Centro de Estudios Económicos

www.colmex.mx

El Colegio de México, A.C.

Serie documentos de trabajo

EXPLAINING CURRENCY CRISES

Gerardo Esquivel and Felipe Larraín

DOCUMENTO DE TRABAJO

Núm. IV – 1999

EXPLAINING CURRENCY CRISES

Gerardo Esquivel

and

Felipe Larraín B.[*]

This Version: January 2000

Abstract: This paper examines the determinants of currency crises with a panel annual dataset for 30 countries between 1975 and 1996. We estimate a probit model with random effects, and find that high rates of seignorage, current account imbalances, real exchange rate misalignment, low foreign exchange reserves, negative terms of trade shocks, poor growth performance, and a measure of *regional contagion* all have significant power to explain the presence of currency crises in our sample. In general, our results can be interpreted as supporting both first and second-generation models of currency crises. Various robustness tests confirm the validity of these results. We also find that currency crises have an important predictable component. Using our benchmark regression we are able to predict correctly a majority of the currency crises that occurred within our sample.

JEL Classification: F31, F33

E-mail addresses: gesquive@colmex.mx, flarrain@hiid.harvard.edu

---

_____

1. Introduction

The 1990s currency crises in Mexico, Asia and, most recently, in Brazil and Ecuador have led to a questioning of what we really know about currency crises, what provokes them and whether they can be predicted or not. In fact, the sheer occurrence of these events, as well as the magnitude of their sequels in other countries, has cast doubts on the ability of economists, traders and international institutions to explain currency crises, let alone to forecast them. Some have gone beyond, stating that we really understand very little about why and when currency crises occur. We believe that this idea is incorrect and that it provides an erroneous account of our current understanding of what causes a currency crisis.

This paper develops a formal empirical analysis on the determinants of currency crises. The objective of the analysis is twofold. First, we attempt to simultaneously test the main predictions of two groups of models of currency crises (the so-called first and second-generation models of currency crises) to investigate whether these theoretical models have helped us understand why currency crises occur and to elucidate the question of whether these models are complements or substitutes in explaining the presence of currency crises. Our second objective is to provide an initial evaluation of the predictive power of the variables emphasized in the theoretical literature. So far, most empirical studies on this subject have limited themselves to analyzing the statistical relevance of some of the variables suggested by the theoretical models without discussing in detail whether these results are useful in identifying whether a currency crisis is likely to occur or not. In order to achieve these two objectives, we estimate a model of the determinants of currency crises and evaluate its predictive power in an annual panel dataset for 30 high and middle-income countries between 1975 and 1996.

The general approach followed in this paper has many common elements with the empirical literature on currency crises and is close in spirit, for example, to the work of Frankel and Rose (1996). That is, we start by defining a currency crisis. Next, we choose explanatory variables in close correspondence with the factors highlighted by the theoretical models we are trying to test. We then use multivariate analysis to estimate a

_____

model of the determinants of currency crises. Finally, we use our results to evaluate its in-sample predictive power.

Our methodological approach departs from the literature in at least three ways. First, we propose a definition of currency crises which is based on changes in the real exchange rate. In contrast with definitions based on changes in the nominal exchange rate (i.e. Edwards, 1989 and Frankel and Rose, 1996), our definition of crises allows us to exclude many of the large nominal depreciations that tend to occur during high-inflation episodes. Second, our method of estimation --a Probit model with random effects-- takes into account the cross-section and time-series characteristics of our data. This method of estimation exploits optimally the within-units correlation that results from observing the same countries repeatedly over time. To the best of our knowledge, this is the first study on currency crises that exploits this feature of the data. Finally, the last section of the paper discusses some issues related to the estimated model's predictive power. In particular, we make the point that in evaluating the predictive power or these type of models one should not use the standard probability threshold value of 50 percent to issue a warning of crisis. Instead, we propose to use an intermediate value between the actual percentage of currency crises in the sample and the typical threshold value of 50 percent. While the optimal threshold value is not defined in this paper (it depends on the weights that one wishes to attach to the two possible types of errors), we propose a simple rule that notoriously increases the goodness of fit of the classifications implied by our econometric estimates.

The paper is organized as follows. Section 2 reviews the theoretical literature on currency crises. Section 3 discusses the empirical literature on the determinants of currency crises. Section 4 presents the definition of crisis used in this paper and describes our method of estimation. The next section discusses the data and the explanatory variables. Section 6 presents our main empirical results followed by a preliminary evaluation of the predictive power of the model in section 7. A conclusion closes the paper.

_____

2. Theoretical Models of Crises

First-generation models

The first formal model of balance-of-payments crises was put forward by Krugman (1979), based on the work of Salant and Henderson (1978). Krugman argued that crises occur when a continuous deterioration in the economic fundamentals becomes inconsistent with an attempt to fix the exchange rate. The original source of problems in Krugman's model is the excessive creation of domestic credit to either finance fiscal deficits or to provide assistance to a weak banking system. More specifically, the model assumes that the government has no access to capital markets, thereby forcing it to monetize its expenditures. In this context, an interest rate parity condition induces capital outflows and a gradual loss of foreign exchange reserves. Further down the road, the economy eventually becomes the victim of a speculative attack on its foreign exchange reserves, which triggers the collapse of the fixed exchange rate system. The timing of the attack in Krugman's model is determined by a critical level in the amount of reserves. Once reserves reach such threshold level, speculators are induced to exhaust the remaining reserves in a short period of time to avoid capital losses.

Krugman's work was later extended and simplified by several authors. Flood and Garber (1984) constructed a simplified linear model, introducing a stochastic component. Connolly and Taylor (1984) analyzed a crawling-peg regime and stressed the behavior of the relative prices of traded goods preceding the collapse of the exchange rate regime. In their analysis, the real exchange rate appreciates and the current account deteriorates prior to the collapse. In related contexts, Edwards (1989) has also stressed the patterns of currency overvaluation and current account deterioration that tend to precede devaluations, while Calvo (1987) analyzes the role of overvaluation in a cash-in-advance model.

Krugman's model has been further extended to the case of speculative attacks in target zones by Krugman and Rotemberg (1991). More recently, and inspired by the Mexican crisis of 1994, Flood, Garber and Kramer (1996) have incorporated the role of an active sterilization policy into the analysis.

3

_____

The Krugman model and its extensions represent what has become known as *first-generation models* of balance-of-payments crises.[1] Their main insight is that crises arise as a result of an inconsistency between an excessive public sector deficit that becomes monetized and the exchange rate system. In this sense, a crisis is both unavoidable and predictable in an economy with a constant deterioration of its fundamentals.

Second-generation models

More recently, a number of authors have come up with alternative explanations of currency crises. A unifying theme of these alternative models is their focus on the possibility of crises even in the absence of a continuous deterioration in economic fundamentals. Models built along these lines are known as *second-generation models* of balance-of-payments crises. Some papers along this vein are Calvo (1996), Cole and Kehoe (1996), Obstfeld (1994, 1996), Sachs, Tornell and Velasco (1996), and Drazen (1999).

Two key characteristics of many second-generation models are the assumptions that (a) the government is an active agent that maximizes an objective function, and (b) that a circular process exists which may lead to multiple equilibrium.[2] Since pure expectations may lead to one or another equilibrium, many of these models implicit or explicitly accept the possibility of *self-fulfilling crises*. This type of crises occur, for example, when the sheer pessimism of a significant group of investors provokes a capital outflow that leads to the eventual collapse of the exchange rate system, thus validating the negative expectations. In this sense, some second-generation models emphasize the reinforcing effects of the actions of economic agents in determining the movements from one equilibrium position to another. Second-generation models also underscore the role of expectations by considering the strategic complementarities of the actions of economic agents in determining the final outcome.

_____

[1] For an excellent discussion of the early first-generation models of balance of payments crises see Agenor, Bhandari and Flood (1992).

[2] Krugman (1997) discusses some characteristics of these models in more detail.

_____

Although second-generation models have several features in common, they also differ in crucial aspects. Particularly important to us is the role they assign to economic fundamentals. In some models, fundamentals play a key role in determining when a crisis may occur. In particular, they identify an intermediate range for crucial variables where a crisis may or may not occur. Thus, the probability of a crisis is determined by the position of the fundamentals, and a country with relatively "good" fundamentals will not experience a currency crisis.[3] This result suggests that even though it may not be possible to predict the timing of a crisis, it is possible to infer which countries are susceptible of falling into a currency crisis. Some of these models also suggest that unexpected shocks or sudden changes in the macroeconomic environment may induce the authorities to abandon the exchange rate system (Obstfeld, 1996).

In contrast, other second-generation models suggest that crises are not affected by the position of the fundamentals. Instead, they may simply occur as a consequence of pure speculation against the currency. There are at least two types of analyses along these lines. Models of *herding behavior* stress that information costs may lead foreign investors to take decisions based on limited information and therefore to be more sensitive to rumors (Calvo and Mendoza, 1999).

A second line of thought stresses the possibility of c*ontagion effects*. We identify two main variants of this hypothesis. The first variant focuses on trade linkages and in the loss of competitiveness associated to devaluation by a main trading partner, which in turn leaves the domestic currency more vulnerable to an attack (Gerlach and Smets, 1995).[4] The second variant is related to multiple-equilibrium, and suggests that a crisis in one country may rise the odds of a crisis elsewhere by signaling that a devaluation is more likely as a result of the initial crisis. This signal may then lead to a self-fulfilling speculative attack (Masson, 1998).[5]

_____

[3] See, for example, the model in Sachs, et al. (1996), and the strategic exercise in Obstfeld (1994).

[4] Recently, Masson (1998) has termed this interpretation as a *spillover effect* to differentiate it form a pure *contagion* effect.

[5] Yet another variant emphasizes the political nature of the devaluation decision when a policymaker is interested in enhancing political integration with its neighbors. In this context, a

_____

3. Empirical Determinants of Currency Crises: An Overview

There is by now a fairly large number of empirical studies on the determinants of currency crises. Among them, we distinguish two basic lines of analysis.[6] One focuses on the determinants of crises in a single country during periods of economic turbulence. The other relies on a multi-country analysis, and uses either a cross-section of countries or a panel-data structure.

The single-country studies usually try to explain the timing of devaluation in a specific country based on the behavior of several macroeconomic indicators, often attempting to test a specific structural model of currency crises. The classic study here is by Blanco and Garber (1986), who analyze the devaluations of the Mexican peso between 1976 and 1982 and show that large exchange rate adjustments in Mexico were preceded by substantial increases in the ex-ante probability of devaluation. Subsequent studies along this line have focused on Argentina (Cumby and Van Wijnbergen, 1989), Mexico in the 1980s (Goldberg, 1994), Mexico between 1982 and 1994 (Pazarbasioglu and Otker, 1997), and the experiences of several European countries in the context of the European Monetary System (Otker and Pazarbasioglu, 1997).

These works have generally found strong evidence suggesting that domestic macroeconomic indicators play a key role in determining currency crises. Crises tend to be preceded by foreign reserve losses, expansionary fiscal and monetary policies (usually measured by net domestic credit creation) and by high interest rate differentials.[7] These results, although suggestive, are somewhat limited since they are obtained from a small number of countries during very specific situations.

_____

devaluation in one of the neighboring countries may increase speculation against the domestic currency (see Drazen, 1999).

[6] This section focuses on econometric or quantitative studies only. There is also a vast literature on currency crises that uses a qualitative approach. A recent example is Dornbusch, Goldfajn and Valdes (1995).

[7] A more detailed summary of the main findings of each one of these papers is provided in the Appendix to Kaminsky, Lizondo and Reinhart (1998).

_____

Multi-country studies recognize the limitations of country-specific analyses, and attempt to exploit the higher variability associated with cross-country information. A growing number of studies along these lines has come out in recent years.[8] Because our paper belongs to this branch of analysis, we provide here a brief summary of this literature. In doing so, we also highlight some of the main differences between our work and the existing literature.[9]

One of the first multi-country studies on currency crises is Edwards (1989), who studies the determinants of devaluation in a sample of 17 developing countries between 1962 and 1982. Using a probit model, he finds evidence that a real exchange rate appreciation and a deterioration of the foreign assets position of the central bank increase the probability of a devaluation.

Frankel and Rose (1996) use a panel of annual data for 105 developing countries from 1971 through 1992 to analyze the determinants of "currency crashes". They define a currency "crash" as a nominal depreciation of at least 25 percent in the bilateral exchange rate *vis-à-vis* the U.S. dollar with respect to the previous year, with the rate of depreciation at least 10 percent higher than the previous year's. The authors also require "crashes" to be at least 3 years apart. In their study, they follow two different methodologies. One is an event-study approach reminiscent of that used by Eichengreen, Rose and Wyplosz (1995). Through graphic analysis, they find evidence suggesting that several economic variables behave quite differently in tranquil periods as compared to

_____

[8] Recent papers along these lines include Eichengreen, Rose and Wyplosz (1995, 1996), Frankel and Rose (1996), Sachs, Tornell and Velasco (1996), Flood and Marion (1997), Martinez-Peria (1997), Goldfajn and Valdes (1998), Klein and Marion (1997), and Kaminsky, Lizondo and Reinhardt (1998). The latter also includes an excellent summary of some of the main findings of the empirical literature.

[9] A recent line of research discusses the predictive power of multi-country studies. Some papers along this line are Berg and Pattillo (1998), Tornell (1999), and Radelet and Sachs (1998). We do not discuss these works in detail here as they are generally based on one of the papers reviewed in this section and they mainly focus on the out-of-sample predictions of some empirical estimates rather than on the in-sample explanatory power of their results. Esquivel and Larrain (1999b) discuss these papers in more detail.

_____

crises periods.[10] Interestingly, the authors find that neither the current account deficit nor the fiscal deficit behave significantly different during tranquil and crisis episodes.

Using probit regression as another methodology, Frankel and Rose find that low levels of foreign direct investment (FDI), low international reserves (as a share of imports), high domestic credit growth, high foreign interest rates and overvaluation of the real exchange rate increase the probability of a currency crash. Consistent with their previous results, they also find that neither the current account nor the fiscal balance has a significant effect on the likelihood of a currency crash.

Although many of Frankel and Rose's results are consistent with both theory and previous empirical evidence, they should be interpreted with care. As recognized by the authors, the event-study analysis has multiple disadvantages, including the partial nature of the results. The regression results, which control for such problem are somewhat sensitive to the specification and many of the variables that they claim to be important in determining currency crashes are non-significant in some of their regressions.[11] Furthermore, the explanatory power of their results is rather disappointing since their best model is able to explain correctly only 5 out of 69 currency crises in their sample.[12] [13]

Sachs, Tornell and Velasco (1996) analyze the spillover effects of the Mexican crisis of 1994/95 on a group of 20 emerging market economies. They find that low international reserves relative to broad money (M2 to foreign exchange reserves ratio), real exchange rate appreciation, and a weak banking system (as measured by the existence of a credit boom to the private sector) explain about 70 percent of the variation of their "crisis index", a composite measure of the change in reserves and the nominal

---

[10] A similar analysis has also been performed by Kaminsky and Reinhart (1999).

[11] See Milesi-Ferreti and Razin (1998) and Berg and Patillo (1998) for more details on the sensitivity of the results in Frankel and Rose (1996).

[12] There are also other problems with the definition of currency crisis suggested by Frankel and Rose. For example, using their methodology they incorrectly identify some episodes of currency crisis with a lag of up to one year. This is the case of the Mexican devaluations of 1976 and 1985, which they classify as currency crisis in 1977 and 1986.

[13] Milesi-Ferreti and Razin (1998) and Berg and Patillo (1999) have recently extended and improved upon some of the results of Frankel and Rose (1996).

depreciation. Cooper (1996), however, has warned against overemphasizing these results, since they are drawn from a single crisis episode.

Kaminsky, Lizondo and Reinhart (1998) present a comprehensive review of the literature on balance of payments crises. They study 76 currency crises in 20 countries (15 developed and 5 developing countries) from 1970 through 1995. Their definition of crisis is based on an exchange market pressure index that consists of changes in the nominal exchange rate and in the international gross reserves. These authors identify a number of indicators that tend to behave systematically different in the months previous to the crisis. Based on their results, they propose an early-warning system to try to prevent future currency crises.

Goldfjan and Valdes (1998) use survey data (May 1984-May 1997) for 26 (mostly high-income) countries to analyze whether currency crises are predictable or not. They use three alternative definitions of crises. First, they define a crisis as a large nominal devaluation (larger than 1.96 times the standard deviation of the country's nominal devaluation rate in the sample period) that is also larger than 2 percentage points plus 1.5 times last-month's devaluation. Crises are required to be two months apart. Their second measure is a large change in the real exchange rate (larger than 2 standard deviations from the mean). Third, they use the crisis episodes reported by Kaminsky and Reinhart (1999) which combine information about devaluation and reserve losses.

Goldfajn and Valdes then apply a logit model to predict the one-month ahead probability of a currency crisis as a function of the expected devaluation and the real exchange rate misalignment.[14] Their results show that overvaluation helps to explain the presence of crises, but the measure of expected devaluation does not. When both variables are included as explanatory variables, none is significant possibly as a result of their collinearity. The authors conclude that "exchange rate crisis are largely unpredictable events".

---

[14] Misalignment is measured by the deviation between the actual and predicted real exchange rate (RER) series, where the latter is obtained from a regression that includes trends and a constant and the RER is computed using the CPI.

_____

In summary, the empirical evidence on the determinants of currency crises is far from conclusive, and most of the interesting and robust results come from country-specific studie s. Evidence from multi-country studies is mixed and not very robust. Other results, like those of Sachs, Tornell and Velasco (1996), come from a sample that is far from random and that focuses on a very specific event (the aftermath of the Mexican crisis of 1994). In the next section we attempt to overcome some of these problems, analyzing the empirical determinants of currency crises in a broad sample of countries.

4. Definition of Crisis and Estimation Method

Defining a Currency Crisis

We consider that a currency crisis exists *only when there is an abrupt change in the nominal exchange rate*. Thus, unlike previous studies,[15] we exclude unsuccessful speculative attacks from our definition of crisis. The main reason to exclude these episodes from our definition of crisis is that it is very hard and subjective to define when a speculative attack has occurred. Moreover, the standard measure that has been used to identify instances of speculative attack has several problems of its own. This procedure—first suggested by Eichengreen, *et al.* (1995)—uses a "speculative pressure index", a weighted average of the changes in reserves, interest rates and the nominal exchange rate.

This index has been criticized at least on three grounds. First, there is no clear guidance on the weights that should be attached to each variable, and studies that make use of this index tend to exclude a sensitivity analysis of the weighting scheme. Second, as pointed out by Flood and Marion (1998), this measure is plagued by a series of time aggregation problems that cast doubt on the effects it is capturing. Third, the index is defined in such a way that it tends to select situations which are largely unpredictable from a "bad fundamentals" perspective (Flood and Marion, 1998). Finally, we are interested in *actual* currency crises, and thus prefer to focus on "successful" speculative attacks.

_____

[15] Eichengreen, Rose and Wyplosz (1995, 1996), Kaminsky and Reinhart (1996), and Sachs, Tornell and Velasco (1996).

_____

For a nominal devaluation to qualify as a currency crisis, we use two criteria. First, the devaluation rate has to be large relative to what is considered standard in a country (we will be more precise about this later). Second, the nominal devaluation has to be meaningful, in the sense that it should affect the purchasing power of the domestic currency. Thus, nominal depreciations that simply keep up with inflation differentials are not considered currency crises even if they are fairly large. Our definition of crises therefore excludes many of the large nominal depreciations that tend to occur during high-inflation episodes.

These two considerations imply that a currency crisis exists only if a nominal devaluation is accompanied by a large and abrupt change in the real exchange rate (at least in the short run). Because the general price level reacts slowly to changes in the nominal exchange rate, in practical terms we can detect a currency crisis simply looking at changes in the real exchange rate. Before doing so, however, we need to define how large the real exchange rate (RER) movement must be in order to be considered a crisis.

We consider that a currency crisis has occurred when one of the following conditions is met:

Condition A:

The accumulated three-month real exchange rate change is 15 percent or more:

$$\Delta^3 \varepsilon_{it} > 15\%$$

or,

Condition B:

The one-month change in the real exchange rate is higher than 2.54 times the country-specific standard deviation of the RER monthly growth rate, provided that it also exceeds 4 percent:

$$\Delta^1 \varepsilon_{it} > 2.54 \; \sigma_i^{\Delta\varepsilon} \quad \text{and} \quad \Delta^1 \varepsilon_{it} > 4\%$$

_____

where:

ε_{it} is the real exchange rate in country i in period t

$\Delta^1\varepsilon_{it}$ is the one-month growth rate of the RER in country i in period t

$\Delta^3\varepsilon_{it}$ is the accumulated three-month RER's growth rate in country i at time t

$\sigma_i^{\Delta\varepsilon}$ is the standard deviation of $\Delta^1\varepsilon$ in country i

Condition A is intended to make sure that any large real depreciation is counted as a currency crisis. The threshold value of 15 percent is certainly somewhat arbitrary, but sensitivity analysis shows that the precise threshold is largely irrelevant for our results.[16] Condition B, on the other hand, attempts to capture changes in the RER that are sufficiently large relative to the historical country-specific monthly change of the RER.[17]

Estimation Methodology

We now describe our approach to estimate the determinants of currency crises. The variable to be explained (y_{it}) is dichotomous, and takes the value of 1 if a currency crisis occurred during year t, according to the criteria outlined before, and 0 otherwise.

We assume that there is an unobservable or latent variable ($y_{it}{}^*$) which is described by

$$y_{it}{}^* = \textbf{\textit{b}}'\mathbf{X}_{it-1} + u_{it}$$

where $\mathbf{X}_{it-1}$ is a vector of explanatory variables from country i in period $t-1$, $\textbf{\textit{b}}$ is a vector of coefficients to be estimated, and u_{it} is a composite error term defined as

$$u_{it} = \alpha_i + v_{it}$$

---

[16] Other authors have also used thresholds in their definition of crisis. Frankel and Rose (1996), for example, use a 25 percent *nominal* exchange rate change as a threshold value. Eichengreen, Rose and Wyplosz (1995, 1996), Goldfajn and Valdes (1998), and Kaminsky, Lizondo and Reinhart (1998) have instead used a definition that is closer to our condition B.

[17] Assuming that changes in the RER are normally distributed, Condition B is defined as to capture changes in the RER that lie in the upper 0.5% of the distribution.

_____

where α_i is a random, country-specific effect, and v_{it} is a normally distributed error term with zero mean and unit variance.

We now assume that the observed currency crisis variable behaves according to

$$y_{it} = 1 \quad \text{if } y_{it}* > 0$$

and

$$y_{it} = 0 \quad \text{otherwise}$$

Because our sample has both a cross-section and a time series dimension, it is advisable to use panel data methods to fully exploit the information contained. Thus, we estimate a *probit model with random effects,*[18] of the form:

$$\text{Prob (Crisis}_{it}) = \text{Prob } (y_{it}{=}1) = \mathbf{F} \; (\mathbf{X}_{it\text{-}1})$$

where $\mathbf{X}_{it\text{-}1}$ and $\boldsymbol{b}$ are as before, and $\mathbf{F}$ represents the standard normal distribution.

Two characteristics of this methodology are worth mentioning. First, the *probit with random effects* is the most efficient method to estimate a model that has a dependent binary variable and repeated observations of the same group of countries over time. Second, to the best of our knowledge, this is the first paper that attempts to explain currency crises exploiting all the information contained in the panel data structure of a data set.

_____

[18] As discussed in Maddala (1987) and Greene (1996) the probit model it is not well suited to deal with fixed effects. Similarly, the logit methodology does not lend itself well to deal with random effects. An alternative would have been to assume fixed effects and to estimate a Conditional Logit Model as suggested by Chamberlain (1984).

_____

5. Data and Explanatory Variables

The Data

We have collected annual data for a panel of 30 countries from 1975 through 1996. Since we are interested not only in explaining currency crises but also in evaluating the predictive power of our model, most explanatory variables enter in lagged form. Thus, explanatory variables run from 1975 to 1995, whereas our dependent variable goes from 1976 to 1996. We have then a panel data set of 21 years for 30 countries, which makes a total of 630 potential observations. Since our dependent variable is dichotomous and takes the value of 1 when there is a crisis and 0 otherwise, our fitted values may then be interpreted as the one-step-ahead probabilities of a currency crisis.

The sample size is dictated by the availability of data on the real exchange rate. We use the J.P. Morgan multilateral real exchange rate database, available for 45 countries on a monthly basis since January 1970. From this group we exclude 15 countries based on several criteria. First, we exclude countries for which we could not find comparable or reliable data for some of the explanatory variables in the whole period under analysis (Taiwan, Honk Kong, Nigeria and South Africa). Second, we exclude countries that we expect a priori to behave very differently from the rest of the group: high-income oil countries (Kuwait and Saudi Arabia); countries whose currency plays a key role in the international monetary system (the United States, Germany and Japan); and low-income countries whose capital markets are relatively illiquid (India and Pakistan). Finally, we also exclude countries that do not have a single currency crisis according to our previous definitions (Austria, Canada, France, and the Netherlands).[19] After applying these criteria to our original data we are left with a sample of 30 countries, of which half are high-income and half are middle-income countries. Regionally, we have

_____

[19] It is worth emphasizing that all these considerations were done *a priori*, because we do believe that the most adequate sample should not include these countries. In fact, later in the paper we test the robustness of our results to the inclusion of some of these countries into our estimation.

_____

8 Latin American countries, 6 Asian economies, 12 European countries and 4 from other regions.[20]

Number of Crises

The number of crises in the 30 countries of our sample is obtained through the imposition of conditions A and B to our monthly real exchange rate dataset. In addition to A and B, we further assume that crises have to be at least five-months apart so as to avoid double-counting.[21] Thus, we are able to identify 117 crises episodes. Figures 1 and 2 provide a quick overview of the number of currency crises in our sample.[22]

Figure 1. Currency Crises per Year

---
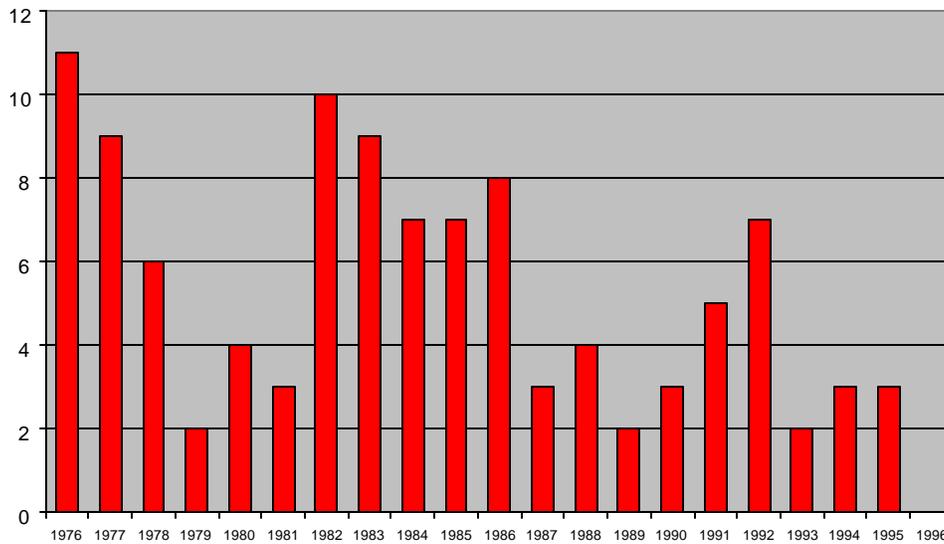
[20] The complete list of countries is as follows: Argentina, Australia, Belgium, Brazil, Chile, Colombia, Denmark, Ecuador, Finland, Greece, Indonesia, Ireland, Italy, Korea, Malaysia, Mexico, Morocco, New Zealand, Norway, Peru, Philippines, Portugal, Singapore, Spain, Sweden, Switzerland, Thailand, Turkey, United Kingdom and Venezuela.

[21] This implies that there may be more than one crisis per year in a given country, but not more than two crises per year. Goldfajn and Valdes (1998) assume a two-month window around each crisis, whereas Frankel and Rose(1996) use a three-year window.

[22] A complete list of crisis dates by country is available from the authors upon request.

_____

Figure 1 shows the number of crises per year during the period 1976-96. It shows a clear oscillatory pattern in this variable during the whole period, with three identifiable peaks. The first peak corresponds to 1976, during the period of financial turmoil that followed the collapse of the Bretton Woods system. A second peak is observed in 1982, the year the debt crisis exploded in Latin America. The most recent peak occurred in 1992, when financial instability affected the European Monetary System. Interestingly, there have always been at least two currency crises per year during the whole period with the exception of 1996, when no crisis occurred.

Figure 2. Currency Crises per Country
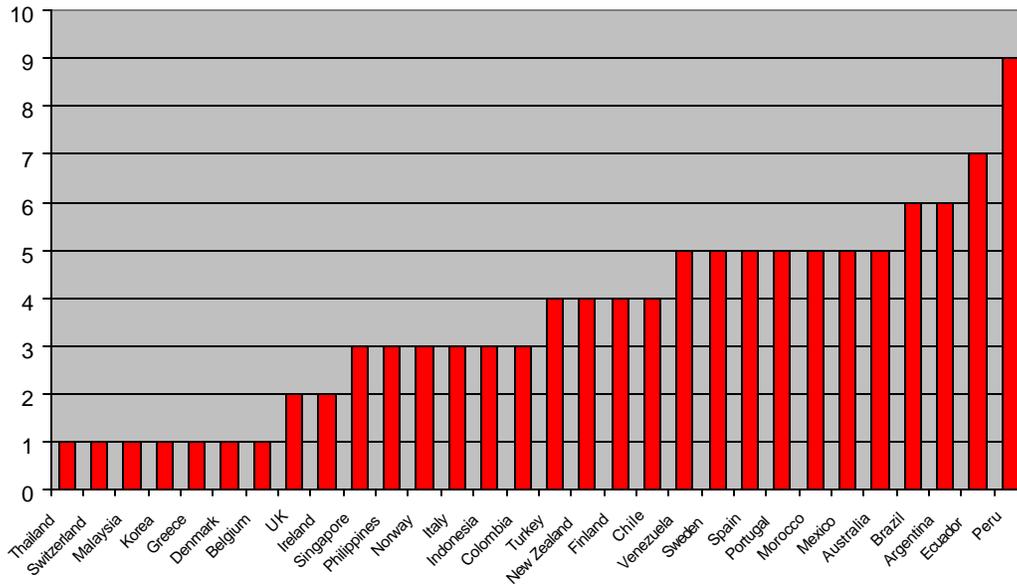
Figure 2 shows the number of currency crises per country. As expected, given the economic turbulence that afflicted Latin America during this period, the countries with the largest number of crises are from the region: Brazil, Argentina, Ecuador and Peru had six or more currency crises each between 1975 and 1996. Peru, with 9 crises, has the most number of crises in our sample.[23]

_____

[23] Figures 1 and 2 plot only one crisis per country per year. Thus, Figure 1 represents the number of countries with a currency crisis in each year, while Figure 2 shows the number of years in which a country had at least one crisis.

_____

Explanatory Variables

Below we define and explain the explanatory variables used in our analysis. They can be divided into two groups: those that are more closely associated with first-generation models of crises, and those that capture some of the insights developed by second-generation models. Other variables and alternative definitions are described later in the paper. Here we only focus on the variables used in our benchmark case. [24]

Seignorage

This variable, defined as the annual change in reserve money as a percent of GDP, attempts to capture Krugman's original insight that monetization of the government deficit is key to explain exchange rate collapses. Other authors have preferred to use the public sector balance directly. Krugman, however, assumed that the government had no access to capital markets and therefore had to monetize the deficit. If governments running large deficits have access to capital markets (as many of the countries in our sample have had during the sample period), then the deficit by itself may be a bad predictor of exchange rate crises. Thus, we believe that seignorage better captures the essence of first-generation models. The appropriateness of this variable has also been acknowledged by Krugman himself: "Old-currency crisis models were essentially seignorage-driven: countries were assumed to have an uncontrollable need to monetize their budget deficits" (Krugman, 1996, p.345). We expect this variable to have a positive effect on the probability of a crisis.

Real Exchange Rate Misalignment

Several authors have emphasized that currency crises are usually preceded by periods of exchange rate overvaluation or misalignment.[25] Some previous empirical studies of crises

_____

[24] A referee suggested to include the debt structure as an explanatory variable in our estimation. The role of this variable has been emphasized, among others, by Cole and Kehoe (1996). In fact, some authors have even used this variable in similar empirical contexts (Radelet and Sachs [1998] and Tornell [1999]). Unfortunately, although we acknowledge the relevance of this type of variable, cross-country information is not readily available for periods before 1990.

[25] See, among others, Connolly and Taylor (1984), Edwards(1989), and Dornsbuch et al. (1995).

_____

have simply used a RER index as an explanatory variable. While this procedure may be adequate in single-country studies, it is hardly acceptable in multi-country analyses where the cross-section information should also be exploited. Note that by using a RER index one is implicitly assuming that the RERs of all countries in the sample are equally aligned during the base year, which is an untenable assumption.

Our RER misalignment variable measure overcomes this problem in a simple and straightforward way. We define "misalignment" as the negative of the percentage deviation of the RER from its average over the previous 60 months.[26] This definition makes our variable easily comparable in both dimensions, across time and across countries. A related variable had predictive power to explain currency crises in Goldfajn and Valdes (1998).[27] Furthermore, Kaminsky *et al.* (1998) found that various measures of the RER are among the variables that have worked best in empirical analysis of the determinants of crises. An increase in the RER misalignment is expected to increase the risk of a currency crisis.

Current Account Balance

Along with an appreciation of the RER, a deterioration of the current account balance is also expected in anticipation of a currency crisis. If the RER variable were an exact measure of the relative price of tradable to non-tradable goods and if countries responded the same to changes in the RER, the current account variable would likely not add any extra information to that contained in the RER variable. However, if either of these two assumptions does not hold (and they most likely do not), we should expect the current account balance to add to the RER in explaining currency crises. We expect to find a negative relationship between the current account balance and the probability of crisis.

_____

[26] Note that the RER misalignment variable is defined so that RER appreciation (or overvaluation) with respect to the previous 5-year average enters with a positive sign. An *increase* in the misalignment variable then represents a larger appreciation and a higher risk of a crisis.

[27] Goldfajn and Valdes (1998) use three alternative definitions of RER misalignment. Most of their results, however, are obtained using a variable calculated as the deviation of the actual RER series from a predicted series obtained from a regression of the RER using trends and a constant.

_____

M2/Reserves

A number of studies argue that governments usually lose substantial reserves in the months previous to a currency crisis. Edwards (1989), Eichengreen *et al.* (1996), Frankel and Rose (1996) and Martinez-Peria (1997) provide empirical evidence in this regard. In order to make foreign exchange reserves comparable across countries we need to use a scale variable. Many authors have used the months of imports that that can be covered with foreign exchange reserves. More recently, others have suggested that official foreign exchange reserves relative to a liquid monetary assets is more appropriate, since it reflects better the vulnerability of the central bank to possible runs against the currency. Following Sachs, Tornell and Velasco (1996) we have chosen the ratio of M2 to reserves. This variable has worked well in previous empirical studies and has been identified as a leading indicator of exchange rate crises by Kaminsky *et al.* (1998). To reduce dispersion in this variable and to facilitate the interpretation of its associated coefficient, we use it in log form. We expect to find a positive association between this variable and the probability of crisis.

Terms of Trade Shock

There is a fair amount of evidence showing that some currency crises are preceded by negative terms of trade shocks (e.g. Edwards, 1989). While it is not clear whether the crisis results from the shock or from the policy reactions to the shock, the relationship between terms of trade shocks and crises is well established. Moreover, the literature on equilibrium RERs has shown that a terms of trade deterioration usually leads to a depreciation of the equilibrium rate, which may in turn force a devaluation of the nominal exchange rate. In the context of second-generation models, the terms-of-trade shock may capture a pure exogenous effect that can move an economy from one equilibrium situation to another. This variable is defined as the annual percentage change in the terms-of-trade, and we expect a negative effect of this variable on the probability of a crisis.

_____

Per Capita Income Growth

This variable tries to capture the escape-clause interpretation that has been developed in various second-generation models of exchange rate crises (Obstfeld, 1994 and 1996). Negative per capita growth is assumed to increase the policymaker's incentives to switch to a more expansionist policy, which can be achieved through a nominal devaluation of the currency. Our variable is dichotomous and takes the value of 1 if per capita income growth is negative in a given year and 0 otherwise.[28] Consequently, we expect a positive coefficient associated to this variable.

Contagion Effects

Contagion effects are the most recent contribution of second-generation models. There are several channels through which they may be transmitted across countries. Most explanations, however, imply that *contagion* effects tend to occur at the regional level.[29] We make use of this result in the definition of our contagion variable, proceeding as follows. First, we define our geographical regions and assign countries to each one of them. Most countries in our sample can be easily allocated into one of four regions: Europe (12 countries), Latin America (8), Asia (6), and Oceania (2). The remaining two countries in our sample, Turkey and Morocco, cannot be immediately allocated to any of these regions. We describe later how we proceed in these two cases.

Next, we specify a criterion that attempts to capture the concept of *contagion*. We define a dichotomous variable that takes the value of 1 for countries belonging to a region where at least one other country has had one exchange rate crisis in the current year. We also assign the value of 1 to this variable for the first country in the region with a crisis in the current year if another country in the same region had a crisis in the last six months of the previous year. Otherwise, we assign the value of 0. For Turkey and

---

[28] Results are not significantly different if we use a continuous version of this variable. However, we prefer to use the dummy variable since it may capture better any possible non-linearity around the zero growth rate of per capita income.

[29] See, for example, Glick and Rose (1998) and the models discussed in Drazen (1999).

_____

Morocco, we assign a value of 1 to the variable if any of their three most important trading partners in our sample had a crisis in the current year. Otherwise, the value is 0.[30]

6. Empirical Implementation and Results

Empirical Implementation

Before discussing results, it is important to explain in some detail the process of empirical implementation. As explained above, our definition of a currency crisis requires that either Condition A or B is satisfied on a monthly basis, and crises are also required to be at least five months apart. Crisis periods—by month, year and country— are therefore identified using this set of conditions. Ideally, we would conduct our empirical analysis on a monthly basis, but we face two major obstacles. First, using monthly data would make our sample highly unbalanced, with many more periods of tranquility than crisis. As discussed later, this would complicate the evaluation of our results from a predictive point of view. A second, insurmountable problem is that some of our explanatory variables are available only on an annual basis. Thus, we use annual data.

Because we would like to interpret our results as one-step-ahead probabilities of the occurrence of a crisis, we need to address the issue of whether it is adequate to use current-year values to explain next-year crises. The answer depends on when the actual crisis takes place. Assume that our explanatory variables work well and that a crisis occurs early in year *t+1*. If we use year *t* values to try to explain it, our model would likely work well since our explanatory variables would have been signaling high risks of crisis at the end of year *t*. Now assume that the crisis occurs late in year *t+1*. In this case, our model will not necessarily do well using year *t* values for the explanatory variables, because many of them may change very rapidly in the months preceding the collapse. In fact, Martinez-Peria (1997) and others suggest that a lot of the action in some of the explanatory variables (the real exchange rate and reserves, for example) takes place only a few months before the collapse.

_____

[30] We use the following trade partners. Turkey: Germany, Italy and the United Kingdom. Morocco: France, Spain and Italy.

_____

Now, there is a way to overcome this problem while keeping our objective of estimating one-step-ahead probabilitie s. Before explaining the procedure to deal with this issue, note that we have three types of explanatory variables in our set: lagged stock variables (like the degree of RER misalignment or the M2/Reserves ratio), lagged flow variables (such as the current account and seignorage), and contemporaneous variables (the contagion variable). Variables of the first type are available on a monthly basis, whereas most of the remaining variables are not.

In order to avoid using contemporaneous and/or future information in our estimation process, we apply the following *ad-hoc* procedure: if a crisis occurs between September and December of year *t,* we consider it as having occurred in year *t+1*.[31] In this situation, we adjust our stock explanatory variables to take a mid-year (June) value instead of taking the usual year-end value. This adjustment is crucial to obtain accurate estimates of the impact of our variables on the probability of crisis. Using the December RER, for example, to explain the occurrence of a crisis in November of the same year could seriously undermine the ability of our model to predict crises. The opposite would happen if we use year-end values of foreign reserves, for example, to explain a crisis in the late part of the same year. In this case it is likely that foreign reserves may be depleted by year-end, and using this value would overestimate the ability of our model to anticipate a crisis.

The contagion variable has been redefined so that crises are considered contemporaneous if they occur during the same September-August period. As for the flow explanatory variables, we still use their year *t* values to explain crises occurred between September and December of that same year (which, as stated before, are considered as to have occurred in year *t+1*). Although this means that we are partly using some concurrent or future information to explain these crises we believe that the flow characteristic of these variables reduces the risk of under or overestimating their effect on the probability of a crisis.

_____

[31] The cut-off month is not crucial for our results. We could also have used August or October without a significant change in our empirical results.

_____

Empirical Results

Table 1 presents our main results on the determinants of currency crises, while tables 2 through 5 discuss their robustness. We use a probit model with random effects which, in turn, utilizes a maximum quasi-likelihood procedure.[32] There are no overall goodness-of-fit measures for this methodology, and thus we rely on the individual and joint significance of the coefficients to evaluate our model. In the next section we discuss the prediction performance of our results as an alternative fitness measure.

Except when noted, coefficients are reported in the z-metric and, therefore, they cannot be immediately interpreted as changes in probability. The signs of the coefficients, however, correspond with the effect of the explanatory variables on the probability of a crisis. All regressions include annual dummies and a constant. These annual dummies are intended to capture any worldwide effect that may have an impact on the likelihood of currency crises in our entire sample of countries. Thus, these variables may capture not only effects on world interest rates but they may also be reflecting any other similar worldwide phenomenon.

The numbers in parentheses in Tables 1-5 are z-statistics that test the null hypothesis of no significance, and we use stars to identify the coefficients' level of significance. Most regressions in Tables 1-5 use Huber-White standard errors which are robust to misspecification of the correlation within groups. The bottom part of each table includes a chi-square statistic that tests for the joint significance of all coefficients other than the constant and the time dummies. The *p*-value of the test statistic is also included.

Table 1 presents our benchmark estimates of the determinants of currency crises. Regression (1) uses the four explanatory variables that are more closely associated with first-generation models: seignorage, RER misalignment, current account balance and the log of M2/reserves. All the coefficients are significant at conventional levels and they all have the expected signs. Moreover, they are jointly significant at the 1 percent level.

---

[32] See Hamerle and Ronning (1995) for a description of this method and for an excellent discussion on the alternative methods of estimation for panel data models with qualitative dependent variables.

_____

Regressions (2) through (4) introduce three additional explanatory variables in sequential form. As discussed above, these variables attempt to capture the insights of second-generation models. Several interesting results appear here. First, all coefficients have the expected signs. Second, most coefficients in regression (4) are statistically significant at the 5 percent level. The only exception is seignorage, which is significant at 10 percent. Third, the chi-square statistic at the bottom of Table 1 shows that all coefficients in regression (4) are jointly significant at the 1 percent level. Finally, a quick comparison across columns in Table 1 shows that the estimated coefficients tend to be very stable and that their significance is not significantly affected by the introduction of new variables. In this sense, *our results suggest that the insights of second-generation models complement rather than substitute the explanations provided by first-generation models.*

In what follows we use regression (4) as our *benchmark*. The last column in Table 1, equation (4a), translates the coefficients from regression (4) into marginal effects on the probability of crisis, evaluated at the mean values of the explanatory variables. For coefficients associated to dummy variables we have computed the actual change in probability that occurs when the dummy switches from 0 to 1, assuming that all the other explanatory variables remain at their mean values.[33]

The first coefficient in column (4a) shows that a one percentage point increase in the rate of seignorage to GDP increases the probability of crisis in more than 1 percent. Note, too, that the marginal effect of RER misalignment is highly significant and positive, as expected. At first sight, its absolute impact on the probability of crisis looks small, less than half of 1 percent. In evaluating the impact of this variable, however, consider that our regression controls for one of the most direct effects of the misalignment variable, the current account balance, which partially explains the relatively small size of this coefficient. We should also note that RER misalignments as large as 25 percent are common in our sample, which by itself implies a risk of crisis up to 8 percentage points higher than that of a country with an equilibrium RER.

_____

[33] This procedure is standard in situations with discrete explanatory variables and a qualitative dependent variable. See Greene (1996) for more details.

_____

Column (4a) shows that a one-percentage-point increase in the current account deficit to GDP increases the probability of crisis in slightly less than 1 percent. The coefficient associated to the current account deficit is always negative and strongly significant in the four regressions in Table 1. Our current account results are of special interest since other empirical studies such as Frankel and Rose (1996) and Kaminsky and Reinhart (1999) *inter alia*, found this variable to be non-significant as a determinant of currency crises. In fact, the survey of empirical studies on currency crises by Kaminsky, Lizondo and Reinhart (1998) reports that "contrary to expectations, *the current account balance did not receive much support as a useful indicator of crises*."[34] They also argue that this may be explained because the current account provides no additional information to that already conveyed by the RER. It is worth emphasizing the empirical relevance of this result since the current account has often been interpreted by analysts and practitioners as an indicator of an economy's vulnerability to a currency crisis. Our results provide some support for such interpretation.

Our fourth explanatory variable is the log of (M2/reserves); column (4a) shows that a doubling of this ratio increases the probability of crisis by around 7 percentage points. This reflects the widely documented result that this ratio rises very quickly during the months preceding currency crises.[35]

Column (4a) also shows that a 10 percent terms-of-trade decline translates into a 5 percent increase in the probability of crisis. Additionally, a period of negative per capita income growth increases the probability of crisis in more than 8 percent. The magnitude of these two effects confirms the relevance of models that characterize the devaluation decision as the result of balancing conflicting objectives. In cases where the exchange rate is a policy variable, these results may be interpreted as providing some support to the escape-clause models developed by Obstfeld (1994, 1996) as well as to other models that stress the "political" nature of some currency crises.[36]

---

[34] Emphasis in the original.

[35] See, for example, Kaminsky and Reinhart (1999).

[36] See Drazen (1999) for a brief review of this literature.

_____

The last explanatory variable in our benchmark regression is the *contagion* dummy. Its coefficient suggests that the occurrence of a currency crisis in any given country raises the contemporaneous probability of a crisis for all other countries of the same region by more than 7 percent. This result is highly significant and provides strong support for some second-generation models that have recently emphasized this effect.

Two additional aspects about this result are worth emphasizing. First, the estimated impact of our contagion variable on the probability of crisis is remarkably similar to that of Eichengreen, Rose and Wyplosz (1996). These authors found that a currency crisis elsewhere in the region leads to an increase of 7.3 percent on the probability of a speculative attack on other country's currency. The similarity of these results is all the more striking since we use different samples and definitions of the contagion variable and of currency crisis.

Second, as long as our set of explanatory variables captures fundamentals reasonably well, the estimated impact of our contagion variable can be interpreted as a probabilistic *pure contagion effect* in the sense described by Masson (1998), who argues that contagion reflects a situation where "a crisis in one country may trigger a crisis elsewhere for reasons unexplained by macroeconomic fundamentals." He also distinguishes between true *contagion* effects and s*pillover* effects, where the latter occur when a crisis in one country affects competitiveness in other countries, making them more likely to devalue (Gerlach and Smets, 1995). Since our regressions already control for the multilateral real exchange rate and terms of trade changes, the contagion dummy variable does not pick the loss of competitiveness.

_____

Table 1: Determinants of Currency Crises

Variables	Regression Coefficients (z-statistics)				dF/dx
	(1)	(2)	(3)	(4)	(4a)
Seignorage	0.050***	0.060***	0.054***	0.046***	0.010***
(as percent of GDP)	(1.84)	(1.89)	(1.94)	(1.89)	
RER Misalignment	0.014**	0.016**	0.016**	0.016*	-0.0036*
	(1.98)	(2.42)	(2.49)	(2.65)	
Current Account Balance	-0.049*	-0.043*	-0.042**	-0.042**	-0.0092**
(as percent of GDP)	(-3.00)	(-2.60)	(-2.48)	(-2.40)	
Log(M2/Reserves)	0.34*	0.33*	0.31*	0.33*	0.071*
	(3.50)	(3.24)	(3.09)	(3.14)	
Terms of Trade Shock		-0.021***	-0.021***	-0.023**	-0.0049**
		(-1.76)	(-1.69)	(-1.96)	
Negative Growth Dummy			0.37*	0.36**	0.087**
(1 if per capita income growth <0)			(2.59)	(2.54)	
Contagion Effect				0.34**	0.073**
(1 if at least one country in the region had a crisis)				(2.10)	
Number of Observations	630	611	611	611	611
Number of Countries	30	30	30	30	30
X^2 (H$_o$: Coefficients = 0)	22.65	25.47	26.46	25.93	25.93
P-Value	(0.0001)	(0.0001)	(0.0002)	(0.0005)	(0.0005)

Note: All regressions include time dummies and a constant.
    One star (*) indicates statistical significance at a 1% level,
    Two stars (**) indicates significance at a 5% level.
    Three stars (***) indicates significance at a 10% level.

_____

Robustness Tests

We test the robustness of our benchmark case in tables 2 through 5. Table 2 shows the effects of including two additional variables that have often been mentioned as likely determinants of currency crises, namely, fiscal balance and credit boom. The latter is defined as a dummy variable that takes the value of 1 when bank credit to the private sector (as a share of GDP) grows more than 50 percent in the previous three-year period. It takes the value of 0 otherwise. Neither of these variables turns out to be statistically significant nor they had they any influence on the significance or magnitude of our benchmark coefficients. We tried alternative definitions of the credit boom variable (different thresholds and/or credit in real terms), and none of them worked well. These results suggest that these two variables add no extra information to that already embodied in our benchmark explanatory set of variables. It seems as if the effects of the fiscal balance are better captured by either the seignorage rate and/or by the current account balance. On the other side, the credit boom impact on the likelihood of a crisis may be captured by the current account variable, as we have speculated in another paper (Esquivel and Larrain, 1999a).

Table 3 shows that our results are largely independent of the estimation method. For comparison purposes, the first column simply repeats our benchmark regression. The second column presents probit with random effects estimates, without using Huber-White robust standard errors. As expected, the coefficients become even more significant. Now, every coefficient is statistically significant at the 5 percent level. The last two columns in Table 3 show the estimation results with simple probit and simple logit methodologies, respectively, both using robust standard errors. Logit estimates have been divided by 1.81 ($\pi/3^{1/2}$) to make them comparable to probit results.[37] Note that results generated by simple probit and simple logit are remarkably similar to our probit with random effects estimates in both size and significance. This confirms that our results are not driven by our specific method of estimation.

_____

[37] Rationale for this transformation is provided by Maddala (1987) and Greene (1996).

_____

Table 2: Additional Variables

Variables	Regression Coefficients (z-statistics)			
	(4)	(5)	(6)	(7)
Seignorage	0.046***	0.048***	0.047***	0.049***
(as percent of GDP)	(1.89)	(1.82)	(1.85)	(1.78)
RER Misalignment	0.016*	0.016*	0.017*	0.016*
	(2.65)	(2.60)	(2.64)	(2.62)
Current Account Balance	-0.042**	-0.045*	-0.042**	-0.046*
(as percent of GDP)	(-2.40)	(-2.78)	(-2.41)	(-2.82)
Log(M2/Reserves)	0.33*	0.36*	0.32*	0.35*
	(3.14)	(3.43)	(3.10)	(3.37)
Terms of Trade Shock	-0.023**	-0.023**	-0.023**	-0.023**
	(-1.96)	(-2.03)	(-1.97)	(-2.04)
Negative Growth Dummy	0.36**	0.38*	0.36*	0.38*
(1 if per capita income growth <0)	(2.54)	(2.67)	(2.61)	(2.78)
Contagion Effect	0.34**	0.36**	0.34**	0.36**
(1 if at least one country in the region had a crisis)	(2.10)	(2.29)	(2.11)	(2.32)
Fiscal Balance		0.021		0.022
(as percent of GDP)		(1.47)		(1.53)
Credit Boom			-0.059	-0.098
(1 if 3-year growth rate > 50%)			(0.27)	(-0.45)
Number of Observations	611	609	611	609
Number of Countries	30	30	30	30
X^2 (H$_o$: Coefficients = 0)	25.93	30.51	25.99	30.82
P-Value	(0.0005)	(0.0002)	(0.0011)	(0.003)

Note: All regressions include time dummies and a constant.

　　One star (*) indicates statistical significance at a 1% level,

　　Two stars (**) indicates significance at a 5% level.

　　Three stars (***) indicates significance at a 10% level.

_____

Table 3: Robustness to Other Estimation Methods

Variables	Regression Coefficients (z-statistics)			
	Probit with Random Effects (robust s.e.)		Probit (robust s.e.)	Logit[1] (robust s.e.)
	(4)	(8)	(9)	(10)
Seigniorage (as percent of GDP)	0.046*** (1.89)	0.046** (2.28)	0.047*** (1.77)	0.044*** (1.66)
RER Misalignment	0.016* (2.65)	0.016* (2.79)	0.016* (2.94)	0.019* (3.33)
Current Account Balance (as percent of GDP)	-0.042** (-2.40)	-0.042** (-2.31)	-0.039** (-2.39)	-0.041** (-2.49)
Log(M2/Reserves)	0.33* (3.14)	0.33* (3.57)	0.22** (2.44)	0.26* (2.64)
Terms of Trade Shock	-0.023** (-1.96)	-0.023* (-2.73)	-0.024* (-3.19)	-0.030* (-3.55)
Negative Growth Dummy (1 if per capita income growth <0)	0.36** (2.54)	0.36** (2.35)	0.38* (3.00)	0.39* (3.05)
Contagion Effect (1 if at least one country in the region had a crisis)	0.34** (2.10)	0.34** (2.15)	0.43* (3.19)	0.46* (3.18)
Number of Observations	611	611	611	611
Number of Countries	30	30	30	30
Chi2	696.36	696.36	1882.89	8783.58
P-Value	(0.00)	(0.00)	(0.00)	(0.00)
Log Likelihood			-242.74	-239.90
Mc Faddens' R^2			0.16	0.17

Note: All regressions include time dummies and a constant.

One star (*) indicates statistical significance at a 1% level,
Two stars (**) indicates significance at a 5% level.
Three stars (***) indicates significance at a 10% level.

[1] Logit coeficients divided by 1.8138

_____

Table 4 presents a sensitivity analysis to alternative definitions of the explanatory variables. The first column uses the average current account balance as a percent of GDP during the previous two years; the second uses a dummy variable that takes the value of 1 if the current account deficit is higher than 3 percent of GDP, and 0 otherwise. The next regressions in Table 4 use alternative measures of the real exchange rate variable. Column 3 uses a dummy for countries with real exchange rate misalignment higher than 15 percent, whereas column 4 adds another dummy variable for countries with a real exchange rate misalignment beyond 25 percent. Column 5 uses a terms-of-trade shock dummy that takes the value of 1 if the negative shock is larger than 10 percent and 0 otherwise, instead of its continuous counterpart (the annual percentage change in the terms of trade index). Column 6 in Table 4 uses GNP per capita growth instead of the negative growth dummy we had used before. Finally, the last column in Table 4 uses (M2/reserves) instead of the log version used in our benchmark regression.

Interestingly, none of the alternative variables we introduce in Table 4 produces any major change in the meaning or significance of our results. This conclusion also holds when we use alternative threshold values in the construction of the dummy variables. Generally speaking, all of our explanatory variables remain strongly significant to changes in the definition or construction of our explanatory variables.[38] All in all, we interpret the results in Table 4 as providing strong evidence of the robustness of our benchmark regression.

Finally, Table 5 tests the robustness of our results to changes in the sample of countries. Recall that we originally excluded several countries based on various objective criteria. In Table 5 we present the estimates of our benchmark regression after reintroducing some of the previously excluded countries. In addition to our original sample of 30 countries, the first column in Table 5 includes the two low-income countries for which we have available information, India and Pakistan.

---

[38] There are just two exceptions to this statement: the seignorage rate and the terms of trade shock variables, which lose statistical significance when we use the RER misalignment dummy and the growth rate variable, respectively.

_____

Table 4: Robustness to Alternative Definitions

Variables	Regression Coefficients (z-statistics)						
	(11)	(12)	(13)	(14)	(15)	(16)	(17)
Seignorage (as percent of GDP)	0.045*** (1.77)	0.050*** (1.78)	0.031 (1.51)	0.031 (1.44)	0.04*** (1.74)	0.043** (1.97)	0.046*** (1.71)
RER Misalignment	0.017* (2.95)	0.016* (2.59)			0.016** (2.48)	0.016** (2.42)	0.019* (3.27)
Current Account Balance (as percent of GDP)			-0.043* (-2.61)	-0.043* (-2.58)	-0.044* (-2.62)	-0.40** (-2.13)	-0.040* (-2.71)
Log(M2/Reserves)	0.31* (3.10)	0.34* (3.27)	0.29* (3.29)	0.28* (3.15)	0.30* (3.09)	0.29* (2.73)	
Terms of Trade Shock	-0.025** (-2.35)	-0.023** (-1.97)	-0.020** (-2.07)	-0.020** (-2.00)		-0.019 (-1.38)	-0.023** (-2.16)
Negative Growth Dummy (1 if per capita income growth <0)	0.31** (2.27)	0.37** (2.50)	0.36* (2.56)	0.34** (2.30)	0.35** (2.42)		0.39* (2.85)
Contagion Effect (1 if at least one country in the region had a crisis)	0.35** (2.17)	0.33** (2.13)	0.34** (2.12)	0.31*** (1.88)	0.33** (2.10)	0.32** (1.98)	0.34** (2.17)
Current Account Average (as percent of GDP)	-0.47** (-2.07)						
Current Account Dummy (1 if Current Account Balance < -3%)		0.52* (3.77)					
RER Misalignment Dummy (1 if RER Misalignment > 15%)			0.92* (5.37)	0.46 (1.67)			
RER Misalignment Dummy (1 if RER Misalignment > 25%)				1.04** (2.52)			
Terms of Trade Shock Dummy (1 if shock < -10%)					0.42** (2.06)		
Growth Rate of GNP per capita)						-0.042** (-2.28)	
M2/Reserves							0.022* (4.37)
Number of Observations	611	611	611	611	611	611	611
Number of Countries	30	30	30	30	30	30	30
X^2 (H⁰: Coefficients = 0)	33.34	38.51	58.67	104.73	24.95	20.12	35.85
P-Value	(0.00)	(0.00)	(0.00)	(0.00)	(0.0008)	0.0053	(0.00)

Note: All regressions include time dummies and a constant.
  One star (*) indicates statistical significance at a 1% level,
  Two stars (**) indicates significance at a 5% level.
  Three stars (***) indicates significance at a 10% level.

_____

The second column in Table 5 adds Japan to our benchmark equation, while the next regression includes the four countries that did not have a single currency crisis throughout our sample period: Austria, Canada, France, and Netherlands. The next column adds Japan and the four countries without crises to our original sample of countries. The last regression puts together all the 37 countries for which we have information. The results in Table 5 suggest that our benchmark results are remarkably robust to the selection of countries: all the explanatory variables remain statistically significant and their associated coefficients are very stable.

Table 5: Robustness to Sample Definition

Variables	Regression Coefficients (z-statistics)				
	Benchmark + Low-Income Countries (19)	Benchmark + Japan (20)	Benchmark + Countries w/o Crisis (21)	Benchmark + Japan + Countries w/o Crisis (22)	All Countries (23)
Seigniorage (as percent of GDP)	0.046*** (1.95)	0.047*** (1.88)	0.049*** (1.84)	0.047*** (1.86)	0.050*** (1.91)
RER Misalignment	0.015** (2.46)	0.016* (2.73)	0.016** (2.52)	0.016* (2.60)	0.015** (2.34)
Current Account Balance (as percent of GDP)	-0.042** (-2.36)	-0.045* (-2.63)	-0.050* (-2.82)	-0.051* (-2.97)	-0.052* (-2.89)
Log(M2/Reserves)	0.34* (3.13)	0.31* (3.15)	0.27** (2.53)	0.28* (2.64)	0.30* (2.78)
Terms of Trade Shock	-0.023** (-1.96)	-0.023** (-2.03)	-0.022*** (-1.95)	-0.023** (-1.99)	-0.023** (-1.98)
Negative Growth Dummy (1 if per capita income growth <0)	0.34** (2.38)	0.38* (2.69)	0.38* (2.73)	0.40* (2.83)	0.37* (2.60)
Contagion Effect (1 if at least one country in the region had a crisis)	0.33** (1.99)	0.36** (2.29)	0.44* (2.58)	0.46* (2.70)	0.43** (2.53)
Number of Observations	652.00	632.00	693.00	714.00	755.00
Number of Countries	32	31	34	35	37
X^2 (H₀: Coefficients = 0)	22.76	24.60	25.10	25.87	23.43
P-Value	(0.0009)	(0.0004)	(0.0003)	(0.0002)	0.0007

Note: All regressions include time dummies and a constant.
    One star (*) indicates statistical significance at a 1% level,
    Two stars (**) indicates significance at a 5% level.
    Three stars (***) indicates significance at a 10% level

_____

In sum, all the exercises undertaken in this section point towards the same conclusion: *our benchmark results are strikingly robust*. The significance and magnitude of the effects discussed above are not affected by the addition of new variables, changes in the estimation method, changes in the definition of variables, or changes in the sample of countries.

7. Predicting Crises: A Preliminary Evaluation

In this section we present a preliminary evaluation of our model's ability to predict in-sample currency crises. Given that our dependent variable is binary and that our model uses mostly past information, fitted values from our regression can be interpreted as the one-step-ahead probabilities of crisis. However, since we are restricting our analysis to the in-sample prediction of crises events, the results in this section should be viewed more as a discussion of the goodness of fit of our results rather than as a true measure of the ability of our model to predict currency crises in the future. [39]

Hits and Misses

A standard goodness-of-fit measure for models with a binary dependent variable is a 2x2 matrix with the hits and misses that result from following a certain prediction rule. Table 6 describes the characteristics of such a table in the context of this paper. The columns and rows of the matrix are defined by two mutually exclusive outcomes for either the actual or the predicted situation: tranquil or crisis. Other than headings and total columns, Table 6 has four zones identified with letters A, B, C, and D. Elements in the main diagonal represent situations where the prediction corresponds with the actual situation (*the hits*, zones A and D), whereas the elements off the main diagonal represent *the misses* (zones B and C).

_____

[39] A more detailed analysis of the issues discussed in this section is pursued in Esquivel and Larraín (1999b). This paper also evaluates the out-of-sample prediction ability of our model.

_____

Table 6: Hits and Misses

Actual Situation

		Tranquil	Crisis	Total
Predicted Situation	**Tranquil**	A	B	Predicted Number of Tranquil Periods (A+B)
	Crisis	C	D	Predicted Number of Crisis Periods (C+D)
	Total	Actual Number of Tranquil Periods (A+C)	Actual Number of Crisis Periods (B+D)	Total Number of Periods (A+B+C+D)

Prediction Rule

A standard rule is used: we predict a crisis whenever the predicted probability (defined as P_{it}) is higher than a certain threshold value (P*). That is, our prediction rule is:

a) If P_{it} > P* a crisis is predicted (i.e. an alarm is issued)

b) Otherwise, a tranquil period is predicted

As in many other situations where we try to map from a continuous to a discrete variable, the number of correct predictions depends on the threshold value used in the rule. The most commonly assumed threshold value in hits-and-misses exercises is 0.5, as it is usually assumed that an event should be predicted only when the model estimates that the event is more likely to occur than not. We believe, however, that using P* = 0.5 is not always appropriate.

_____

An important and often overlooked result in the estimation of models with dichotomous dependent variables, is that the average predicted probability generated by most estimation methods is exactly equal to the proportion of ones in the sample.[40] Thus, if the sample is unbalanced towards one of the two possible outcomes (as it is in our study), the average predicted probability will be very different from 0.5. If, for instance, there are relatively few ones in the sample, then only extreme combinations of the independent variables will generate a predicted probability above 0.5. If under such circumstances one uses this value as a threshold in the prediction rule, it may result in a severe underestimation of the number of events predicted. Thus, using P* = 0.5 when the proportion of ones in the sample is relatively low may lead to an underestimation of the model's ability to predict.

What threshold value should we use, then? One possibility is to use the in-sample average number of crises. The prediction rule in this case would imply that whenever the predicted probability is higher than the in-sample average number of crises, a crisis is predicted. The problem with this option is that there may be many more observations above the average predicted probability than the proportion of ones in the sample, which may easily lead to overprediction in the number of crises. Since it does not make sense to use a threshold value below the average predicted probability, this solution would provide, at best, a lower bound on the threshold value.

It is thus clear that an adequate threshold value for our prediction rule lies somewhere between the proportion of ones in the sample and 0.5. Lacking any objective measure to define such threshold, we present the results obtained using different threshold values. Since the proportion of ones in our sample is around 18 percent, we start with a threshold value close to this number. Table 7 shows three indicators of the prediction performance of our benchmark regression for values of P* that range from 0.20 to 0.50.

---

[40] Greene (1996) provides a short discussion of this result. Maddala (1983) presents a proof of this result for various estimation methods.

The first column in Table 7 shows the percentage of crises predicted correctly, which range from 70 percent (when P* = 0.20) to 17 percent (when P*= 0.5). The second column shows the percentage of tranquil periods predicted correctly. This variable increases with the threshold value and fluctuates much less than the number of crises predicted correctly. With P* = 0.20 we already predict more than 76 percent of all tranquil periods. This number quickly rises with further increases in P* and reaches 98 percent when P* = 0.5. Finally, the third column of Table 7 shows, in percent, the number of crises that actually happen out of those that we predict as crisis. This number also rises with P* (because our predictions are more selective) and ranges from 40 percent when P* = 0.20 to more than 65 percent when P* = 0.5. It is important to note that this last indicator is simply equal to 100 minus the number of false alarms as a percentage of total alarms (that is, it equals 100 – C/(C+D) according to our notation above). Thus, false alarms as a percentage of total alarms go from 60% when P* = 0.20 to 35% when P* = 0.5.

Table 7: Prediction Performance

Threshold Values	Percentage of Crises Predicted Correctly D/(B+D)	Percentage of Tranquil Periods Predicted Correctly A/(A+C)	Percentage of Crises given that a Crisis was predicted D/(C+D)
P*=20	70.3	76.6	40.0
P*=25	63.1	84.8	47.9
P*=30	54.1	90.0	54.5
P*=35	38.7	94.6	61.4
P*=40	27.9	96.4	63.3
P*=45	22.5	97.2	64.1
P*=50	17.1	98.0	65.5

_____

The main message conveyed by Table 7 is that the prediction performance of our model varies substantially depending on the threshold value in our prediction rule. Since there is a trade-off between the number of correct predictions in column 1 and the number of correct predictions in the last two columns, there is no immediate way to select a threshold value. One option would be to select P* so as to maximize the total number of correct predictions. Since we may be more interested, however, in predicting correctly crises rather than tranquil periods, we may not want to give equal weight to both types of predictions. In the absence of any other criterion to decide which P* to use, we have followed a simple rule: choose the threshold value that maximizes the simple average of the three types of predictions described in Table 7. With this criterion, the value that results is P* = 0.3. Using this threshold value we are able to predict correctly 90 percent of tranquil periods and more than half of the crises (54 percent). The percent of crises that actually occurred given that a crisis was predicted is 54.5 percent and thus false alarms as a percentage of total alarms is 45.5.

Table 8 shows the equivalent of Table 6 for our benchmark regression, using the threshold value P* = 0.30. The elements in the main diagonal represent the hits, and the elements off the diagonal are the misses. The numbers in parentheses are percentages with respect the total number of actual events. Table 8 shows that we predict correctly 450 out of 500 tranquil periods, and 60 out of 111 crises. That is, we classify correctly more than 83% of total observations. In contrast, we misclassify 51 crises periods as tranquil ones and 50 tranquil periods as crises.

Two observations are worth on the goodness of fit of our model. First, our rate of success in classifying crisis and non-crisis situations is significantly more promising than previous studies had suggested. As mentioned above, while the estimates from Frankel and Rose (1996) were statistically and economically significant, they failed to classify correctly a large number of crises events. In their best model, Frankel and Rose (1996) correctly predict only 5 out of 69 currency crashes. This represents less than 8 percent of all the situations they identified as crashes. While it may be argued that these results are low because they use a high threshold value (P*=0.50), Berg and Pattillo (1998) show that using a P*=0.25 with the original Frankel and Rose model would have led to a

correct prediction of only 25% of all crashes events. This result is rather low when compared with the 63% of crises correctly called by our model when using a similar threshold value. Other recent studies have also achieved relative success in classifying correctly crisis events (Milesi-Ferreti and Razin, 1998, and Berg and Pattillo, 1998).

Second, the results show that our in-sample forecasts are much better than pure random guesses. Table 7 shows that the probability of a crisis conditional on an alarm is 54.5% (when using $P^*=0.30$), which is significantly larger than the unconditional probability of 18%. This result is confirmed by a simple Pesaran-Timmermann (1992) test which strongly rejects the null hypothesis that the forecasts are no better than guesses based on the unconditional probability of a crisis.

Table 8: Hits and Misses

Threshold Level = 0.30

		Actual				
		Tranquil	(%)	Crisis	(%)	Total
Predicted	Tranquil	450	(90)	51	(46)	501
	Crisis	50	(10)	60	(54)	110
	Total	500	(100)	111	(100)	611

_____

8. Conclusions

This paper examines the determinants of currency crises in a broad sample of countries between 1975 and 1996. We found that a relatively small set of macroeconomic variables play an important role in the empirical determination of crises. More specifically, we found that high rates of seignorage, current account deficits, real exchange rate misalignments, low foreign exchange reserves relative to a broad measure of money, negative terms of trade shocks, negative per capita income growth, and a contagion effect, all help to explain the presence of currency crises in our sample. Our results are robust to changes in the specification, definition of variables, method of estimation and country sample.

Interestingly, most of these variables had already been identified and suggested by the theoretical literature. In this sense, our results could be interpreted as supporting both first and second-generation models of currency crises. More important, however, is our finding that the insights developed by second-generation models complement rather than substitute the explanation provided by first-generation models. Therefore, while neither of the two types of models tells the whole story about currency crises, they both add to our understanding of this phenomenon. Moreover, our results suggest that there may be instances in which a country falls into a crisis by factors purely associated to first-generation models, while in other situations the relevant factors might be those stressed by second-generation models. These results explain why currency crises are not all alike, but they also explain the existence of common patterns across various crises episodes.

Our results also indicate that currency crises have a significant predictable component. Using our empirical estimates, we are able to predict correctly a majority of the currency crises in our sample. This suggests that at least some currency crises could have been prevented with sounder macroeconomic policies, and that certain policies could have been implemented earlier to reduce the risk of a crisis. In this sense, we interpret our results as supporting the view that an early-warning system could help reduce the number of currency crises in both emerging and industrialized economies.

_____

References

Agenor, P., J. Bhandari and R. Flood (1992); "Speculative Attacks and Models of Balance-of-Payments Crises," *Staff Papers*, **39**, International Monetary Fund, 357-394.

Blanco, Herminio and Peter M. Garber (1986); "Recurrent Devaluations and Speculative Attacks on the Mexican Peso," *Journal of Political Economy*, **94**, February, 148-166.

Berg, Andrew and Catherine Pattillo (1998); "Are Currency Crises Predictable? A Test", IMF Working Paper 98/154 (Washington: International Monetary Fund, November).

Calvo, Guillermo (1987); "Balance of Payments Crises in a Cash-in-Advance Economy," *Journal of Money, Credit, and Banking*, **19**, February, 19-32.

Calvo, Guillermo (1996); "Varieties of Capital-Market Crisis," mimeo, University of Maryland.

Calvo, Guillermo and Enrique G. Mendoza (1999); "Rational Contagion and the Globalization of Securities Markets," forthcoming, *Journal of International Economics*.

Cole, Harold. R. and Timothy J. Kehoe (1996); "A Self-fulfilling Model of Mexico's 1994-95 Debt Crisis," *Journal of International Economics*, **41**, November, 309-330.

Connolly, Michael and Dean Taylor (1984); "The Exact Timing of the Collapse of an Exchange Rate Regime and Its Impact on the Relative Price of Traded Goods," *Journal of Money, Credit, and Banking*, **16**, 194-207.

Cooper, Richard (1996); "Comment," *Brookings Papers on Economic Activity:* **1**, 203-208.

Cumby, Robert E. and Sweder Van Wijnbergen (1989); "Financial Policy and Speculative Runs with a Crawling Peg: Argentina 1979-1981," *Journal of International Economics*, **27**, 111-127.

Dornsbusch, R., I. Goldfajn and R. Valdes (1995); "Currency Crises and Collapses," *Brookings Papers on Economic Activity*, **1**, 219-270.

Drazen, Allan (1999); "Political Contagion in Currency Crises," NBER Working Paper no. 7211, July.

_____

Edwards, Sebastian (1989); *Real Exchange Rates, Devaluation and Adjustment: Exchange rate Policy in Developing Countries* (Cambridge, Massachusetts: MIT Press).

Eichengreen, B., A. Rose and C. Wyplosz (1995); "Exchange Market Mayhem. The Antecedents and Aftermath of Speculative Attacks," *Economic Policy*, **21**, October, 249-312.

Eichengreen, B., A. Rose and C. Wyplosz (1996); "Contagious Currency Crises: First Tests," *Scandinavian Journal of Economics*, **9**, No. 4, 463-484.

Esquivel, Gerardo and Felipe Larraín (1999a); "Latin America Confronting the Asian Crisis," Documento de Trabajo V-99, Centro de Estudios Económicos, El Colegio de México, Abril, 1999

Esquivel, Gerardo and Felipe Larraín (1999b); "Predicting and Preventing Currency Crises," Harvard Institute for International Development, work in progress.

Flood, Robert P. and Peter M. Garber (1984); "Collapsing Exchange Rate Regimes: Some Linear Examples," *Journal of International Economics*, **17**, 1-13.

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

Flood, Robert and Nancy Marion (1997); "The Size and Timing of Devaluations in Capital-Controlled Economies," *Journal of Development Economics*, **54**, 123-147.

Flood, Robert and Nancy Marion (1998); "Perspectives on the Recent Currency Crisis Literature," NBER Working Paper No. 6380 (Cambridge, Massachusetts: National Bureau of Economic Research, January).

Frankel, Jeffrey and Andrew K. Rose (1996); "Currency Crashes in Emerging Markets: An Empirical Treatment," *Journal of International Economics*, **41**, November, 351-366.

Gerlach, Stefan and Frank Smets (1995); "Contagious Speculative Attacks," *European Journal of Political Economy*, **11**, 45-63.

Glick, Stephen and Andrew Rose (1998); "Contagion and Trade: Why are Currency Crises regional?", NBER Working Paper no. 6806, November.

Goldberg, Linda S. (1994); "Predicting Exchange Rate Crises: Mexico Revisited," *Journal of International Economics*, **36**, May, 413-430.

_____

Goldfajn, Ilan and Rodrigo Valdés (1998); "Are Currency Crises Predictable?", *European Economic Review,* Papers and Proceedings, Mayo, **42**, pp. 873-885.

Goldfajn, Ilan and Rodrigo Valdés (1999); "The Aftermath of Appreciations," *Quarterly Journal of Economics*, **CXIV**, 1, February, pp. 229-262.

Greene, William H. (1996); *Econometric Analysis*, 3rd ed. (New Jersey: Prentice Hall).

Hamerle, Alfred and Gerd Ronning (1995); "Panel Analysis for Qualitative Variables," in G.Arminger, C.C. Clogg and M.E. Sobel (eds.), *Handbook of Statistical Modeling for the Social and Behavioral Sciences*", Chapter 8, New York and London: Plenum Press.

Kaminsky, G. L., S. Lizondo and C. M. Reinhart (1998); "Leading Indicators of Currency Crises," *Staff Papers*, International Monetary Fund, **45**, No. 1, March, 1-48

Kaminsky, G. and C. M. Reinhart (1999); "The Twin Crises: The Causes of Banking and Balance-of-Payments Problems," *American Economic Review,* **89**, 3, June, pp. 473-500

Khan, Moshin S. and Jonathan D. Ostry (1992); "Response of the Equilibrium Real Exchange Rate to Real Disturbances in Developing Countries," *World Development*, **20**, 1325-34.

Klein, Michael W. and Nancy P. Marion (1997); "Explaining the Duration of Exchange Rate Pegs," *Journal of Development Economics,* **54** (2), 387-404.

Krugman, Paul (1979); "A Model of Balance of Payments Crises," *Journal of Money, Credit and Banking*, **11**, 311-325.

Krugman, Paul (1996); "Are Currency Crises Self-Fulfilling?" *NBER Macroeconomics Annual 1996*, National Bureau of Economic Research, 345-407.

Krugman, Paul (1997); "Currency Crises," mimeo, MIT.

Krugman, Paul and Julio Rotemberg (1991); "Speculative Attacks on Target Zones," in P. Krugman and M. Miller (eds.), *Target Zones and Currency Bands* (Oxford: Oxford University Press).

Maddala, G. S. (1983); *Limited Dependent and Qualitative Variables in Econometrics* (New York: Cambridge University Press).

Maddala, G. S. (1987); "Limited Dependent Variables Using Panel Data," *Journal of Human Resources*, **XXII**, no. 3, 307-338.

_____

Martinez-Peria, Ma. Soledad (1997); "Understanding Devaluations in Latin America: A 'Bad Fundamentals' Approach," CIDER Working Paper 97-86, University of California, Berkeley, May.

Masson, Paul R. (1998); "Contagion: Monsoonal Effects, Spillovers and Jumps Between Multiple Equilibria," IMF Working Paper 98/142 (Washington: International Monetary Fund, October).

Milesi-Ferreti, Gian Maria and Assaf Razin (1998); "Current Account Reversals and Currency Crises", IMF Working Paper 98/89 (Washington: International Monetary Fund, June).

Obstfeld, Maurice (1994); "The Logic of Currency Crises," NBER Working Paper No. 4640 (Cambridge, Massachusetts: National Bureau of Economic Research).

Obstfeld, Maurice (1996); "Models of Currency Crises with Self-fulfilling Features," *European Economic Review*, **40**, 1037-1047.

Otker, Inci and Ceyla Pazarbasioglu (1997); "Speculative Attacks and Macroeconomic Fundamentals: Evidence from Some European Currencies," *European Economic Review*, Papers and Proceedings, April, **41**, 847-860.

Pazarbasioglu, Ceyla and Inci Otker (1997); "Likelihood versus Timing of Speculative Attacks: A Case Study of Mexico," *European Economic Review*, Papers and Proceedings, April 1997, **41**, 837-845.

Pesaran, M Hashem and Allan Timmermann (1992); "A Simple Nonparametric Test of Predictive Performance", *Journal of Business & Economic Statistics*. Vol. 10 (4). p 561-65. October.

Radelet, Steve and Jeffrey Sachs (1998); ""The East Asian Financial Crisis: Diagnosis, Remedies, Prospects", *Brookings Papers on Economic Activity*, **1**, pp. 1-74.

Salant, Stephen and D. Henderson (1978); "Market Anticipation of Government Policy and the Price of Gold," *Journal of Political Economy*, **86,** 627-648.

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

Tornell, Aaron (1999); "Common Fundamentals in the Tequila and Asian Crises", NBER Working Paper no. 7139, May.