippines, Singapore, and Thailand), South America (Argentina, Bolivia, Brazil, Chile, Colombia, Mexico, Peru, Uruguay, and Venezuela), and other (Turkey and South Africa). In contrast to Kaminsky's model, I have replaced European countries with Asian ones, as the latter have seen more currency crises in recent years, making them more relevant to the study.

The historical data horizon for my model spans from 1980 to 2002, whereas Kaminsky's model covers the period from 1970 to 1995. I have excluded the 1970s from my study as many data points from that period are no longer available and it would not be relevant to include outdated information. Additionally, I have chosen not to extend beyond 2002 as there have been relatively few noteworthy currency crises in recent years. This near absence of currency crises in the 21st century can be attributed to several factors. After the crises of the 1990s, many emerging economies, particularly in South America, adopted restrictive monetary and fiscal policies. These measures helped prevent future crises, but also slowed economic growth in these countries.

An alternative explanation for the absence of financial crises in emerging countries is the expansionary monetary policy of the United States. As the largest economy in the world and a global leader, the US plays a significant role in the global economy. The Federal Reserve's monetary policy, particularly the low interest rates implemented after the 2008 real estate crisis, has allowed emerging nations to access loans at favorable rates. The weakening of the US dollar also plays a crucial role in sustaining the economies of these nations. This is because international investors prefer to hold the bonds of emerging nations in US dollars, as it reduces the risk of inflation eroding the value of their investments. The recent weakness of the dollar has also enabled these nations to pay off their debts and obtain new loans at favorable exchange rates, further supporting their economic stability.

Currency crisis identification

In this study, the identification of currency crises is based on the KLR method and the use of the exchange market pressure index. The index of foreign exchange pressure was constructed for each of the 18 countries included in the sample over the 1980–2002 period. A currency crisis is identified when the index exceeds 3 standard deviations above the mean.

The distribution of these crises over time is shown in Table 5 (Appendix A gives details on the dating of individual country crises). The last column of table 5 contains aggregate numbers, while the second and fourth columns show the distribution by geographical area. Between 1980 and 2002, the exchange market pressure index has identified 58 episodes of countries experiencing currency crises. As shown in the table, the distribution of crises in Latin America and Asia differs significantly. Between 1980 and 1989, the average number of crises per year in South American countries was 1.8, while the average number of crises in Asian countries in the same period was just 0.6. Asian countries, on the other hand, had the most crises between 1995 and 1999, with an average of 2.2 per year (mostly because the Asian crisis of 1997 and 1998)

Years	Latin America	Asia	Other	Number of Crises
1980-1984	10	3	1	14
1985-1989	8	3	1	12
1990-1994	5	5	1	11
1995-1999	3	11	0	14
2000-2002	4	1	2	7

Table 5: The numbers reported in the table summarize the data for the expanded sample (20 countries) and the entire historical sample (1980-2002). See Appendix A for details on the dating of individual country crises.

Source: Author's calculations based on data obtained from the International Monetary Fund Database

Empirical Results

The effectiveness of the signal approach developed in the KLR model is evaluated at both the level of individual indicators and the level of aggregate indicators. In the section that follows, I will evaluate the effectiveness of each individual indicator. In order to accomplish this, I will employ the two-by-two matrix introduced in the previous chapter:

Performance of an Indicator		
	crisis within 24 months	No crisis with 24 months
Signal issued	A	B
No signal issued	C	D

Table 5: The table provides a concise summary of a variable's potential outcomes. We concentrate on entries A and B, which are considered a signal (cell A) and noise (Cell B). A perfect indicator would only contain entries in cells A and D.

Sources: Kaminsky 1998:" Leading indicators of currency crises"

In this matrix, A represents the number of months in which the indicator issued a good signal, B represents the number of months in which the indicator issued a bad signal, C represents the number of months in which the indicator failed to issue a good signal, and D represents the number of months in which the indicator refrained from issuing a signal that would have been a bad signal. The perfect indicator should yield results that fall into boxes A and D. It should issue a signal every month that is followed by a crisis (within the next 24 months), such that A>0 and C=0, and no signal in months that are not followed by a crisis (within the next 24 months), such that B=0 and D>0.

Before I talk about the model's results, I will talk about the indicators again by giving a short explanation of what they are and how they are calculated:

1. **Foreign Exchange Reserves**: These are assets held by a central bank in the form of foreign currency, government bonds, and other securities. They serve to support liabilities and influence monetary policy.
2. **Exports:** export are things that are made in one country and sold to people in another country.
3. **Imports**: Imports are goods or services purchased in one country that were produced in another country.
4. **Real Exchange Rates:** The real effective exchange rate (REER) is found by multiplying the nominal exchange rate between two currencies by the difference in prices between the two countries.
5. **Index of Equity Prices:** This statistical indicator tracks changes in the market value of a particular group of shares.
6. **Commercial Bank Deposits**: These deposits include both demand deposits (funds that can be withdrawn at any time) and time, savings, and foreign currency deposits. which is the total number of deposits in foreign currency for the purpose of using the foreign currency in the future or hedging against fluctuations.
7. **Output Index:** This index, which is based on industrial production, looks at how much is made each month in areas like manufacturing, mining, electricity, and gas.

8. **Excess Real M1 Balances:** It is defined as M1 deflated by consumer prices less an estimated demand for money. Demand for real money balances is estimated as a function of GDP (interpolated monthly), domestic consumer price inflation, and time.
9. **M2 Multiplier:** This ratio compares the money supply measure (M2, which includes cash and other easily convertible deposits) to the monetary base, which is the total amount of money in circulation or held in central bank reserves.
10. **M2/Reserves Ratio:** This ratio compares the M2 money supply measure to foreign exchange reserves.
11. **Domestic Credit/GDP Ratio**: This ratio represents the total domestic credit provided by financial corporations to the private sector as a percentage of nominal GDP and is calculated on a monthly basis.
12. **Real Interest Rate:** This rate, which is the interest rate that banks pay on deposits, takes inflation into account.
13. **Real Interest Rate Differential:** This is the difference between the real lending interest rates of the domestic country and the United States.
14. **Lending to Deposit Rate Ratio:** This ratio compares the lending interest rate to the deposit interest rate.

Table 6 presents data on the effectiveness of various indicators in predicting currency crises (for detailed analysis see appendix B). The first column displays the number of crises for which data is available, which ranges from 20 to 58, with an average of 42 crises per indicator. The only indicators for which data are available for all crises are "Foreign Exchange Reserves”. Column 2 shows the noise-to-signal ratio, which is determined by dividing the proportion of false signals (B/(B+D)) by the proportion of accurate signals (A/(A+D)). Indicators with ratios greater than or equal to 1 are not effective in preventing crises. According to a study by Kaminsky, López, and

Reinhart (for more details about Kaminsky results see Appendix A Table 10) four indicators (lending/deposit rate, commercial bank deposit, imports, and real interest differential) are not effective in preventing crises. My sample is consistent with these results, with the noise-to-signal ratio of "lending/deposit rate" and imports being above 1, and the ratio for "commercial bank" and "real interest rate differential" being 0.98. The only exception is the "output" indicator, which is considered a poor indicator in my sample (NtS=1.05) but one of the best in the KLR sample. This discrepancy may be due to the limited data available for this indicator in the countries included in my sample (data is only available for 20 of 58 crises). Column 3 shows the percentage of crises correctly predicted by each indicator, defined as the number of crises for which the indicator issued at least one signal in the previous 24 months. In my sample, 11 out of 12 indicators correctly predicted at least half of the crises. In both my sample and the KLR sample, the real interest rate is the best indicator. The last column presents the probability of a crisis occurring, calculated as A/(A+B). This probability, like the noise-to-signal ratio, indicates the trend of the variable. For example, the probability of a crisis occurring is 43% with the Real Exchange rate, but only 14% with the Lending/Deposit Rate indicator.

Table 6[1]				
Variables[2]	Number of crisis[3]	Noise/Signal Ratio[4]	Share of crisis called[5]	P(Crisis/Signal)[6]
Reserve	58	0,49	0,71	0,40
Export	55	0,67	0,75	0,32
Real Exchange Rate	36	0,43	0,56	0,42
Index of Equity Prices	34	0,77	0,74	0,26
Commercial Bank Deposits	40	0,98	0,33	0,24
Output	19	0,96	0,53	0,21
Excess M1 Balances	N/A	N/A	N/A	N/A
M2 Multiplier	49	0,81	0,57	0,27
M2/Reserves	54	0,57	0,59	0,36
Domestic Credit/GDP	29	0,67	0,52	0,31
Real Interest Rates	26	0,70	0,77	0,27
Real Interest Rates Differential	28	0,98	0,54	0,20
Lending/Deposit Rate	23	1,90	0,61	0,14
Imports	55	1,19	0,56	0,20

Table 6: 1. Estimation period January 1980 to December 2002 (276 observations) using 18 Countries (Argentina, Bolivia, Brazil, Chile, Colombia, India, Indonesia, Malaysia, Mexico, Pakistan, Peru, Philippines, Singapore, South Africa, Thailand, Turkey, Uruguay, Venezuela) 2. Variables are measured as 12-month percentage changes, except interest rates (12-month level change) 3. Number of crises for which data exist for this variable. 4. Ratio of false signals to total number of months there is no crisis relative to proportion of good signals. 5. Defined as the number of crises for which indicator issued at least one signal during the twenty-four months prior to the crisis. 6. Probability of a crisis. A/(A+B) given signal was issued.

Source: Author's calculations based on data obtained from the International Monetary Fund Database

Overall, the results reported in Table 6 are similar to Kaminsky results. "Real exchange rate", "Foreign international reserves", "Exports" and the "ratio of M2 to foreign exchange reserves" are the best indicators in both samples. At the same time, I notice several differences in the results. The differences are due to the fact that we use different time horizons, and my sample focuses primarily on emerging markets, whereas KLR includes many European countries. Furthermore, despite the fact that we use the same data source (the International Monetary Fund database), the time series is revised on a regular basis. Second, it is unclear how KLR accounted for all of the missing data points in the crisis windows. I accounted for those absences within my sample, corrected for the total number of observations, and attempted to account for multiple signals in the seizure windows.

"Excess real M1 balances" is the only indicator for which I encountered calculation issues. It is equal to the difference between M1 and the estimated money demand. Money demand is estimated based on GDP, internal consumer price inflation, and time. In the last 20 years, M1 has experienced unprecedented growth, driven by a combination of extremely low interest rates, which make it more convenient for people and businesses to borrow money, and a rapid increase in government spending to revive the economy, which directly added to the money supply. This exponential growth of M1 has greatly deviated from the potential money demand based on GDP and the consumer price index. As a result, this indicator has been signaling only in the last years of the sample for all countries, making the indicator statistically irrelevant.

Regional Differences

We can determine the robustness of the model as a whole by analyzing the results in the various regions. Table 7 summarizes the performance of the indicators in the two regional groups: Latin America (Argentina, Bolivia, Brazil, Chile, Colombia, Mexico, Peru, Uruguay, and Venezuela) and Asia (India, Indonesia, Malaysia, Pakistan, the Philippines, Singapore, and Thailand). The time horizon used for each region is 1980 to 2002, with a maximum of 30 crises for Latin America and 23 for Asia.

Based on the signal-to-noise ratio, the key indicators are the same to those of the aggregated model. The best performing indicators are Real Exchange rate, M2/reserves, exports, and international reserves; the only exception is the sample of Asia, where "real interest rates" have a much lower NtS (0.35) than in the aggregate model (0.77). The percentage of crises correctly called shows the main difference between the two regions. The three best indicators of this ratio for Latin America are: the equity index (90%), the real interest rate (90%), and exports (88%). While for Asia the best indicators are: M2/Reserves (79%), International Reserves (74%), and the Real Interest Rate.

	Table 7[1]					
	Latin America			Asia		
Variables[2]	Number of crisis[3]	Noise/Signal Ratio[4]	Share of crisis called[5]	Number of crisis[3]	Noise/Signal Ratio[4]	Share of crisis called[5]
Reserve	30	0,43	0,70	23	0,55	0,74
Export	32	0,56	0,88	21	0,89	0,52
Real Exchange Rate	14	0,26	0,64	19	0,69	0,53
Index of Equity Prices	10	0,96	0,90	19	0,77	0,68
Commercial Bank Deposits	16	0,43	0,38	19	2,21	0,32
Output	10	1,09	0,60	6	0,57	0,50
Excess M1 Balances	N/A	N/A	N/A	N/A	N/A	
M2 Multiplier	27	1,06	0,41	17	0,63	0,706
M2/Reserves	30	0,62	0,47	19	0,45	0,79
Domestic Credit/GDP	5	0,30	0,60	21	0,87	0,43
Real Interest Rates	10	1,18	0,90	14	0,35	0,714
Real Interest Rates Differential	7	0,77	0,71	18	1,42	0,44
Lending/Deposit Rate	10	1,39	0,80	13	3,18	0,46
Imports	30	1,02	0,53	23	1,66	0,57

Table 7: 1. Estimation period January 1980 to December 2002 for Latin American Region (Argentina, Bolivia, Brazil, Chile, Colombia, Mexico, Peru, Uruguay, Venezuela) and Asian Region (India, Indonesia, Malaysia, Pakistan, Philippines, Singapore Thailand). 2. Variables are measured as 12-month percentage changes, except interest rates 3. Number of crises for which data exist for this variable.4. Ratio of false signals to total number of months there is no crisis relative to proportion of good signals. 5. Defined as the number of crises for which indicator issued at least one signal during the 24 months prior the crisis.

Source: Author's calculations based on data obtained from the International Monetary Fund Database

Average Lead Time

The indicators were ranked based on their ability to predict crises. Before concluding this chapter, it is necessary to classify the various indicators based on signal delivery time. Tables 6 and 7 do not make differences between a signal sent 15 months before the crisis and one given one month before. This information is critical for a policymaker who wants to put preventive measures in place. Table 11 presented in Appendix A ranked the indicators based on the average number of months since the first signal. The outcome is quite surprising; in fact, all of the indicators first signaled between a year and a half before the crisis, with the M2 multiplier being the best indicator. Based on this result, all indicators can be considered leading rather than coincident, which is consistent with the early warning system philosophy.

Chapter 3: Emerging Markets' Susceptibility to Currency Crises: A Quantitative Approach.

Introduction

The COVID-19 pandemic caused a significant downturn in the global economy in 2020. The spread of the virus resulted in a decrease in international trade and a contraction in global economic activity. Measures taken to control the virus's spread led to a reduction in consumer spending, resulting in a significant decrease in economic output. In response to the economic recession, many governments have implemented large-scale stimulus packages, including low-interest loans, grants, and increased government spending. Additionally, central banks have implemented monetary policies such as interest rate cuts and quantitative easing to encourage lending and spending.

The combination of expansionary economic policies implemented by governments and supply chain disruptions caused by the pandemic resulted in a significant price increase for goods and services in 2021. In addition, the war between Russia and Ukraine in 2022 drove up the prices of raw materials, particularly energy. The combination of these factors caused inflation to reach levels not seen for decades. Developed economies recorded higher inflation rates compared to developing economies. In particular, in the United States, inflation reached levels not seen in 40 years. To deal with this situation, the United States central bank, the Federal Reserve, decided to adopt an extremely restrictive policy by raising interest rates from 0% to 4.25% in just one year. This maneuver led to an appreciation of the dollar to levels not seen in twenty years.

The economic stability of the United States, particularly the strength of the US dollar, plays a critical role in the global economy. A strong dollar can make exports from emerging markets more expensive, which can decrease demand for their goods and services and reduce their foreign exchange earnings. This can have a negative impact on emerging economies that rely heavily on exports for revenue. Additionally, many of these economies have a large amount of debt denominated in US dollars, which becomes more costly as the dollar appreciates. High interest rates also increase the cost of debt and increase the risk of insolvency for these countries.

In this final chapter, we will employ a quantitative methodology to identify which emerging countries are most susceptible to currency crisis in the foreseeable future. By utilizing the early warning system developed in the previous chapter, we will analyze macroeconomic factors and generate a ranking of these countries based on their likelihood of experiencing a crisis.

Construction of Composite Crisis Indicators

In the previous chapter, we examined the performance of indicators individually, but now I must combine the results to create a composite indicator of vulnerability. As I wrote in the first chapter, Kaminsky presented two main methods to calculate this composite indicator. The first one is based on summing the number of indicators that signal a crisis at a specific point in time and so the maximum value that this indicator can reach is 13. The problem with this methodology is that it assigns equal weight to each indicator, ignoring all the information gained in the previous chapter regarding the accuracy of indicators in identifying a crisis. For this reason, I decided to use the second method introduced by Kaminsky which is a weights composite indicator. This approach gives more weight to signals from indicators that have demonstrated a consistent level of performance in the past.

I have decided not to build the composite indicator for Venezuela, Singapore, and India. The omission of Venezuela was forced due to a lack of sufficient data points, which may have led to a skewed result. On the other hand, the decision to exclude Singapore and India was arbitrary. Singapore, known as a global financial hub, has one of the safest currencies in the world with a 290-billion-dollar reserve held by the Monetary Authority. India, while still considered an emerging country, is currently the sixth largest economy in the world. Moreover, the International Monetary Fund predicts that by 2027 India will be the third largest, behind only China and the United States with an estimated GDP of $5.17 trillion, up 95% from its current level of $2.66 trillion. Its recent economic stability makes it unlikely that it would experience a severe currency crisis, making its presence within the model useless.

In Table 8, I have presented the findings of composite indicators for a selection of Asian and Latin American countries. These indicators are based on data collected from July 2020 to December 2022 and are considered to be out of sample for the period of January 2003 to December 2022. To aggregate the individual indicators into a composite model, weights were calculated using data from January 1980 to December 2002. The weights used were equivalent to the inverse of the noise-to-signal ratio (NtS) reported in Table 6. This means that the real exchange rate, which had the best NtS of 0.43, was given a weight of 2.33 in the model, while the loan-to-deposit rate ratio, which had the worst NtS of 1.9, was given a weight of only 0.53, with a maximum value of 17.6.

Table 8

	Bolivia		*Brazil*		*Uruguay*		*Indonesia*		*Malaysia*		*Philippines*	
Dates	**Number of Signals[1]**	**Weighted Composite index[2]**	**Number of Signals[1]**	**Weighted Composite index[2]**	**Number of Signals[1]**	**Weighted Composite index[2]**	**Number of Signals[1]**	**Weighted Composite index[2]**	**Number of Signals[1]**	**Weighted Composite index[2]**	**Number of Signals[1]**	**Weighted Composite index[2]**
Jul 2020	2	3,22	2	3,8	2	2,01	1	1,29	1	1,43	1	1,29
Aug 2020	2	3,22	2	3,8	1	0,53	2	2,53	1	0,53	1	1,29
Sep 2020	2	3,22	2	3,8	1	0,53	1	1,29	1	0,53	1	1,29
Oct 2020	1	1,74	2	3,8	1	0,53	1	1,29	1	0,53	1	1,29
Nov 2020	1	1,74	1	1,74	1	0,53	0	0	1	0,53	0	0
Dec 2020	1	1,74	1	1,74	1	0,53	0	0	1	0,53	0	0
Jan 2021	2	3,8	1	1,74	1	0,53	0	0	1	0,53	0	0
Feb 2021	2	3,8	1	1,74	1	0,53	0	0	1	0,53	0	0
Mar 2021	2	3,8	0	0	1	0,53	0	0	1	0,53	1	0,84
Apr 2021	3	4,64	0	0	1	0,53	0	0	2	1,37	1	0,84
May 2021	4	5,17	0	0	1	0,53	1	0,84	2	1,37	1	0,84
Jun 2021	3	4,64	3	2,39	1	0,53	1	0,84	2	1,37	1	0,84
Jul 2021	2	3,8	4	3,63	1	0,53	0	0	1	0,53	0	0
Aug 2021	2	2,58	3	2,39	0	0	1	0,84	1	0,53	1	0,84
Sep 2021	1	1,74	4	3,63	1	0,84	0	0	0	0	1	0,84
Oct 2021	0	0	4	3,63	1	0,84	1	0,84	1	0,84	1	0,84
Nov 2021	1	0,84	3	2,39	0	0	1	0,84	1	0,84	1	0,84
Dec 2021	0	0	2	1,55	0	0	1	1,24	0	0	1	0,84
Jan 2022	0	0	2	1,55	0	0	2	1,77	0	0	0	0
Feb 2022	0	0	2	1,55	0	0	1	0,53	0	0	0	0
Mar 2022	0	0	2	1,55	1	1,02	1	0,53	0	0	0	0
Apr 2022	1	0,84	3	3,88	0	0	1	0,53	0	0	0	0
May 2022	1	0,84	3	2,79	2	3,35	1	0,53	0	0	0	0
Jun 2022	0	0	4	4,08	2	3,35	1	0,53	1	0,84	2	3,35
Jul 2022	1	0,84	4	4,22	2	3,35	1	0,53	1	0,84	1	2,06
Aug 2022	3	4,64	4	4,85	2	3,35	1	0,53	1	0,84	1	2,06
Sep 2022	2	2,58	5	8,29	3	5,82	2	2,9	0	0	3	5,09
Oct 2022	1	2,06	6	7,64	2	3,35	3	3,83	0	0	3	5,09
Nov 2022	0	0	5	6,59	2	3,35	1	0,53	0	0	2	3,8
Dec 2022	1	2,06	5	6,59	0	0	1	0,53	0	0	0	0

Table 8: Results are based on a subset of indicators reported in Table 6. 1. Number of indicators that were signaling 2. Weighted sum of indicators signals with weights given by the signal-to-noise ratio (the inverse of the noise-to-signal ratio calculated in chapter.

2). Source: Author's calculations based on data obtained from the International Monetary Fund Database

Table 10 displays significant variations in results for Asia and South America. Brazil leads with the highest signal output, sending at least two signals from July 2021 to the end of the period, with a noticeable increase in the composite index value during the last half of 2022. Bolivia, on the other hand, alternates between low and high values of the composite indicator and experiences a sharp rise in the recent period. Uruguay, in contrast, shows a calm trend until April 2022, but experiences a consistent presence of at least two signals from May to November. The economic and financial situation in Asian countries differs from that of South America. Malaysia stands out with the lowest signal output, only sending two signals in a few months, with none in the final period, when stress is expected to be at its highest. Indonesia's situation is similar to Malaysia's, with three signals sent in the final months, but its composite index remains below four. The Philippines is the only Asian country analyzed in the table that sends stronger signals, with a composite indicator exceeding 5 for two consecutive months, yet its overall economic and financial situation remains less challenging than that of South American nations.

Probabilities of Currency Crisis

The value of the composite indicator alone cannot accurately predict the likelihood of a crisis. To determine this probability, we will use Edison's formula from Chapter 1. The probability of a crisis increases as the composite index value rises, indicating increased of possibility of a crisis. However, this method states that the maximum probability cannot exceed 50%. Research in the field has commonly found low probabilities due to indicators often signaling a crisis but not resulting in one. Another explanation is that the period following the crisis is included in the tranquil period, but it takes time for macroeconomic adjustment and the economy to return to 'normal'.

We will analyze these probabilities using two methods: cross-country comparison and intertemporal comparison. In cross-country comparison, we will examine the probabilities across countries at two points in time. In intertemporal comparison, we will show the probabilities over time for a selected group of countries. Figure 1 displays the results of the crisis probabilities for December 2021 and September 2022 for the 15 countries in our sample. The countries are arranged in ascending order based on their crisis probabilities in September 2022.

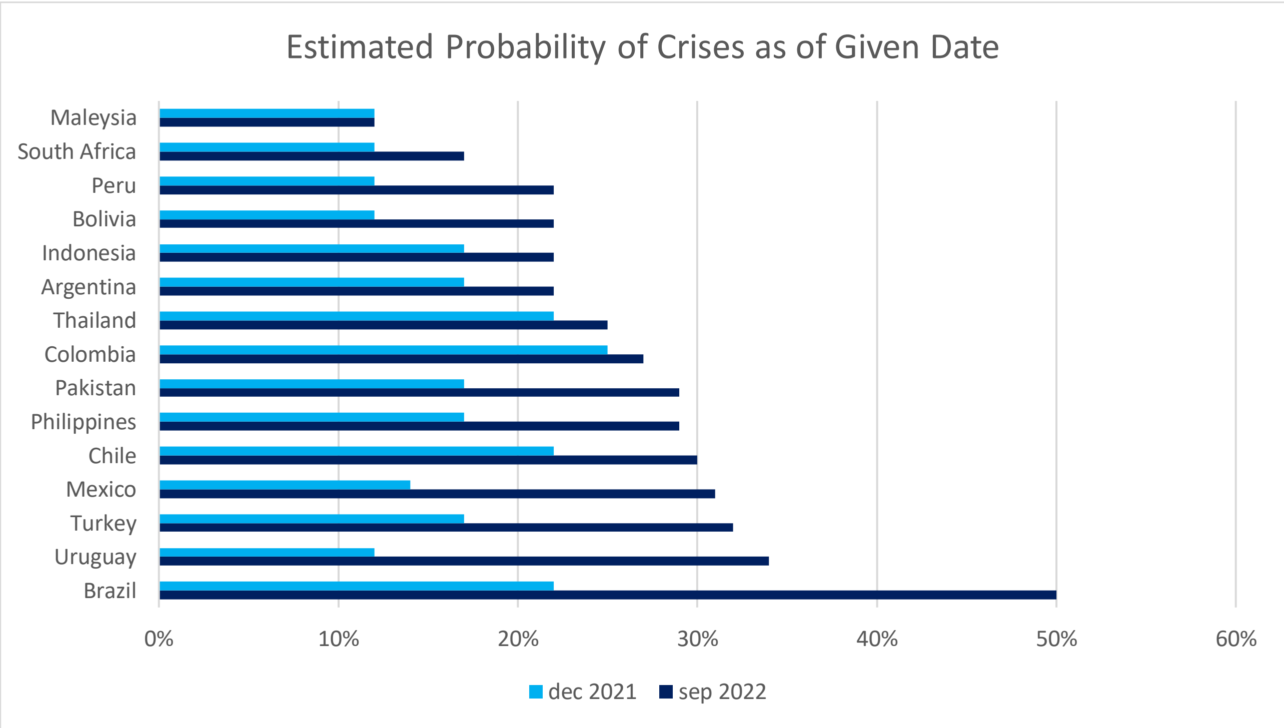

Figure 1 : Source: Author's calculations based on data obtained from the International Monetary Fund Database

The country with the highest probability in December 2021 is Colombia, at 25%. Many countries had probabilities below 20% during this period. This can be attributed to the economic prosperity in 2021, driven by the post-COVID recovery and accommodative economic and monetary policies. The picture painted in September 2022, 10 months later, was vastly different than before. Out of all the countries analyzed, only Malaysia and Peru had a currency crisis probability below 20%. The nations at the greatest risk were Brazil, Uruguay, Turkey, Mexico, and Chile. Figure 1 revealed a noticeable contrast, with South American countries being more susceptible to currency crises compared to South Asian nations. This disparity could be attributed to the remarkable economic progress made in Southeast Asian countries in recent years. A number of factors have fueled this growth, including:

- Cheap labor that has attracted investment from western companies looking for cost reduction
- Economic policies aimed at promoting the development of commercial activities, such as tax incentives.
- A dramatic increase in the demand for goods and services from emerging countries, such as China or India.
- A large amount of capital from foreign investors, attracted by the possibility of high returns in the medium and long term.

All these factors have made it possible to create a favorable economic environment that has accelerated the development of these nations, strengthening their health from an economic point of view and from a currency point of view.

Brazil is the most vulnerable country to a currency crisis, with an index of 8.29 and a 50% chance. The latest news confirms that Brazil is not having a rosy moment in terms of currency. The Financial Times reports that Brazil and Argentina are in talks to adopt a shared currency, a bold move considering Argentina's recent economic instability. Brazil may hope that this union will help mitigate potential currency issues brought on by current macroeconomic conditions.

To summarize the chapter, Table 9 displays the probabilities and signals for 15 countries in September 2022. The 2nd and 3rd columns show the signals sent and the composite index for each country. Columns 4-13 display the indicators signaling a crisis. As you can see, the indicators that send the most signals are Reserves, M2/reserves and Real interest rate.

Table 9

Country	# of Sig	Wt Sigs	Reserve	RER	Stock Price	M2 Mult	M2/R	Real Int	Real Int dif	Imports	Lending/deposit
Argentina	2	2,98				X	X				
Bolivia	2	2,58					X			X	
Brazil	5	8,29	X		X	X	X	X			X
Chile	3	5,23	X				X	X			
Colombia	3	4,51	X					X	X		
Indonesia	2	2,9	X								X
Malaysia	0	0									
Mexico	3	5,5		X			X	X			
Pakistan	3	5,04	X			X	X				
Peru	2	2,27						X			X
Philippines	3	5,09	X		X		X				
South Africa	1	1,43						X			
Thailand	3	3,8	X				X				X
Turkey	3	5,23	X				X	X			
Uruguay	3	5,82	X	X				X			

Table 11: It is a Cross-Sectional View of the Out-of-Sample Performance – September-2022

Source: Author's calculations based on data obtained from the International Monetary Fund Database

Conclusion

The aim of this study was to design a warning system that serves as a benchmark for determining the likelihood of a currency crisis in a country during this era of significant unpredictability. The results of the model described in the third chapter can only be assessed over time. This is because the probability of a crisis was calculated in September 2022, and it will only be known in the forthcoming years whether the model has provided accurate predictions. Nevertheless, we can still make some observations about the model's performance based on the test conducted in previous chapters.

The findings in Table 6 of Chapter 2 are in close alignment with the results produced by Kaminsky. Both studies identified the real exchange rate, international reserves, exports, and M2/Reserves as the most effective indicators for predicting a currency crisis, despite some differences in the countries and time frames analyzed. The results from Table 7 also demonstrate the robustness of the model. Although some disparities across regions have been observed, the performance of the indicators remains relatively stable. Additionally, the results presented in the final chapter reveal that in the latter part of 2022, the indicators that generated the most alarms are related to international reserves and money supply, confirming their significance as predictors of a potential crisis. It is also noteworthy that in the model developed in Chapter 2, some variables generated a high number of false or premature signals. This is due to the inherent uncertainty and unpredictability of currency crises.

It is crucial to acknowledge that while an early warning system provides a useful means for quickly evaluating the probability of a currency crisis, it is not without limitations. There may be political or institutional factors that are specific to a country and time that are not accounted for in the warning system, and these factors could significantly impact the likelihood of a crisis.

APPENDIX A

1	ARGENTINA	APR89-APR89-FEB90-JAN02	**4**
2	BOLIVIA	NOV82-FEB85-SEP85	**3**
3	BRAZIL	SEP82-JAN90-JAN99	**3**
4	CHILE	JUN82-JUL85	**2**
5	COLOMBIA	JAN85-SEP98-JUL02	**3**
6	INDONESIA	MAR83-SEP86-JAN98-JUN98	**4**
7	INDIA	JUL91-MAR93	**2**
8	MALAYSIA	FEB85-DEC92-JUL97-JAN98	**4**
9	MEXICO	FEB82-DEC82-DEC94	**3**
10	PAKISTAN	JUL93-OCT95-OCT96-MAY99-SEP00	**5**
11	PERU	OCT87-SEP88-AUG90	**3**
12	PHILIPPINES	OCT83-JUN84-FEB86-DEC97	**4**
13	SINGAPORE	DEC97-MAY98	**2**
14	SOUTH AFRICA	JUL84-AUG85-DEC01	**3**
15	THAILAND	JUL97-JAN98	**2**
16	TURKEY	APR94-FEB01	**2**
17	URUGUAY	DEC82-NOV84-JUL02	**3**
18	VENEZUELA	FEB84-DEC86-MAR89-MAY94-APR96-FEB02	**6**
		TOTALE	**58**

Note: The crises dates are derived from calculating an index of weighted average of exchange rate changes and reserve losses. Index that was 3 standard deviations or more above the mean was considered as a crisis.

Source: Author's calculations based on data obtained from the International Monetary Fund Database

Table 10[1]

Variables[2]	Number of crises[3]	Noise/Signal Ratio[4]	Share of crisis called[5]	P(Crisis/Signal)[6]
Reserve	72	0,55	0,75	0,41
Export	72	0,42	0,85	0,49
Real Exchange Rate	72	0,19	0,57	0,67
Index of Equity Prices	53	0,47	0,64	0,49
Commercial Bank Deposits	69	1,20	0,49	0,25
Output	57	0,52	0,77	0,49
Excess M1 Balances	66	0,52	0,61	0,43
M2 Multiplier	70	0,61	0,73	0,40
M2/Reserves	70	0,48	0,80	0,46
Domestic Credit/GDP	62	0,62	0,56	0,39
Real Interest Rates	44	0,77	0,89	0,34
Real Interest Rates Differential	42	0,99	0,86	0,29
Lending/Deposit Rate	33	1,69	0,67	0,18
Imports	71	1,16	0,54	0,26

Note: 1. Estimation period January 1970 to December 1995 (320 observations) using 20 Countries (Argentina, Bolivia, Brazil, Chile, Colombia, Denmark, Finland, Indonesia, Israel, Malaysia, Mexico, Norway, Peru, Philippines, Spain, Sweden, Thailand, Turkey, Uruguay, Venezuela) 2. Variables are measured as 12-month percentage changes, except interest rates (12-month level change) 3. Number of crises for which data exist for this variable. 4. Ratio of false signals to total number of months there is no crisis relative to proportion of good signals. 5. Defined as the number of crises for which indicator issued at least one signal during the twenty-four months prior to the crisis. 6. Probability of a crisis. A/(A+B) given signal was issued. Source: KLR calculations.

Table 11	
Indicator	Number of months in advance of the crisis when first signal occurs
M2 Multiplier	18
Lending/Deposit Rate	16
Imports	16
Commercial Bank Deposits	16
Real Interest Rates	15
Real Interest Rates Differential	15
Reserve	15
Export	15
Real Exchange Rate	15
Index of Equity Prices	14
M2/Reserves	14
Domestic Credi/GDP	14
Output	11
Excess M1 Balances	N/A

Table 11: Source: Author's calculations based on data obtained from the International Monetary Fund Database

APPENDIX B

Country	Crisis Dates	Foreign reserves	Export	RER	Equity price	Commerical deposit	Output	M2 multiplier	M2 Reserves	Domestic credit	real interest	real interest differential	Lending/deposit rate	import
		sig/a.d.	sig/a.d.	sig/a.d.	sig/a.d.	sig/a.d.	sig/a.d.	sig/a.d.	sig/a.d.	sig/a.d.	sig/a.d.	sig/a.d.	sig/a.d.	sig/a.d.
Argentina	**Jul-82**	10/24	4/24	0/0	0/0	0/0	0/0	2/24	0/24	0/0	0/0	0/0	0/0	1/24
	apr-89	5/24	2/24	0/0	0/0	0/0	0/0	13/24	0/24	0/0	0/0	0/0	0/0	0/24
	feb-90	3/10	1/10	0/0	0/0	0/0	0/0	0/10	9/10	0/0	0/0	0/0	0/0	0/10
	Jan-02	0/24	1/24	0/0	0/0	0/0	0/0	0/24	0/24	0/0	0/0	0/0	0/0	0/24
Bolivia	**nov-82**	6/24	1/10	12/24	0/0	0/24	0/0	0/24	0/24	0/0	0/0	0/0	0/0	0/10
	nov-83	0/11	1/12	3/12	0/0	2/11	0/0	0/12	0/12	0/0	0/0	0/0	0/0	2/12
	sep-85	1/22	1/22	11/22	0/0	22/23	0/0	0/22	13/22	0/0	0/0	0/0	0/0	10/22
Brazil	**sep-82**	3/24	10/24	5/22	0/0	0/21	0/0	0/24	0/24	0/0	0/0	0/0	0/0	0/24
	mar-90	0/24	6/24	11/24	0/0	2/24	4/24	0/24	0/24	0/0	0/24	0/0	0/0	2/24
	jan-99	0/24	0/24	0/24	7/24	0/24	1/24	0/24	0/24	0/0	12/24	0/0	0/0	3/24
Chile	**jun-82**	3/24	10/24	14/18	0/0	0/24	8/24	0/24	0/24	5/24	0/0	0/0	0/0	5/24
	jul-85	4/24	6/24	2/24	0/0	10/24	1/24	11/24	7/24	14/24	0/0	0/0	0/0	0/24

	Crisis Dates	Foreign reserves	Export	RER	Equity price	Commerical deposit	Output	M2 multiplier	M2 Reserves	Domestic credit	real interest	real interest differential	Lending/deposit rate	import
		sig/a.d.	sig/a.d.	sig/a.d.	sig/a.d.	sig/a.d.	sig/a.d.	sig/a.d.	sig/a.d.	sig/a.d.	sig/a.d.	sig/a.d.	sig/a.d.	sig/a.d.
Colombia	**jan-85**	24/24	4/24	0/24	0/0	0/0	0/0	0/0	0/0	0/0	0/0	0/0	0/0	0/0
	sep-98	0/24	2/24	5/24	0/0	0/0	0/0	0/0	0/0	0/24	5/24	1/24	3/24	0/0
	jul-02	0/24	8/24	0/24	0/0	0/0	0/0	0/0	0/0	7/24	7/24	0/24	7/24	0/0
India	**jul-91**	10/24	0/24	0/0	0/24	6/23	2/24	3/24	8/24	0/0	0/0	0/24	0/0	2/24
	mar-93	2/19	3/19	0/0	0/19	4/21	7/20	12/19	2/20	0/0	0/0	4/20	0/0	2/20
Indonesia	**mar-83**	12/24	5/24	0/0	0/0	6/23	0/0	7/24	12/24	13/24	0/0	0/0	0/0	5/24
	sep-86	0/24	6/24	0/0	0/0	4/21	0/0	12/24	0/24	0/24	0/0	0/0	0/0	0/24
	jan-98	0/24	1/24	0/0	2/18	0/24	0/0	0/24	0/24	0/24	2/24	0/24	0/24	0/24
	jun-98	2/5	0/5	0/0	3/5	0/5	0/0	0/5	1/5	0/5	1/5	0/5	0/5	0/5
Malesya	**feb-85**	0/24	0/24	7/24	3/24	0/24	12/24	0/0	0/0	2/24	2/24	0/0	0/0	0/24
	dec-92	0/24	0/24	6/24	0/24	1/24	0/24	0/0	0/0	0/24	3/24	2/24	0/0	3/24
	jul-97	2/24	0/24	3/24	0/24	0/24	0/24	0/0	0/0	0/24	5/24	0/24	0/24	0/24
	jan-98	2/6	0/6	0/6	4/6	0/6	0/6	0/0	0/0	0/6	0/6	0/6	0/6	0/6
Mexico	**feb-82**	0/24	3/13	5/15	14/24	0/13	0/0	0/24	0/24	0/0	11/24	0/0	0/0	3/13
	dec-82	7/10	2/10	0/10	10/10	0/10	3/9	0/10	5/10	0/0	0/10	0/0	0/0	0/10
	dec-94	0/24	0/24	0/24	3/24	0/24	0/24	15/24	6/24	0/0	8/24	0/0	0/0	0/24
Pakistan	**jul-93**	1/24	4/24	0/0	5/24	2/24	0/0	1/24	1/24	8/24	0/0	0/0	0/0	4/24
	oct-95	2/24	1/24	0/0	9/24	0/24	0/0	2/24	2/24	0/24	0/0	0/0	0/0	5/24
	oct-96	3/12	1/12	0/0	6/12	4/12	0/0	5/12	3/12	0/12	0/0	0/0	0/0	2/12
	may-99	3/24	2/24	0/0	18/24	0/24	0/0	7/24	3/24	0/24	0/0	0/0	0/0	1/24
	sep-00	0/16	0/16	0/0	0/16	4/16	0/0	1/16	0/16	0/16	0/0	0/0	0/0	0/16
Peru	**oct-87**	3/24	4/24	0/0	0/0	0/24	0/0	0/24	0/24	0/0	0/0	0/0	0/0	12/24
	sep-88	11/11	0/11	0/0	0/0	0/11	0/0	0/11	11/11	0/0	0/0	0/0	0/0	2/11
	aug-90	5/23	3/23	0/0	0/0	3/24	0/0	0/23	6/23	0/0	0/0	0/0	0/0	5/24
Philippines	**oct-83**	13/24	8/24	0/24	3/24	0/0	0/0	9/23	12/24	0/0	0/0	2/24	2/11	0/0
	jun-84	2/8	0/8	1/7	0/8	0/0	0/0	0/0	2/8	0/0	0/0	0/8	1/8	0/0
	feb-86	2/20	9/20	7/20	0/20	0/0	0/0	0/0	2/20	0/0	0/20	11/20	5/20	0/0
	dec-97	0/24	0/24	0/24	7/24	0/0	0/0	0/24	0/24	7/24	4/24	3/24	2/24	0/0

Country	Crisis Dates	Foreign reserves	Export	RER	Equity price	Commerical deposit	Output	M2 multiplier	M2 Reserves	Domestic credit	real interest	real interest differential	Lending/deposit rate	import
		sig/a.d.	sig/a.d.	sig/a.d.	sig/a.d.	sig/a.d.	sig/a.d.	sig/a.d.	sig/a.d.	sig/a.d.	sig/a.d.	sig/a.d.	sig/a.d.	sig/a.d.
Singapore	**dec-97**	2/24	5/24	1/24	2/24	0/24	0/0	1/24	1/24	0/0	0/24	0/0	0/24	1/24
	may-98	5/5	0/6	0/6	5/5	0/6	0/0	4/5	5/5	0/0	4/5	0/0	0/5	0/5
South Africa	**jul-84**	2/24	0/0	9/24	3/24	0/24	0/0	14/24	2/24	5/24	0/0	8/24	0/0	0/0
	aug-85	4/13	0/0	0/12	2/12	0/13	0/0	0/13	2/13	0/13	0/0	3/14	0/0	0/0
	dec-01	0/24	0/0	0/24	0/24	0/24	0/24	7/24	0/24	1/24	0/0	0/24	0/0	0/0
Thailand	**jul-97**	2/24	3/24	0/0	0/0	0/24	0/0	0/24	0/24	2/24	4/24	0/0	7/24	2/24
	jan-98	6/6	2/6	0/0	0/0	0/6	0/0	0/6	6/6	0/6	1/6	0/0	0/6	0/6
Turkey	**apr-94**	3/24	3/24	0/0	2/24	4/24	0/0	7/24	8/24	0/0	0/0	0/0	0/0	1/24
	feb-01	0/24	4/24	0/0	0/24	0/24	4/24	1/24	0/24	0/0	2/24	0/0	0/0	1/24
Uruguay	**dec-82**	8/24	4/24	8/24	0/0	0/24	0/0	10/24	8/24	0/0	2/24	3/24	0/24	1/23
	nov-84	5/23	4/23	1/24	0/0	5/23	0/0	1/23	5/23	0/0	6/23	5/23	2/24	6/23
	jul-02	1/24	6/24	0/24	0/0	0/24	0/0	2/24	0/24	0/0	17/24	5/24	2/24	0/24
Venezuela	**feb-84**	1/24	2/24	0/24	2/24	0/0	0/0	0/24	1/24	0/0	0/0	0/0	0/0	0/24
	dec-86	0/24	11/24	0/24	0/24	0/0	0/0	8/24	1/24	0/0	0/0	0/0	7/21	0/24
	mar-89	10/24	0/24	5/24	1/24	0/0	0/0	15/24	12/24	0/0	0/0	0/0	0/24	1/24
	may-94	0/24	0/24	0/24	12/24	0/0	0/0	0/24	0/24	0/0	0/0	0/0	1/24	0/24
	apr-96	2/24	0/24	7/24	3/23	0/0	0/23	0/24	5/24	0/0	0/0	0/0	9/23	3/23
	feb-02	4/21	5/24	0/24	1/24	0/0	2/24	5/24	1/24	0/0	0/0	0/0	3/24	3/24

In this table, each column gives the results for a variable. The first number in each box indicates the number of signals given before the crisis, while the second number refers to the number of available data for that indicator.

Source: Author's calculations based on data obtained from the International Monetary Fund Database

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