Leading indicators of balance-of-payments crises: a partial review

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Abstract

This paper reviews the theory of balance-of-payments crises, and its implications for identifying potential leading indicators of crises. It discusses and evaluates three different empirical approaches to balance-of-payments crises: the signalling, discrete-choice, and structural approaches. Despite claims of success in predicting currency crises, we note some serious theoretical and empirical qualifications which throw these claims into question. Nevertheless, we conclude that a range of indicators supported by theory may still be useful for policy-makers interested in preventing financial instability.

JEL classification: F31, F47.

Key words: Balance-of-payments crisis, leading indicators.

Summary

During the 1990s, many countries, developed and developing alike, experienced severe financial difficulties, including balance-of-payments crises and systemic banking failures. Events such as the 1994 Mexican peso crisis and the Asian turmoil seem likely to have been a mixture of both. The scale and impact of these events have renewed interest in the existing literature and stimulated a large volume of new theoretical and empirical work to explain and/or predict crises, and to provide countries with appropriate policy advice to avert an impending crisis. While this paper gives a brief overview of the theoretical context, it concentrates on the empirical literature, with special emphasis on the search for potential leading indicators.

There are in general three different empirical approaches to analysing currency crises. The first is the 'signalling' method. In such models, the behaviour of a number of individual variables, such as the real effective exchange rate or the debt to GDP ratio, is evaluated against certain threshold levels. Once any of these indicators moves beyond its threshold, it signals a potential crisis in waiting. The 'optimal' threshold is selected on an indicator-by-indicator basis, so as to balance out the risks of failing to predict the crisis and giving a false signal of an impending crisis.

The second method borrows a technique widely used in the discrete-choice literature to analyse the probability of a currency crisis. The basic idea is first to sort different countries and time periods into two discrete episodes: a crisis and a tranquil period. Then, by mapping a set of possible indicators (chosen on the basis of *a priori* economic theory) into some known probability distribution function of these episodes, the likelihood of a currency crisis can be evaluated.

The third method is largely descriptive and often based on specific case studies. The primary concern of these studies is to establish structural relationships between particular variables and currency crises.

While most studies claimed to be successful in identifying leading indicators, the accuracy of their prediction deteriorates out of sample. The poor predictive power can be for several reasons: the difficulties in defining the dependent variable (or a crisis), changes in the structural relationships in an economy, overemphasis on some crisis-specific indicators, and other technical problems such as data quality and revision.

Nonetheless, whichever approach the research is based on, an interesting fact is that a particular set of indicators always emerges as informative in predicting an impending crisis. This includes indicators of real exchange rate overvaluation, liquidity problems, lending growth/boom and contagion. Focusing on

the evolution of these indicators might usefully complement the whole set of indicators currently monitored for surveillance purposes.

1 Introduction

During the 1990s, many countries, developed and developing alike, experienced severe financial difficulties, including balance-of-payments crises and systemic banking failures.[(1)] Events such as the 1994 Mexican peso crisis and the Asian turmoil seem likely to have been a mixture of both. The scale and impact of these events have renewed interest in the existing literature and stimulated a large volume of new theoretical and empirical work to explain and/or predict crises, and to provide countries with appropriate policy advice to avert an impending crisis. The literature grows at such a speed that it is very difficult to keep track of all the theoretical and empirical developments. So while this paper gives a brief overview of the theoretical context, it concentrates on the empirical literature, with special emphasis on the search for potential leading indicators.[(2)]

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The third method is largely descriptive and often based on specific case studies (see, for example, Dornbusch, Goldfajn and Valdés (1995) and Sachs, Tornell and Velasco (1996)). The primary concern of these studies is to establish structural relationships between particular variables and currency crises.

The rest of the paper is organised as follows. In Section 2, we review the theoretical literature, and note its implications for using certain variables as potential leading indicators. Section 3 presents in detail the different approaches adopted by economists in building leading indicator models. In Section 4, we

(1) Throughout this paper, we use the terms balance-of-payments crisis and currency crisis interchangeably, but strictly speaking, while the former mostly refers to a forced devaluation from a currency peg, the latter includes events such as a sharp depreciation and large capital outflow.

(2) For a more up-to-date survey on the theoretical models, see Flood and Marion (1999).

discuss the success or failure of the empirical models, with special emphasis on the variable-selection process and econometric method. Section 5 draws some conclusions with implications for surveillance work on risks to financial stability.

2 Theoretical models

One of the very early currency-crisis studies was Krugman (1979) who extends the Salant and Henderson (1978) model of speculative attacks on a government-controlled price of gold to fixed exchange rate. Krugman (1979) maintained that the abandonment of a fixed exchange rate regime is largely due to unsustainable credit expansion and unsound economic fundamentals. This genre of models is usually referred to as 'first-generation' crisis models.(3) The 1992/1993 ERM crises suggested factors other than weak economic fundamentals and irresponsible credit expansion could lead to currency crises, prompting the emergence of so-called 'second-generation' crisis models, which emphasised the contingent nature of economic policies that may give rise to multiple equilibria—under one equilibrium, the fixed exchange rate regime is sustainable, but not under another equilibrium.

The debate on the causes of crises continued until 1997 when a number of Asian economies were forced to devalue their currencies. The Asian crisis took many observers by surprise, partly because of the exceptional growth rate of these countries in the 1980s and early 1990s, and partly due to the apparently sound pre-crisis macroeconomic environment such as low unemployment and a large trade surplus.(4) The essential features that characterised earlier theoretical models—weak fundamentals, excessive monetary expansion, and conflicting government policy goals—were not apparent in these countries either. The speed that crisis spread from one country to another also raised the question of whether crises were predictable and/or contagious. As a result, a whole 'new' generation of models were developed (the yet to be agreed 'third-generation models'), to enhance our understandings on the modern crises.

2.1 First-generation models

This type of model was first put forward by Krugman (1979) and modified by Flood and Garber (1984). In its simplest form, the model assumes that under a pegged exchange rate system, whenever investors

(3)This taxonomy was first suggested by Eichengreen, Rose and Wyplosz (1996) and has since become a common standard in discussing crisis. However, this classification is by no means exhaustive and this paper adopts it mainly for its familiarity.
(4)However, before the Asian crises, Young (1992), and Kim and Lau (1993) and Krugman (1994) suggested that the high growth rates enjoyed by the Asian economies in the 80s and early 90s were largely due to their success in mobilising labour, physical, and human capital. Their growth rates eventually would level out once they reached the point of diminishing returns.

rebalance their portfolios by selling domestic assets, the central bank has to intervene to prop up the fixed rate. However, if the government runs excessively expansionary fiscal and monetary policies, these will not be consistent with the fixed rate, eventually leading to a speculative attack, which will exhaust the entire foreign reserves. For example, if a government has a large budget deficit, which is mainly financed by monetary expansion, the increase in domestic credit will in turn lead to a gradual depreciation in the 'shadow' exchange rate (the exchange rate which prevails if not fixed). The *timing* of a successful attack will be at the point when the shadow exchange rate equals the pegged rate (see Appendix A).

The Krugman-Flood-Garber model fits very well the experience of many Latin American countries in the late 1970s and 1980s. During that time countries like Argentina, Chile, and Brazil embarked on stabilisation programmes to curb high inflation and large public sector deficits (see Blackburn and Sola (1993) Section 2 for details). The results of these programmes were largely the same: the collapse of their fixed-rate regimes as a result of a rapidly expanding stock of credit (in some cases because of the central banks' responses to a succession of commercial bank failures), and a massive depletion of the central banks' foreign exchange reserves. For this reason, Krugman (1996) described these as 'seignorage-driven' models which suggested that fiscal variables such as fiscal deficit to GDP ratio, the government consumption to GDP ratio and financial variables such as credit growth and the growth in M2 could act as leading indicators.(5)

A number of papers have extended the Krugman-Flood-Garber model in other directions (see Agénor, Bhandari and Flood (1992)). In these models, expansionary fiscal and monetary policies led to higher domestic demand for both traded and non-traded goods. The former causes a deterioration of the trade balance while the latter causes a real appreciation of the currency. Thus external variables such as trade and current account balances, and the evolution of the real exchange rate can also be used as leading indicators of currency crises under the first-generation approach.

2.2 Second-generation models

Obstfeld (1986), adopting the Flood and Garber (1984) framework, demonstrates that if agents expect a speculative attack to cause the government to switch to an inflationary domestic credit policy, crisis can be self-fulfilling. Obstfeld (1994, 1996) developed Barro-Gordon type models in which conflicting policy goals combined with private agents' self-fulfilling expectations could drive a fixed rate off the peg even when the fundamentals (such as unemployment or monetary policy) were sound (see

(5)Notice that the variables are expressed in ratios or growth terms rather than levels mainly for international comparison.

Appendix B). Krugman (1998) described these so-called 'second-generation' models in a succinct way. Basically, they require three elements: i) a motivation for the government to opt out of the fixed-rate system; ii) a reason why the government would like to defend the exchange rate (note that i) and ii) create a tension in policy-making); and iii) the cost of defending a fixed rate increases when people expect that the fixed rate will go. All three elements combine to create a circularity that leads to the possibility of multiple equilibria. Under one equilibrium, the fixed rate is consistent with the fundamentals. But a sudden worsening of expectations may lead to changes in policies that result in the collapse of the fixed-rate regime, hence validating agents' expectations (another equilibrium).(6) In the case of the ERM crises, on this reading, the German unification created a big demand shock that placed pressure on other European countries to raise interest rates. With European labour markets slow to adjust, this led to rising unemployment. Under such circumstances, markets expected a government with higher unemployment to be more likely to abandon the policies of austerity to head off the possibility of losing the next election. As a result, speculators attacked the currencies of the countries with high unemployment rates (see Masson (1995) and Ozkan and Sutherland (1995)).

One of the implications of the self-fulfilling multiple-equilibrium crisis models is that it is extremely difficult (if not impossible) to predict accurately an impending crisis because of the absence of a tight relationship between fundamentals and crises.(7) This property of unpredictability, together with the recent experience that crisis in one country can spread to a set of seemingly unrelated countries, brought up the issue of contagion, especially when the shift of agents' expectations was due to external shocks. We discuss contagion in greater detail later in Section 2.4.

But Morris and Shin (1998) have pointed out that multiplicity of equilibria in the second-generation models arises largely because private agents are assumed to have 'common knowledge', ie each can observe the others' actions perfectly. Adopting a game-theoretic framework, they show that small information discrepancies between private agents could lead to a unique equilibrium within certain levels of fundamentals. Specifically, if a country is endowed with very weak fundamentals, it will not be feasible to defend a peg even if no speculator is ready to launch an attack. On the other hand, a country with very strong fundamentals will be able to defend its peg even if all speculators synchronise a massive attack. It is only within certain levels of fundamentals that a country will be vulnerable to speculative attacks (ie, multiple equilibria exist). However, if each speculator individually can observe

(6) Similar to the second-generation currency crisis model, Diamond and Dybvig (1983) demonstrate that bank run can be a self-fulfilling equilibrium. In fact, the model has since been assimilated into a macroeconomic framework to analyse currency crisis (see Section 2.3).

(7) Jeanne (1998) adopted the non-linear technique developed by Dagsvik and Jovanovic (1994) to test for multiple equilibria. He estimated a model in the case of the French franc during the 1992 ERM crisis and found some evidence that self-fulfilling speculation was at work.

the fundamentals only up to a certain degree of accuracy, a unique trigger point will exist within the multiple-equilibrium region where all speculators, who observe a poor signal, will launch an attack together. In other words, a belief-driven attack will happen only at a particular (unique) threshold state of fundamentals. The Morris-Shin model, under the specific information assumptions between speculators and policy-maker, implies that there is a systematic (non-linear) mapping between fundamentals and the probability of crisis.

2.3 Third-generation models

Within months of the first attack on the Thai peg around March 1997, the Thai baht, Indonesian rupiah, Korean won and Malaysian ringgit were all forced to devalue.(8) This sudden outbreak of financial turmoil in Asia prompted a further rethink of the nature and/or causes of financial crises. After all, before the onset of the crises, most of the governments involved did not have significant fiscal deficits, nor were they engaged in irresponsibly expansionary monetary policy. Also, both the rates of inflation and unemployment were quite low, hence ruling out the conflicting macroeconomic goals suggested by the second-generation models. In the post-mortem of the Asian crisis, the deterioration in bank and corporate balance sheets in the run-up to crisis have attracted much attention. In particular, the problems of moral hazard (international and domestic over-borrowing) and the liquidity crunch experienced by the private sector once the currency regime collapsed are believed to be the main causes of the currency crises.(9) A flurry of models have been developed, so called ‘third-generation’ models which combine the two important elements (fundamentals-driven and self-fulfilling) of earlier generation models plus some micro-elements such as introducing a banking sector, to analyse these modern crises.

2.3.1 Moral hazard

McKinnon and Pill (1998) and Krugman (1998), among others, suggested that moral hazard and international over-borrowing played a key role in the Asian crisis.(10) According to Krugman, the strong connections between the owners of the local financial institutions and the respective Asian

(8)It should be noted that before the Asian crisis, none of these Asian currencies were officially pegged to the US dollar. However, empirical evidence suggested that over a long period of time before the crisis, these currencies followed the movements of the US dollar very closely (see McKinnon (2000)).
(9)Issues related to monitoring capital flows and their associated risks are now high on the agenda of international meetings (see, eg, the Communique of G-7 Finance Ministers and Central Bank Governors, 20 February 1999; and the Financial Stability Forum Working Group Report on Capital Flows, 5 April 2000).
(10)Krugman (1999) has since changed his view and become rather sceptical of the role of moral hazard. He instead emphasises the loss of confidence in private investment and the eventual capital outflow as the cause of the Asian crisis.

governments led creditors to believe that there were implicit government guarantees. As a result, there appeared to be a serious problem of moral hazard.[11] Krugman (1998) and Corsetti, Pesenti and Roubini (1998b) provided stylised models with the feature of moral hazard to demonstrate how excessive borrowing could lead to a full-blown balance-of-payments crisis. In particular, Krugman (1998) emphasised that with moral hazard, crises could be *self-fulfilling*: if the pre-crisis asset values were not in a 'meta-stable' state (because all capital assets are purchased by the banks regardless of their rates of returns and hence leads to aggregate over-investment), a small shock could cause a slump in asset values which would undermine the banks; the collapse of the banks in turn would ratify the drop in asset prices. Because of the special relations between the government and the private sector, the former might have to resort to money printing to bail out the latter and therefore resembled a first-generation crisis. In short, the models of moral hazard have put renewed emphasis on the role of effective banking supervision in preventing crises. Overall, these models suggest that asset market prices may be useful leading indicators of crisis (eg, equity prices and property price indexes).[12]

2.3.2 Illiquidity

In contemporary banking theory, one of the main reasons for the existence of financial intermediaries is to provide liquidity for private agents by issuing demand deposit contracts. Diamond and Dybvig (1983) formalised the idea by suggesting that in fulfilling this role, banks will be subject to the risk of illiquidity. One of the implications of the Diamond-Dybvig model is that a bank run can be self-fulfilling, ie, a run happens when a large number of depositors individually think that the bank is not able to meet their demand for cash and hence withdraw their deposits, despite the fact that collectively they would be better off by staying put.

Chang and Velasco (2001) extended the Diamond-Dybvig framework into a small open economy context and put international illiquidity at the centre of the analysis. As in a 3-period Diamond-Dybvig setup, the domestic agents discover their 'type' at $t = 1$. Each can be either a 'patient' type who only derives utility from late consumption (at $t = 2$) or an 'impatient' type who only derives utility from early consumption (at $t = 1$). It also assumes that the agents, who also happen to be the investors, are faced with two investment choices at $t = 0$: a short-term investment in the world capital market with a low rate of return at $t = 1$ and a long-term domestic investment with a higher rate of return at $t = 2$. The long-term investment, however, is illiquid in the sense that early liquidation (at $t = 1$) will yield

[11] In an article on his web site, Krugman used the term "ministers' nephews" to describe this special status of the owners.
[12] However, Vila (2000), using data for 14 developed countries, rejects that banking crises systematically cause large-scale liquidations of equity and finds only weak evidence of increased bank lending prior to equity market crises.

relatively little. Each agent is born with an endowment but can also borrow a limited amount from abroad. Assume that there is no co-ordination problem in the model, the investors will act collectively as ‘a commercial bank’ which pool the resources (including the endowment and the maximum foreign credit level) in order to maximise the welfare of all the agents by providing them with liquidity. However, a problem arises if the agents lose confidence in the bank and demand immediate withdrawal. This forces the liquidation of the more profitable long-term investment. The resulting collapse of the financial intermediaries, coupled with other factors such as weak fundamentals, moral hazard and excessive foreign borrowing (as the bank is committed to repay any foreign debt under all circumstances), leads to a full-blown financial crisis. Thus, those factors that directly or indirectly affect the liquidity of the banking system are signs of financial fragility, eg, high levels of short-term external liabilities, weak banking supervision, and deposit guarantees. On the contrary, longer-term capital inflows such as foreign direct investment, which are less easily liquidated by foreign investors, reduce the likelihood of a financial crisis.

2.3.3 Cross-generational framework

Despite the emphasis on particular features, the moral hazard and illiquidity models have the same main ingredients as the first-generation (fundamentals-driven) and second-generation (belief-driven multiple-equilibrium) models. Flood and Marion (1999) instead suggest a cross-generational framework that combines the main features of both models. They point out that in the simple Krugman-Flood-Garber model, the attack on the currency occurs when the shadow exchange rate (the rate that prevails if the currency is not pegged) equals the pegged rate and the reserves would then be driven to an arbitrary constant, usually zero for simplicity (ie, the timing of the crisis is predictable—a main feature of the first-generation model). However, instead of having the post-attack reserve level fixed at zero, they assume that the government chooses optimally period by period the level of reserves to minimise a loss function that includes other policy-choice variables, such as unemployment and the fragility of the banking system, then multiple equilibria exist. In their own words,

> ‘It allows the first-generation models to pick up what we think is the most important contribution of the second-generation models—state dependence of regime commitment—in a simple and intuitive way.’
>
> —Flood and Marion (1999).

Burnside, Eichenbaum and Rebelo (2001) develop a small open-economy model with four agents—banks, firms, households and a government—to explain the 'twin banking-currency crises' phenomenon. They assume that banks' foreign borrowings are guaranteed by the government. So in the event of a devaluation, banks declare bankruptcy and at least part of the foreign borrowings are transferred to the government's foreign liabilities. In other words, government guarantees to domestic banks' foreign creditors affect the fundamentals. With the assumption that private agents' decisions to attack the peg depends on the government's decision to bail out the banks, multiple equilibria result. They conclude that twin crises are *caused* by government guarantees (fundamental-based) and therefore only happen in certain countries (eg, Mexico 1994 and Thailand 1997). But their *timing* depends on the agents' beliefs (belief-driven), as in second-generation models. So in the same important respects, cross-generational models combine elements of earlier crisis model vintages. Not only do they imply some predictability in the occurrence of a crisis, if less about its precise timing, but they also suggest a wider range of potential indicators of crisis, including government guarantees, asset price movements, and the liquidity of balance sheets.

2.4 Contagion

It is generally acknowledged that most crises in the 1990s contained some evidence of contagion. For example, the collapse of the Soviet Union, which was Finland's major trading partner in 1992, was regarded as the main reason why the markka was attacked. But the subsequent attacks on other European currencies such as the pound sterling were not easily justified by the trade links. Also, the severity of the Thai crisis and the speed with which it spread to the rest of the region surprised most commentators, just as it did in the subsequent Russian crisis (see Blustein (2001) for an excellent documentation of policy-makers' response to these crises). In most of the models discussed above, the main focus is to examine the causes of a currency crisis in a country. So apart from sudden shifts in agents' beliefs which could drive any economy with sound fundamentals off the peg, very little could be said about the issue of contagion.

The term contagion, despite being widely used, is loosely defined. In its broadest sense, it refers to the sudden increase in cross-market linkages after a shock to a country (or group of countries). Thus, it manifests itself as the increase in correlation in asset returns.[13] Masson (1998) was among the first to define the term systematically. He distinguished three contagious effects: 'monsoonal' effects, spillovers and jumps. Monsoonal effects refer to those due to a common external cause such as the

[13] See Wolf (2001), Forbes and Rigobon (2001), and Claessens, Dornbusch and Park (2001) for up-to-date surveys on contagion.

effects of US interest rates rise on all the highly dollar-indebted Latin American countries. The second category, spillovers, relates to the interdependence among the countries involved, which could be trade and/or financial in nature. The last category is jump or pure contagion, which refers to the effects of a shift in agents' expectations and not related to changes in a country's macroeconomic fundamentals. Masson (1998) developed a simple two-country model to demonstrate the existence of all the three effects, with pure contagion represented by jumps between different equilibria.

Forbes and Rigobon (2001) suggest a slightly different taxonomy of the contagion transmission mechanism: crisis-contingent (shift-contagion) and non-crisis-contingent (real linkages) models. In the former, a crisis causes a structural shift in the economy so that shocks are propagated via a channel which does *not* exist pre-crisis. An obvious example is those models with multiple equilibria. Other examples include financial spillovers, and particularly, the so-called 'common lender' effects—during a crisis, if the common lenders fail to cash their claims for *liquidity* in one country, they will seek for it in a second country. For example, shortly after Finland had devalued the markka, the German banks that had relatively heavy exposures to Finland (as well as other European countries) were forced to re-evaluate their portfolios, withdrawing their liquidity from other European countries. Valdés (1997) develops a simple model of capital flows to show that a country-specific fundamental (the liquidity existing in the country) affects the probability of repayment of other countries during a crisis. Financial spillovers can also be due to the *incentive* structure for individual agents. For example, a shock in one country can induce investors to sell off their holdings in other similar countries so as to maintain certain proportions of a country or region's stock in their portfolios. Drazen (1998) studies the political pressure on other central banks to abandon their pegs if one has switched to a floating exchange regime recently.

On the other hand, non-crisis-contingent models assume that the transmission channels after an initial shock are not significantly different from pre-crisis. Thus, the high cross-market correlations that followed a crisis were just a continuation of the 'real linkages' that already existed before the crisis. These include trade, policy co-ordination and Masson's monsoonal effect. A currency crisis in one country can trigger a beggar-thy-neighbour type of devaluation in neighbouring countries with close trade links. Gerlach and Smets (1995) adopted a two-country version of the Flood-Garber model to show that a speculative attack against one currency could accelerate the collapse of a currency peg in another country via induced policy changes in the latter.

Regarding financial linkages, Chari and Kehoe (2000), among others, adopted the herding model developed by Banerjee (1992) to analyse contagion. In their model, the explanation for a currency attack is information cascades under which each investor has some information about the state of the economy and decides sequentially and publicly (in contrast with Morris and Shin's assumption of imperfect information among investors) whether to sell the currency. So if the first n investors receive bad signals about the state of the economy and sell the currency, the $n+1$ investor will disregard his own information and sell the currency. His decision is purely based on the revealed information of those who came before him. Calvo and Mendoza (2000) relax the assumption of sequential decision-making and assume that investors form their decision simultaneously. They show that herding behaviour may become more prevalent as the world capital market expands and investors have fewer incentives to collect country-specific information. As a result, small rumours can trigger herding behaviour among investors which shifts the economy from a good equilibrium to a bad one.

2.5 Summary

According to first-generation models, a country with weak economic fundamentals is more vulnerable to speculative attack. In particular, financing a continued fiscal deficit through money creation is clearly not feasible with an exchange rate peg. In second-generation models, self-fulfilling speculative attacks brought about by the government's time-inconsistent policy goals appear to be the main cause of crisis. This is most likely to happen when fundamentals are weak. Thus under both types of model, the *evolution* or *deterioration* of various economic fundamentals could be key indicators of an impending crisis, though its timing is harder to predict. Post-Asian crisis models including moral hazard and weaknesses in the financial and corporate sectors, in addition to the weak economic fundamentals, have been identified as potential fundamental causes of crisis. Contagion implies that cross-country trade and financial linkages and market sentiment may also have a role.

3 Empirical literature

The debate is continuing about whether the first or the second-generation models are more appropriate. Some economists have developed tests for these theoretical models. However, the main focus of the leading indicator literature is to develop empirical models to help rank the vulnerability of countries and/or predict future crisis in a well-defined statistical framework. In doing so, the majority of these models simply evaluate a set of indicators to reflect all potential causes of a crisis under all the models we discussed above. Another justification for this selection approach is the observational equivalence of first and second-generation crisis models.(14)

(14) As pointed out by Eichengreen, Rose and Wyplosz (1996), while the absence of differences in some indicators in the run up to speculative attacks is consistent with the second-generation models, it is also consistent with a restrictive class of

There are in general three different types of approach in building leading indicator models of currency crisis: the signalling approach, the discrete-choice approach, and the structural approach (see Chart 1). Regardless of the approach adopted, most models share two common features. First, they use an exchange rate pressure measure to proxy or identify a crisis. Second, the models are estimated with a panel of multi-country data covering a period of time before a major international crisis. Kaminsky, Lizondo and Reinhart (1998) examined 28 studies on currency crisis conducted before the Asian crisis and summarised the indicators being used into ten different categories (see Table A). A total of 46 variables were examined by the authors, ranging from standard economic fundamentals to some political stability and institutional measures. In the following subsections, we discuss, with the help of some representative papers, how empirical models are constructed using these variables to provide information on currency crisis.

3.1 Signalling approach

Early papers that adopted this approach were Kaminsky, Lizondo and Reinhart (1998), henceforth KLR for currency crises, and Kaminsky and Reinhart (1999) for both currency and banking crises together. Berg and Pattillo (1998), BP, and Edison (2000), Ed, in evaluating and further developing these approaches, re-estimated the KLR results with revised data.

In KLR, a crisis is defined as a situation in which an attack on the currency leads to a sharp depreciation, a large decline in foreign reserves, or both. Therefore, they created an exchange rate pressure index, p which is a weighted average of percentage devaluation and changes in reserves, measured in US dollars.[15] The index is designed to capture both the actual depreciation of a currency and the scale of unsuccessful speculative attacks (measured by decreases in reserves). Thus p is constructed as

$$p = \frac{\Delta e}{e} - \frac{\sigma_e}{\sigma_r}\frac{\Delta r}{r} = \frac{\Delta e}{e} - \alpha\frac{\Delta r}{r} \qquad \textbf{(1)}$$

where e is the nominal bilateral exchange rate (normally against the US dollar) and r is the total international reserves. The weight is chosen arbitrarily, and in the above equation, the ratio of the sample standard deviation of the two components is used. Note that a minus sign is attached to the weight such that the higher the p, the stronger the pressure on the currency. The exchange rate pressure index is then converted into a binary variable, c, of crises '(1)' and tranquil periods '(0)'. A simple rule is that whenever p exceeds its sample mean, μ_p, by several multiples (ϕ, arbitrarily chosen) of its

first-generation models when policy shift is expected with certainty.

(15) KLR also took into consideration the distortionary effects created by a 'very' high inflation rate. They sub-divided the whole sample into two, then calculated the sample mean, variance and weights according to whether inflation in the previous six months was higher than 150%.

Chart 1: Comparing the three approaches in building indicator models

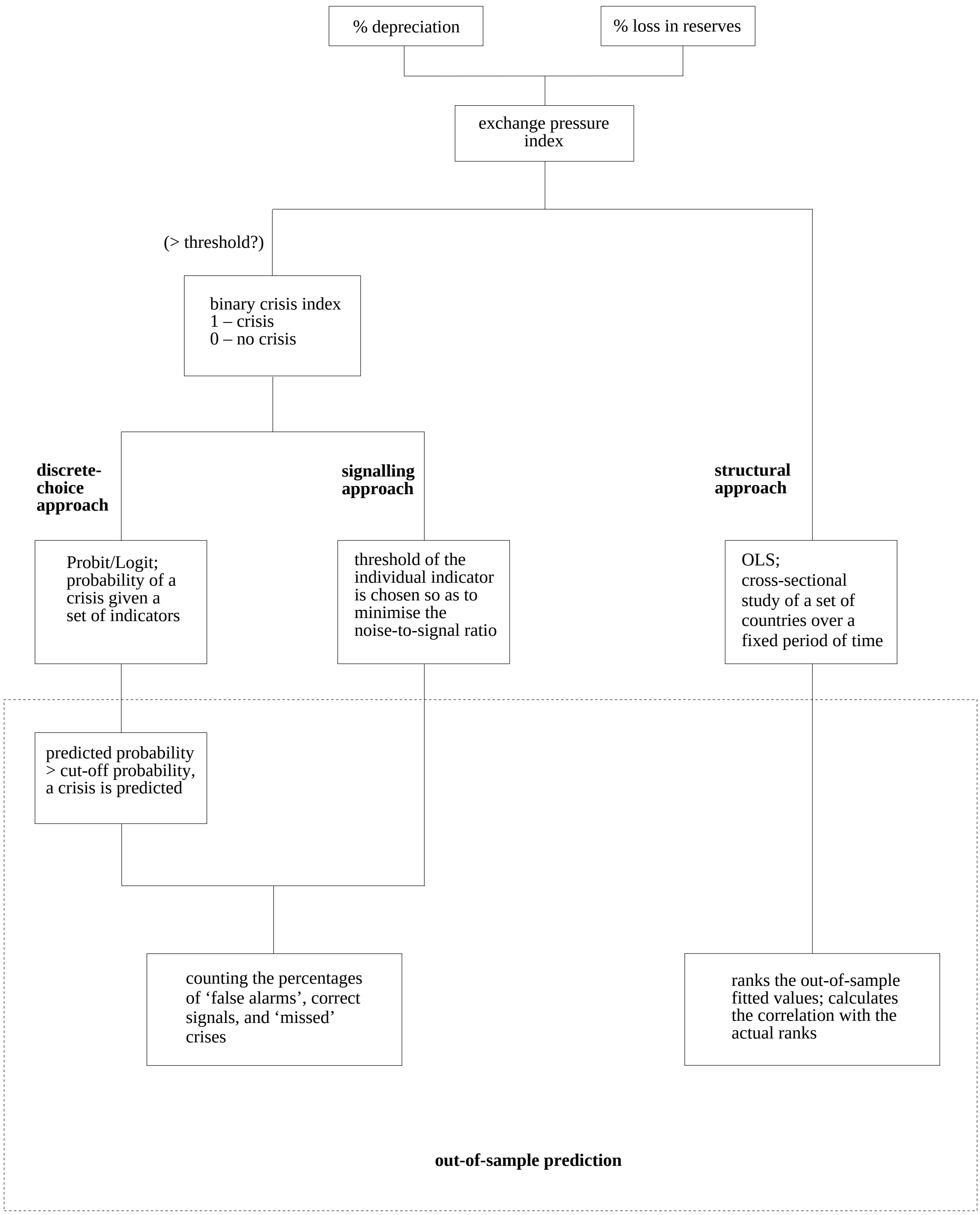


Table A: Potential indicators

Category	Variables*	Comments
1. Capital account	FX reserves, capital flows, short-term capital flows, FDI and interest rate differential. (5)	These variables are mostly related to the first-generation models.
2. Debt profile	Public foreign debt, private debt, short-term debt, debt service and foreign aid. (5)	The debt-profile gives a broad picture of burden of debt-service, liquidity risks and the robustness of a country's foreign exchange reserves.
3. Current account	Real exchange rate, current account balance, trade balance, exports, imports, terms of trade, price of exports, savings, investment, and regional trade links. (11)	Current account relates to the economic fundamentals. Regional trade links can be used as proxy variables for contagion.
4. International variables	Foreign real GDP growth, interest rates and price level. (3)	This is especially important for the structural approach discussed in Section 3, eg, the state of the German economy is crucial for the ERM crisis study.
5. Financial liberalisation	Credit growth, change in the money multiplier, real interest rates, and spread between lending and deposit rates. (4)	Incomplete and uncontrolled financial liberalisation is said to be among the causes of moral hazard.
6. Other financial variables	Central bank credit to the banking system, money growth, bond yields, parallel market rate premium. (4)	Play rather a minor role.
7. Real sector	Real GDP growth, output, output gap, employment or unemployment, wages, and changes in stock prices. (7)	Mainly based on the first-generation models.
8. Fiscal variables	Fiscal deficit, government consumption, and credit to the public sector. (3)	Ditto.
9. Political variables	Political stability index. (1)	Affecting agents' expectations.
10. Institutional factors	Openness, exchange controls, duration of the fixed-rate periods. (3)	Can relate to any type of model.

*Figures in brackets are the number of variables.

sample standard deviation, σ_p, a crisis is recorded,

$$\text{crisis}, c = \begin{cases} 1 & \text{if } p > \mu_p + \phi\sigma_p \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

KLR chose 16 indicators based on theoretical considerations and on the availability of monthly data (see Table B). Apart from the real exchange rate overvaluation (measured as deviation from trend), the 'excess' real M1 balances,(16) the interest rates and banking crises variables, all other indicators are expressed as the year-on-year percentage change in the level of the variable for international comparison and removing seasonal effects. For each indicator, a country-specific threshold is defined according to the percentiles of the distribution of that indicator. A crisis signal is generated whenever the value of the indicator exceeds its threshold. And a signal is said to be 'good' if it is followed by a crisis within a signalling horizon (arbitrarily chosen as 24 months in most studies using monthly data), otherwise, it is known as a 'bad' signal or noise. The 'optimal' set of thresholds (ie, the percentiles) was chosen so as to minimise the noise-to-signal ratio.(17) This can be easily explained with the help of the following matrix:

	Crisis within 24 months	**No crisis within 24 months**
Signal was issued	*A*	*B*
No signal was issued	*C*	*D*

In the above matrix, A represents the number of months in which the indicator generated a good signal, B is the number of months in which the indicator issued a bad signal or 'noise', C is the number of months in which the indicator failed to issue a signal which would have been a good signal, and D is the number of months in which the indicator did not issue a signal that would have been a bad signal. The noise-to-signal ratio is defined as ratio of the share of bad signals to the share of good signals, ie

$$\text{Noise-to-signal ratio} = \frac{B}{B+D} \bigg/ \frac{A}{A+C}$$

The threshold percentile is then chosen so that this ratio is minimised. The indicator is said to be an useful indicator if the noise-to-signal ratio is less than one.(18) Berg and Pattillo (1999) pointed out that

(16)This variable is defined as real M1 (deflated by consumer prices) minus an estimated demand for money, with the latter being a function of real GDP, inflation and time.
(17)This could of course in principle be different for each indicator as well as each country.
(18)Another way to determine the effectiveness of an indicator is to compare the conditional probability of a crisis on a signal being issued, $A/(A+B)$, with the unconditional probability of a crisis, $(A+C)/(A+B+C+D)$. If the former is higher, we

Table B: Performance of indicators of currency crisis (noise-to-signal ratio)

		KLR	BP's re-run of KLR	Ed's re-run of KLR
(1)	Real exchange rate	0.19	0.25	0.22
(2)	Banking crises*	0.34	–	–
(3)	Export growth rate	0.42	0.46	0.52
(4)	Stock price index growth rate	0.47	1.75	0.57
(5)	M2/international reserves (level)	0.48	0.45	0.54
(6)	Industrial production growth rate	0.52	1.24	0.57
(7)	'Excess' M1 balances	0.52	0.67	0.60
(8)	International reserves growth rate	0.55	0.47	0.57
(9)	M2 multiplier growth rate	0.61	0.82	0.89
(10)	Domestic credit/GDP growth rate	0.62	0.70	0.63
(11)	Real interest rate	0.77	0.75	0.69
(12)	Terms of trade growth rate	0.77	1.45	–
(13)	Real interest differential	0.99	1.99	1.20
(14)	Import growth rate	1.16	1.20	1.20
(15)	Bank deposits growth rate	1.20	1.60	1.05
(16)	Lending rate/deposit rate	1.69	1.51	2.30

*KLR added this indicator in the IMF staff papers version. Note that the indicator is said to be useful when the noise-to-signal ratio is < 1.

minimising the above signal is equivalent to minimising B/A as $(A+C)/(B+D)$ is a function of the frequency of crises in the data and hence does not depend on the threshold.

The KLR results (together with the re-runs by BP and Ed) are summarised in Table B.[(19)] The three sets of result are rather similar except that KLR found 13 out of 16 indicators are useful while BP and Ed found only 8 out of 15 and 10 out of 14 respectively.[(20)] In particular, two current account indicators—the deviations of the real exchange rate from trend and export growth—appear to be the top two indicators (ie, with low noise-to-signal ratio) in all three studies. However, the real sector indicators—stock price and industrial production—which were found to be useful by KLR and Edison, were no longer so in the BP results.

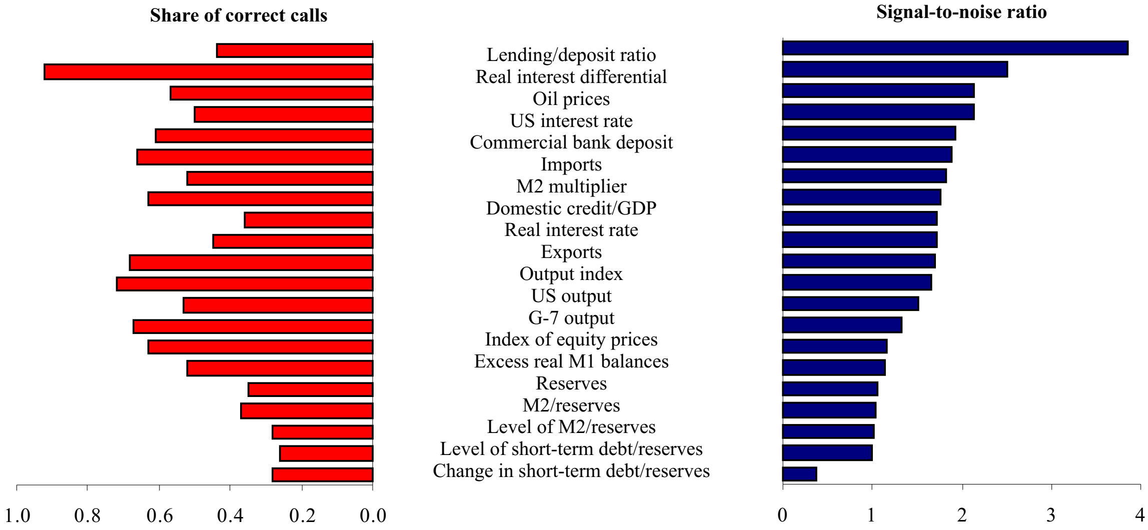
Ed also expanded the KLR study by including eight additional countries (Korea, Portugal, South Africa, Greece, India, Pakistan, Sri Lanka and Singapore) as well as seven extra indicators (annual

conclude that the indicator is informative. In fact, it is easy to prove that this condition is equivalent to the less-than-unity noise-to-signal condition. We first assume $B/(B+D) = kA/(A+C)$, then the noise-to-signal ratio condition implies that $k < 1$. Substituting that into the conditional probability condition, we can see that the conditional probability is larger than the unconditional probability.

(19)Berg and Pattillo of the IMF when their paper was written, and Edison, in evaluating the different indicator models, failed to reproduce the exact KLR results using same data, even though KLR was written when the authors were also at the Fund. They cited data transformation and revision, and missing data as possible causes for the discrepancies (see Section 4).

(20)Ed omitted the terms of trade indicator for being difficult to construct consistently across countries.

Chart 2: Performance of the indicators



growth in US and G-7 countries' income, year-on-year changes in the US three-month Treasury bill rate, oil prices and short-term debt (BIS) to foreign exchange reserves, and the levels of the M2/reserves and short-term debt/reserves ratios) over a longer sample period (from January 1970 to April 1995).[21] He finds the results are broadly the same as in the KLR study and all extra indicators are informative (ie, with noise-to-signal ratio below one). But he notices that the expanded coverage did affect the selection of the optimal threshold as the latter is sample dependent (chosen as the minimum noise-to-signal ratio for an indicator across all countries).

Furthermore, Ed compares the 'performance' of the indicators on the basis on the reciprocal of the noise-to-signal ratio (ie the ratio of good signals to noise) with that of the share of crises called correctly (Chart 2). Interestingly, while the real exchange rate overvaluation indicator is ranked top on the basis of having the highest signal-to-noise ratio, the measure is ranked fifteenth using the share of crises called correctly criterion. He suggested that the high noise-to-signal ratio was due to the fact that prior to the crisis, the real exchange rate had been overvalued for extended periods, and hence yielding a high noise-to-signal ratio. And for many crises the real exchange rate did not issue any signal at all, resulting in a low ranking on the basis of share of correct calls.

Kaminsky and Reinhart (1999) applied these signalling models to analyse banking and currency crises in parallel. They calculated the probability of currency crises conditional on that having been a banking crisis within the past 24 months, and *vice versa*, and then compared these with the unconditional probabilities. They found that problems in the banking sector normally precede a currency crisis, and that a currency crisis in turn could increase the risk of a banking crisis.

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[21] Ed dropped the last eight months of 1995 from the sample so as to evaluate the predictive capabilities (on the basis of 24-month signalling horizon) of the model for the 1997 Asian crisis.

Kaminsky (1999) suggested some ways to aggregate the information provided by all the indicators to assess the likelihood of an impending crisis. The simplest form is to count the number of signals issued by the different indicators of the economy at a particular point in time, and the larger the number of signals, the higher the likelihood of a crisis. Note that this simple aggregation method implies that all indicators have equal importance in inferring a crisis. To take into consideration the different performance of the indicators, Kaminsky suggested a composite index of signals, I_t, at time t for each country, which is a weighted average of the number of indicators which give out a signal,

$$I_t = \sum_{j=1}^{n} \frac{S_t^j}{\omega^j} \qquad \textbf{(3)}$$

where S_t^j equals to one if indicator j issues a signal at t, n is the total number of indicators, and ω^j is the noise-to-signal ratio of indicator j. These composite indices (simple aggregation and weighted by noise-to-signal ratio) provide information on the vulnerability of a country at a particular point in time, and by looking at a series of these snapshots, one can assess whether a country has become more or less vulnerable during the time period studied.

Furthermore, it is also possible to use these composite indices to calculate the probability of a future crisis. For example, the probability that a crisis will occur within h months from t, given that the composite index lies between a particular range of values, say, $\underline{I}$ and $\overline{I}$ is

$$\begin{aligned}&\mathrm{Prob}(\mathrm{crisis}_{t,t+h}|\underline{I} < I_t < \overline{I}) \\ &\qquad = \frac{\text{number of months with a crisis occurs between } t, t+h \text{ given } \underline{I} < I_t < \overline{I}}{\text{number of months with } \underline{I} < I_t < \overline{I}}\end{aligned} \qquad \textbf{(4)}$$

Ed constructed the weighted-average composite index with his extended dataset and found that the maximum value to be 27.1, and the highest conditional probability of a crisis is 50% when the value of the index is over 12.

3.2 Discrete-choice approach

While the signalling approach aims to extract ‘crisis signal’ from each individual indicator, the discrete-choice approach evaluate directly the conditional probability of a crisis given a set of indicators.[22] Studies that have adopted this approach include the Goldman Sachs GS-WATCH,[23]

[22]Discrete-choice theory has long been popular among psychologists and biologists analysing human behaviour and biological experiments respectively (see Finney (1971) for a survey of historical developments). One of its first uses in economics is in the 1960s by economists such as Theil and McFadden in analysing the choice of modes of transport (see Ben-Akiva and Lerman (1985)).
[23]Ades, Masih and Tenengauzer (1998).

JP Morgan Event Risk Indicator (ERI), Frankel and Rose (1996), and Kumar, Moorthy and Perraudin (1998) for currency crises,[24] and Demirgüç-Kunt and Detragiache (1998) for banking crisis.

The technical aspects of these papers are quite similar: first, let y denote the crisis variable that takes a value of either 1 (if a crisis occurs) or 0 (otherwise). Let $\mathbf{x}$ be a vector of potential indicators and β be a vector of parameters. Then we can write the probability of having a crisis as:

$$P(y=1) = f(\beta'\mathbf{x})$$

where $f(\cdot)$ is a probability distribution function. If we assume a logistic distribution, then

$$P(y=1) = \frac{\exp(\beta'\mathbf{x})}{1+\exp(\beta'\mathbf{x})}, \qquad P(y=0) = \frac{1}{1+\exp(\beta'\mathbf{x})}$$

The parameter vector β is estimated by maximum likelihood and the regression is a standard LOGIT one.[25]

However, the differences between the studies stem from their treatment of three important issues: i) the definition of a crisis; ii) sample selection (both frequency and number of countries selected); and iii) the indicators used.

3.2.1 Crisis definition

Similar to the signalling models, most discrete-choice studies define a crisis on the basis on some forms of exchange rate pressure exceeding its threshold. However, as we can see from Table C, the exchange rate variable chosen by the studies varies, ranging from straight nominal depreciation to creating a composite index using changes in reserves and depreciation.[26] And the threshold level chosen also differ between studies.

All the studies except GS-WATCH tested for robustness by varying their respective threshold levels. GS-WATCH adopted a technique called the self-exciting threshold autoregression (SETAR), which has been used in the business cycle literature to identify recessions, to extract the optimal threshold levels for the crisis index y_t (measured as a weighted average of three-month changes in the trade-weighted

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[24] The Kumar-Moorthy-Perraudin (1998) was extended by the Credit Suisse First Boston staff to form the basis of their Emerging Markets Risk Indicator (EMRI).

[25] The decision to use LOGIT or PROBIT (normal distribution) is purely arbitrary as the logistic and normal distributions are quite similar except that the tails are thicker in the logistic case.

[26] Other researchers such as Eichengreen, Rose and Wyplosz (1995) attempt to fine tune the index by taking into account domestic interest rate changes and high inflation period, but encounter the common problem of data availability in most emerging economies.

Table C: Definition of currency crisis

Study	Definition of crisis	Sample freq. & results
Goldman Sachs GS-WATCH	The weighted average of 3-month changes in trade-weighted real exchange rate and reserves. Weights are chosen by the inverse of their standard deviations. A crisis is defined as a period when the index is above its threshold (determined by a signalling autoregression).	Monthly data; data starting from 1983; 27 emerging economies.
JP Morgan ERI	A fall in the real bilateral exchange rate of over 10% over the course of one month or 22 business days.	Monthly data; 1980:1–1994:12, 14 crashes; 1995:1–1997:12, 14 crashes. Two thresholds being tested (8%, and 12%); 25 countries.
Frankel and Rose (1996)	A nominal exchange rate depreciation of at least 25% that also exceeds the previous year's change in the exchange rate by 10%.	Annual data; 1971–1992, 70 crashes out of the total of 803 episodes; 105 countries.
Kumar, Moorthy & Perraudin (1998)	Currency depreciations (nominal) of at least 5%, 10%, and 15%; depreciations can be either total or unanticipated (ie, adjusted for interest rate differentials between the relevant domestic currency and the US dollar).	Monthly data; 1985:1–1998:3 covering 32 emerging markets. Number of crisis episodes varies.

real exchange rate and reserves). In the general form, a SETAR$(1,d,r)$ is specified as:

$$\begin{aligned} y_t &= \alpha_1 + \alpha_2 1(y_{t-d} > r) \\ &\quad + [\phi_1 + \phi_2 1(y_{t-d} > r)]y_{t-1} + [\psi_1 + \psi_2 1(y_{t-d} > r)]\varepsilon_t \end{aligned} \tag{5}$$

where ε_t are i.i.d. with mean zero and unit variances; $1(A)$ is an indicator function which is equal to one if the event A occurs and zero otherwise, d is the delay parameter, and r is the threshold parameter.[27] GS-WATCH estimated a simplified SETAR by choosing a one-period lag, ie,

$$y_t = \alpha_0 + \alpha_2 1_t + \phi_1 y_{t-1} + \phi_2 1_t y_{t-1} + \varepsilon_t \tag{6}$$

and the value of the threshold was chosen such that the model has the lowest standard error in maximum likelihood estimation.

[27] Potter (1995) provides a summary of various approaches to estimate the noise parameters d and r.

3.2.2 Sample selection

The choice of sample frequency also varies between studies. Frankel and Rose (1996) chose annual data on the basis of data availability (eg, comparable debt profile is available only annually). But as for the majority of the studies, (eg, GS-WATCH, JP Morgan, and Kumar, Moorthy and Perraudin (1998)), monthly data were preferred mainly for their interest in providing more frequent and up-to-date early warning signals. Also, while the selection of annual data enabled Frankel and Rose (1996) to cover a larger number of heterogeneous countries (105 of developed and emerging market economies); the models with monthly data confine to the group of emerging market economies.

3.2.3 Indicators

Furthermore, the number of indicators tested/used also differs. The model that examined most variables (a total of 32) is Kumar-Moorthy-Perraudin, which are classified according to the following 12 categories: (1) output and inflation, (2) money and credit, (3) fiscal variables, (4) domestic financial market, (5) trade and current account, (6) capital flows and debt, (7) reserves, terms of funds and the real exchange rate, (8) policy environment, (9) global output, inflation and liquidity, (10) global financial markets, (11) international commodity prices, and (12) regional effects. The other three studies were more parsimonious and examined a much smaller set of variables, which we summarised in Table D.

3.3 Structural approach

While the two approaches above aim to establish the likelihood of impending financial crises, some economists have developed structural models to explain the causes of currency crises in terms of characteristics which make a country more vulnerable to speculative attacks. We consider here a number of key papers that can be classified under this approach.

Dornbusch, Goldfajn and Valdés (1995) (DGV) is largely a descriptive study. Using a mixture of annual and quarterly data, covering the period between 1975 and 1995, they tried to explain the currency crises in Argentina, Brazil, Chile, Finland, and Mexico. They compared the pre and post-crisis behaviour of the following variables: (1) the real exchange rate, (2) real interest rates, (3) GDP growth, (4) inflation, (5) fiscal deficit/GDP ratio, (6) credit growth, (7) trade balance/GDP ratio, (8) current account/GDP ratio, (9) international reserves, and (10) debt/GDP ratio. Their discussion mainly focused on the common patterns observed in the periods leading up to currency crises. They identified the reasons for the crisis as a combination of negative external shocks such as the sharp rise in

Table D: Leading indicators for currency crises

	GS-WATCH	JP Morgan	Frankel & Rose
Capital flows and debt			
Current account/GDP			•
Current account + amortisation	•		
Reserves/M2	•		
Reserves/debt		•	
Reserves/imports			•
Public sector debt			•
Total debt/GDP			•
Government budget deficit/GDP			•
Short-term debt			•
Commercial bank lending	•		•
Concessional lending			•
Debt at variable interest rate			•
IFI lending			•
FDI/debt stock			•
Current account			
Overvaluation	•	•	•
Real sector			
GDP growth		•	•
Export growth	•		•
International variables			
OECD output growth			•
Wtd-average of ‘Northern’ interest rates	•		•
Financial variable			
Equity index	•		
Domestic credit growth			•
Contagion dummy	•	•	
Political risk	•		

Note: GS-WATCH first transforms all the explanatory variables (except export growth and political risk) into signals as specified in equation (**6**). Kumar, Moorthy and Perraudin (1998) examined 32 variables that covered all of the above (in one form or another) except political risk.

US interest rates, and deteriorating economic fundamentals such as fiscal deficits and overvaluation of the real exchange rate.

Sachs, Tornell and Velasco (1996) (STV) examined data on a cross-section of 20 emerging markets during the 1994 Mexican crisis. Using monthly data, they created a crisis pressure index (IND) which was a weighted sum of the percentage decrease in foreign exchange reserves and the percentage depreciation of the exchange rate between the end of November 1994 and the end of each of the first six months of 1995. But unlike the discrete-choice and signalling approaches, which converted the index into a binary variable, STV regressed this (continuous) crisis index on a set of explanatory variables. The explanatory variables consist of a lending boom variable (LB), an overvaluation measure (RER), and dummies for low reserves and weak fundamentals. Lending boom, which is used as a proxy for the strength of the banking system or the 'fundamentals', is measured by the growth in loans in the private sectors between 1990 to 1994. Real exchange rate misalignment is measured as the average real effective exchange rate depreciation of 1986–89 to that of 1990–94. The dummies are designed to test whether a country would suffer more severe speculative attack when its international reserves were low and/or had weak fundamentals. Reserves, measured as the M2/reserves ratio, are said to be 'low' ($DLR = 1$) when they lie in the lowest quartile in the sample. And 'weak' fundamentals ($DWF = 1$) is defined as the case when the exchange rate depreciation is in the lowest three quartiles *and* the lending boom variable in the highest three quartiles. Then they estimated the following regression:

$$\begin{aligned} IND = {} & \beta_1 + \beta_2(RER) + \beta_3(LB) \\ & + \beta_4(DLR \times RER) + \beta_5(DLR \times LB) \\ & + \beta_6(DLR \times DWF \times RER) \\ & + \beta_7(DLR \times DWF \times LB) + \varepsilon \end{aligned}$$

Dummies: $DLR = 1$ when reserves are low

$DWF = 1$ when fundamentals are weak

Table E sets out some of the null hypotheses tested by STV. They found that countries with strong fundamentals but low reserves are not likely to be attacked, (ie, $\beta_2 + \beta_4$ and $\beta_3 + \beta_5$ are not significantly different from zero when $DLW = 1$ and $DWF = 0$). They also found that for those countries with weak fundamentals ($DWF = 0$) and low reserves ($DLW = 1$), a more devalued real exchange rate or a smaller lending boom will lead to a smaller crisis pressure index ($\beta_2 + \beta_4 + \beta_6 < 0$, $\beta_3 + \beta_5 + \beta_7 > 0$).

Corsetti, Pesenti and Roubini (1998a) adopted the STV framework to examine the Asian crisis and found that other variables such as non-performing loans in the banking system, the current account, and

Table E: STV hypothesis testing matrix

		Fundamentals	
		Strong ($DWF = 0$)	Weak ($DWF = 1$)
Reserves	High ($DLR = 0$)	$\beta_2 = 0$, $\beta_3 = 0$	
	Low ($DLR = 1$)	$\beta_2 + \beta_4 = 0$, $\beta_3 + \beta_5 = 0$.	$\beta_2 + \beta_4 + \beta_6 < 0$, $\beta_3 + \beta_5 + \beta_7 > 0$.

M1 to proxy the strength of fundamentals and the position of reserves, were significant explanatory variables.

Bussiére and Mulder (1999), also adopted the STV framework to evaluate the power of the model (estimated with data up to 1997) in predicting crisis out-of-sample (the 1998 Russian crisis). In doing so, they computed the rank correlation between the in-sample predictions and actual values and compared these with the out-of-sample correlation. They found that the out-of-sample prediction of the 1998 Russian crisis based on the STV specification is poor and the rank correlation coefficient of the predicted and the actual rankings of exchange pressure index is negative. On this basis, they claim that the complete set of STV variables behaves as a 'contra-indicator'. They also noticed that for the recovering Asian crisis countries, whose banking systems were still on the mend, the persistent high values of their lending boom variable exaggerated the predicted exchange pressure index with an average of 29.9, compared with the actual average of -7.3. They also examined the five indicators that feature in the early warning system developed by a group of IMF economists (Developing Country Studies Division Model (DCSD), see Berg *et al* (1999) and Berg and Pattillo (1999)), and found that three scored particularly well in predicting the 1998 crisis out-of-sample. These include short-term debt to reserves, the change in the real exchange rate and ratio of current account deficit/GDP.[28] In particular, the short-term debt to reserves ratio is by far the best liquidity indicator, and outperforms the money-based (eg, M2/reserves) and import-based ratios, in predicting the Mexican, Asian, and Russian crises. But the other two indicators tested—the change in the rate of export growth and the percentage change in reserves—are found to be statistically insignificant.

[28] For the first variable, instead of using official short-term debt data, they used the BIS data on short-term debt by residual maturity.

3.4 Contagion

Because of lack of precise definition of contagion, the existing empirical studies on the subject differ considerably. In general, there are two types of motivation. The first is to examine the role of contagion in identifying potential crises and establishing the conditional probability of crisis given the contagion effects. The second focus is on testing whether contagion actually exists by examining the co-movements in asset returns and capital flows pre and post-crisis.

In the discrete-choice models discussed above, various authors included a proxy for contagion into their model and found that it could affect the probability of a future crisis. The contagion variables were either chosen by statistical means or designed to capture regional linkages. Esquivel and Larrain (1998) simply created a regional dummy for each of the countries in Europe, Latin America, Asia and Oceania. The JP Morgan Event Risk Indicator uses two variables to measure contagion: a risk appetite variable to capture the change in investors' preferences before a crisis occurs and a cluster variable to measure the importance of contagion after the first few crises occurred. They assume that the likelihood of financial contagion is higher when investors' risk appetite is falling. Their risk appetite is simply the rank correlation between market returns and risk (measured as a weighted combination of long-term average interest rate differential and deviation of the real effective exchange rate from its long-term average). And the cluster variable is a weighted measure of the number of crises that have occurred within the past six months in either of the two currency blocs ($-bloc and euro-bloc). GS-WATCH adopts an agnostic approach in the sense of relying on the data to reveal the extent to which speculative pressures in one currency transmit to another. Their country contagion variable is calculated as a weighted-average of other countries' crisis pressure index. The weights are chosen according to the historical correlation of the crisis indices across countries.

Glick and Rose (1999) estimated a PROBIT model and found evidence of contagious speculative attacks caused by trade links but not by macroeconomic and financial influences. However, their model is crisis-specific as it needs to specify the 'first victim' or 'ground zero' countries each time. The trade linkage variable is then calculated as an index of the bilateral trade between the ground zero countries and others.

Van Rijckeghem and Weder (2000) test for the 'common lender' effect over the Mexican, Asian and Russian crises using BIS data on bank flows to 30 emerging markets. They found the common lender effect during the Thai crisis to be highly statistically significant and less significant for the Mexican crisis, but not significant during the Russian crisis. They suggest that the lack of the common lender effect during the Russian crisis may be due to the absence of some major players from the BIS data (eg, data on Swiss banks) or the existence of indirect exposures and guarantees not captured by the data. Moreover, as pressures on fund withdrawals can be reflected in either quantities (flows) or prices (yields), spillovers through common lenders may be present even when they are not captured by the flow data.

Kaminsky and Reinhart (2000) employ a signalling model to analyse how non-crisis contagion could arise from trade links and common lender effects. They find evidence that contagion is regional but warn of the danger in extrapolating from historical data. This is because while inter-regional trade in goods and services has increased moderately in the past few years, that in assets has risen sharply, and hence increasing the probability of simultaneous falls in asset prices across regions. They also find that the vulnerability to contagion is highly non-linear, ie, the possibility of a domestic crisis rises more than proportionately with the number of countries in crisis. However, they suggest that it is difficult empirically to differentiate the two linkages, financial versus trade, as most countries that are linked in trade are also linked in finance. Nevertheless, they suggest that the common lender effects were probably at work for Argentina in the 1994 Mexican crisis and for Indonesia after the 1997 Thai devaluation as the two sets of countries' trade links were weak.

While the above models include contagion as an explanatory variable, other approaches take one step back and ask whether contagion really exists. Early attempts include those studies that analyse cross-market correlation coefficients. These measure the correlation in asset and equity returns between two markets during a tranquil period and then test for a significant increase in this correlation coefficient after a shock. Calvo and Reinhart (1996) and Baig and Goldfajn (1998) found significant increases in the correlation of asset returns for the Mexican peso crisis and Asian crisis respectively. Froot, O'Connell and Seasholes (1999) study whether foreign outflows can lead to price overreaction and contagion. Using the State Street Bank & Trust data that cover almost four million trades by client institutions, they find that international portfolio inflows are slightly positively correlated across countries and are more strongly correlated within regions.[29] In particular, the correlation of daily flows in Asia rises strongly during the Asian crisis subsample, but not during the Mexican crisis subsample.

Another approach in testing for contagion is to estimate the (variance-covariance) transmission mechanism across countries with an ARCH or GARCH model. Edwards (1998) examines the

[29] However, owing to the need to protect the confidentiality of their clients' business transactions, the State Street data are not publicly available.

propagation across bond markets after the Mexican crisis, with a focus on how capital controls affect the transmission of shocks. He estimates an augmented GARCH model and shows that there were significant spillovers from Mexico to Argentina, but not from Mexico to Chile. Other studies test for contagion by examining the changes in the co-integrating vector between stock markets instead of any short-run changes after a shock (see, for example, Longin and Slonik (1995)). If tests show that the cointegrating relationship increased over time, this could be a permanent shift in cross-market linkages instead of contagion. But the cointegration analysis may not be an accurate test for contagion due to the long time periods under consideration.

Forbes and Rigoborn (2001) point out that tests for contagion in the presence of heteroskedasticity are inaccurate. This is because the presence of heteroskedasticity will bias the results toward finding contagion even when the underlying propagation mechanism is constant and no shift-contagion actually occurs. Similarly, Loretan and English (2000) point out an important result of probability theory: when the movements of random variables are more volatile, sampling correlations between those variables will be elevated even if the underlying data generating process remains unchanged. This suggest that one should be more cautious in interpreting the fluctuations in correlations during periods of market volatility as true changes in the distribution of asset returns. They went on to draw a rather cautious conclusion: rather than suggesting that 'contagion' does not occur, contagion measured by increased sample correlations between asset returns could be no more than a by-product of high sampling volatilities.

3.5 Selected indicators

As summarised in Tables A, B and D, a rather wide range of indicators have been examined under the three approaches and found to be useful in predicting crisis. However, regardless of the approach adopted, an interesting fact is that a particular set of indicators always emerge as informative in predicting an impending crisis. Apart from the common set of macro indicators, such as GDP growth, export growth and fiscal deficit/GDP, we discuss in this section the indicators that appear more relevant for the crises in the 1990s. These are grouped under the following categories: real exchange rate overvaluation, liquidity problems, weakness in banking sector and contagion.

3.5.1 Real exchange rate misalignment

Almost all studies find that real exchange rate misalignment is a useful predictor of currency crises. Overvaluation can be seen as a summary variable, resulting from economic imbalances in a country.

Consequently, the current account is expected to deteriorate. But a main question is which is the most 'appropriate' measure? While some studies (eg, STV) measure the real exchange rate as a weighted average of the bilateral real exchange rates of a country with respect to three major currency blocs (US$, DM and Yen), others simply adopt the CPI-based real effective exchange rate index as defined by the IMF Information Notice System (INS, a direct trade-weighted system). As Bussiére and Mulder (1999) point out, INS fails to take into account third-party effects and hence neglects the effects of entrepôt trade (that constitutes a substantial part in some Asian countries' total trade) on relative price movement.

Goldfajn and Valdés (1998) used three different measures of real exchange rate misalignment to investigate the effects of overvaluation on predicting future currency crises: deviations from a simple time trend, deviations from a Hodrick-Prescott filtered series, and deviations from fundamental equilibrium (based on a regression on productivity, terms of trade, government spending and openness). They found that the 'best' results came from the simplest method, ie, detrending the real exchange rate, and argued that as a summary variable, overvaluation is a good predictor of crisis on both the three-months and six-months ahead horizon.

Chinn (1998) suggested testing the real exchange rate for cointegration with the drift terms to determine whether the currency is in fact over/undervalued up to the period before a crisis occurred. In doing so, he concluded that not all the Asian currencies were overvalued before the Asian crises. In fact, the Korean won appears undervalued prior to the crisis.

3.5.2 Liquidity problems

One of the main causes of the Asian crisis was the lack of liquidity in both the corporate sector and its banking system once the currency was forced off its peg. Thus, a set of variables that together reflect the internal and external liquidity, such as low international reserves and high short-term debt ratio, could be useful predictors of currency crisis. One of the most commonly cited external vulnerability indicators is the current account balance. In most cross-country analysis, it is either scaled by GDP to reflect the size of the economy or by the total value of trade to reflect the degree of openness. Bussiére and Mulder (1999) tested both ratios and reported the former was more significant by a wide margin.

Calvo and Mendoza (1996) suggested two measures of vulnerability: the M2/reserves and the external short-term debt/reserves ratios.(30) The former ratio measures the adequacy of the reserves to cover the

(30) One may argue that foreign exchange debt is a better measure of external vulnerability than external debt, but owing to data availability, researchers tend to use external debt instead.

domestic liabilities of the central bank and the banking system, the latter the adequacy of reserves to cover short-term debt amortisation. Bussiére and Mulder (1999) claim that the short-term debt/reserves ratio serves better as an indicator of illiquidity than most other measures. By examining various liquidity measures, including imports over reserves and three money-based measures (M0, M1 and M2 over foreign reserves), they find that when the short-term debt/reserves ratio is included, neither the imports/reserves ratio nor any of the four money-based measures are significant or have the expected (positive) sign. Greenspan (1999), following earlier unpublished ideas by former Argentine Finance Minister Guidotti, discusses the possibility that, as a rule of thumb, a country should always have enough foreign exchange reserves to cover a year's foreign currency liabilities (see Bussiére and Mulder (1999) for empirical support for the Guidotti ratio).

3.5.3 Weakness in banking sector

Sachs, Tornell and Velasco (1996) found that the lending boom variable, measured by the increase in banking sector credit to the private sector, was a useful indicator of both the Mexican and Asian crises. This is because the larger the ratio of banking sector credit to the private sector, the higher the probability that the banking system has incurred a high proportion of bad loans. Bussiére and Mulder (1999) concluded that the lending boom variable is, as mentioned above, however a 'contra-indicator' out of sample (eg, as the Asian countries recovered). Other more indicators of weakness in banking sector include the ratio of non-performing loans in total loans, net interest margins and balance-sheet mismatches, but they are not adequately examined mainly due to availability (see Section 4.3).

3.5.4 Contagion

Following the Forbes and Rigoborn (2001) terminology, contagion can be divided into crisis-contingent and non-crisis-contingent components. Most of the discrete-choice models that claim contagion affects the likelihood of crisis refer to the non-crisis-contingent type. For example, Glick and Rose (1999) examined the relation between trade and contagion and concluded that trade linkages did play an important role in explaining how currency crises spread. Specifically, if a group of small countries have close trade linkages with a large country, then a devaluation in one of the former's currency may trigger a round of beggar-thy-neighbour type of devaluation within the group.[31] But we have to emphasise

[31] However, as pointed out by the new trade theorists, intra-industry trade is becoming more important in world trade and countries are importing intermediate goods from others to produce the final products. If that type of trade dominates, higher trade linkages would reduce the possibility of competitive devaluation.

that the results are of little use in terms of predicting currency crises, as we still have to predict the country where crisis first occurs. This may, however, indicate particular vulnerable clusters of counties where trade and financial links are especially strong.

4 Evaluation of the empirical models

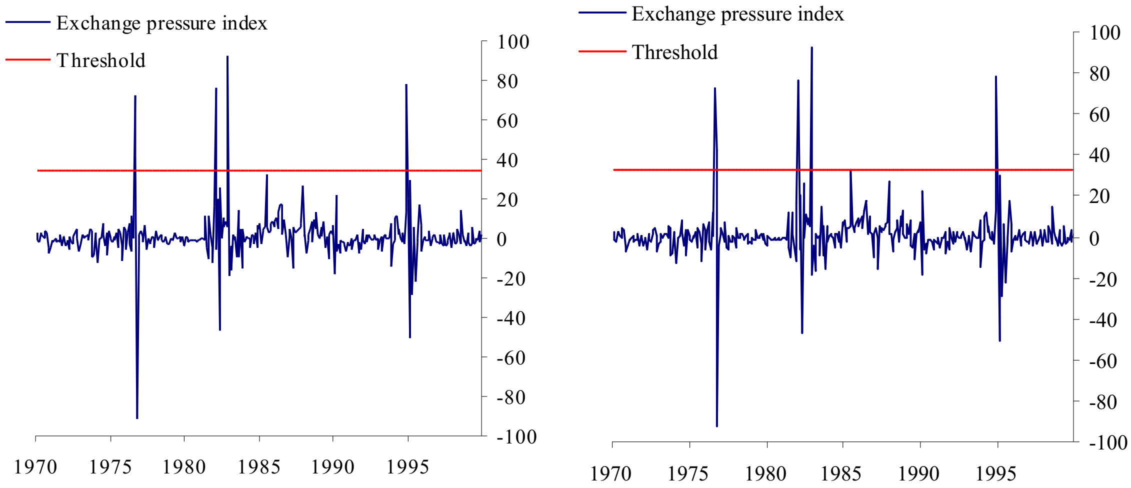
We discussed above two key questions in building leading indicator model of currency crisis—developing a formal statistical framework and identifying the best variables. In this section, we examine the question of whether the models are effective in predicting crises. Key issues in assessing these approaches are how they define crises, their out-of-sample forecasting ability, and a number of data issues.

4.1 Crisis definition

The definition of a crisis is crucial to all models. Unfortunately, there is no objective definition of a crisis. In a narrow sense, a currency crisis takes place when a country is forced to abandon its pegged exchange rate or exchange rate band because of speculative attacks. However, to gauge the vulnerability of a country's exchange rate to speculative attacks, it would be better to include those 'failed' attacks when the authorities successfully fend off speculators by using their international reserves. Thus, in most indicator models, a crisis is represented by an exchange pressure index, measured as a weighted average of the rate of depreciation and the negative of monthly percentage changes in gross international reserves. With no theoretical guidance on choosing the 'optimal' weights, the weights are chosen as the precision (ie, one over the variance) over some arbitrary period. And the higher is the index, the larger the speculative pressure the country is facing. Apart from being sample-dependent, choosing the precision using the inverse of the sample variance over a period that spans two different exchange rate regimes would result in information loss and hence bias the exchange pressure index.

While the structural approach uses this pressure index as dependent variable, the signalling and discrete-choice models first convert it to a dichotomous variable of a crisis and no crisis. In most of the latter models, a crisis episode is defined as the case where the pressure index exceeds an arbitrary threshold value. For example, KLR define a crisis to be the case when the pressure index exceeds its mean by three standard deviations. Again, there is little theoretical guidance on choosing the threshold level. To test for robustness, these studies examined different thresholds, eg, the pressure index exceeds the mean by different number of standard deviations, and most authors claim that different thresholds

Chart 3: Exchange rate pressure index—Mexico



(a) Sample statistics: Jan 70 to Dec 95.

(b) Sample statistics: Jan 70 to Dec 95.

Sources: IMF and author's calculation.

did not change the results significantly.[32]

To illustrate the robustness of the crisis definition, we followed Edison (2000) to construct c (equation (**2**)) from the following data source:

$\Delta e/e$: monthly percentage change of **end-period** nominal bilateral exchange rate, IMF International Financial Statistics (IFS) line ae.

$\Delta r/r$: monthly percentage change of total foreign reserves, minus gold, IFS line 1l.d.

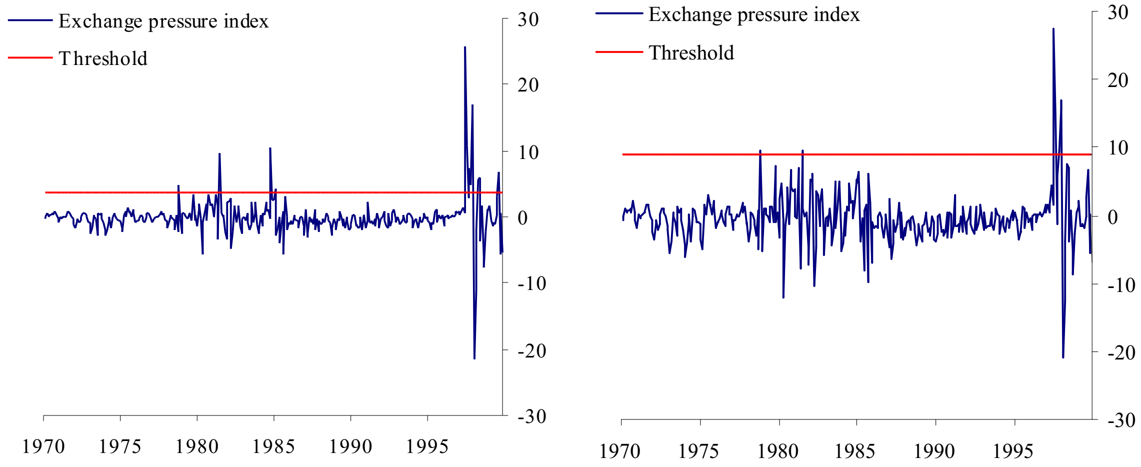
ϕ : the arbitrary constant in crisis threshold is chosen as 2.5. That is, the crisis threshold equals 2.5 times sample standard deviation plus sample mean.

Chart 3(a) and (b) show the Mexican exchange rate pressure index and its threshold with sample statistics calculated (all σ's and μ's) for the periods of January 1970–December 1995 and January 1970–December 1999 respectively. Since the Mexican peso was relatively stable between January 1995 and December 1999, the identified crisis episodes in both cases are largely the same (except the latter sample just identifies July 1985 as a crisis).

However, the number of identified crisis episodes will be quite different when the exchange rate pressure index is very volatile in the extended sample period (see Chart 4(a) and (b) for the case of Thailand). In including the extra data from January 1995 to December 1999, the sample standard

[32]Notice that this is the threshold for determining whether a crisis has occurred or not, and is different from the indicator threshold in signalling models or the threshold above which the predicted value is classified as a crisis in the discrete-choice models.

Chart 4: Exchange rate pressure index—Thailand



(a) Sample statistics: Jan 70 to Dec 95.

Sources: IMF and author's calculation.

(b) Sample statistics: Jan 70 to Dec 95.

deviation of p (equation (**1**)) increases from 1.8 to 3.6, bringing the threshold up to 9 from 3.7. As a result, some of the crisis episodes identified in the smaller sample (November 1984 and February 1985) are no longer 'crises'.

In addition to the problem with data sample selection, we find that the crisis index is also sensitive to the nominal exchange rate series used. In the above example, end-period figures were used. But other authors, Eichengreen, Rose and Wyplosz (1995) adopt period average (IMF IFS line rf) in calculating p. We compare the exchange pressure index using both end-period and period average data. In most cases, the resulting crisis episodes are the same, but on occasions, a crisis in September, say, is identified as an October crisis. Also, the sample standard deviation of period average data is generally smaller and resulting in a lower crisis threshold.

On the other hand, GS-WATCH's more sophisticated time series technique—self-exciting threshold autoregression (SETAR)—is also open to criticism. It chooses a lag structure of one rather than determining the number of lags statistically (as in other SETAR models). Also, the technique involves heavy computing power because of its non-linear nature.

4.2 Forecasting

4.2.1 Out-of-sample prediction

In terms of forecasting performance and/or issuing accurate signals, most of the studies described above perform well in-sample. Berg and Pattillo (1998) was among the first to evaluate some previous studies in terms of their out-of-sample prediction power. They suggest two types of test for this purpose. The first type focuses on the ability of the models in identifying the vulnerabilities of a set of countries to currency crisis. One simple way is to examine the Spearman rank correlation between the actual and predicted exchange rate pressures/probabilities of the countries. The second type relates to the models' ability in predicting the timing of an impending crisis, and therefore applies only to the signalling and discrete-choice approaches. This is normally measured by the out-of-sample goodness of fit, ie, counting the number of false alarms and missed crises.

Berg *et al* (1999) applied this type of test to KLR, Frankel and Rose (1996) (FR), STV, and DCSD.[33] They find that the rankings generated from all four models' predictions are positively correlated with the actual rankings in 1997. The correlation is not very high, ranging from 12% to 53%, with the two models using monthly data (KLR and DCSD) having higher correlation. However, one should bear in mind that the results are not directly comparable as the crisis definitions are different in the models.

In applying the out-of-sample goodness of fit test to the discrete choice and signalling models, two main results emerged. First, Berg *et al* (1999) find that according to the FR definition, there is no actual crisis in 1997 and therefore nothing to predict. They argue that the main deficiency is in using annual data in building leading indicator models; crises tend to happen within a rather short period of time. Second, in comparing the results of KLR (a signalling model) with DCSD (a discrete-choice model), which both have a maximum forecasting horizon of 24 months, they find that the out-of-sample performance of KLR is not as good as that of DCSD. Their results are summarised in Table F. With the low cut-off probability at 25% (and hence more crises predicted), the KLR model correctly signals only 34% of the crisis observations, as opposed to almost one-half within sample. About one half of the crisis signals are false alarms and crises are missed 24% of the time. Notice also that by increasing the cut-off point to 50%, the KLR model do not forecast any crisis over the next 24 months, ie, between May 1995 and December 1997. By contrast, the DCSD model fares much better out-of-sample. With the 25% cut-off, its accuracy in predicting a crisis is 73%, while that of false alarms is at 41%.
Berg *et al* (1999) suggested that the superior performance of DCSD against KLR might be attributed to the fact that the former was formulated post-Asian crisis and hence takes into consideration some of its key features, eg, the inclusion of short-term external debt as an indicator.

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[33]The protocol of the IMF Developing Country Studies Division Model (DCSD) is Berg and Pattillo (1998), and is a discrete-choice based model.

Table F: Out-of-sample predictive power of KLR and DCSD

	KLR		DCSD	
Cut-off probability	25%	50%	25%	50%
% of observations correctly called	70	70	79	74
% of pre-crisis periods correctly called	34	0	73	3
% of tranquil periods correctly called	86	100	81	100
False alarms as % of total alarms	51	N.A.*	41	0
Probability of crisis given				
An alarm	49	0	59	100
No alarm	24	29	11	27

*No crisis predictions.

Source: Berg *et al* (1999).

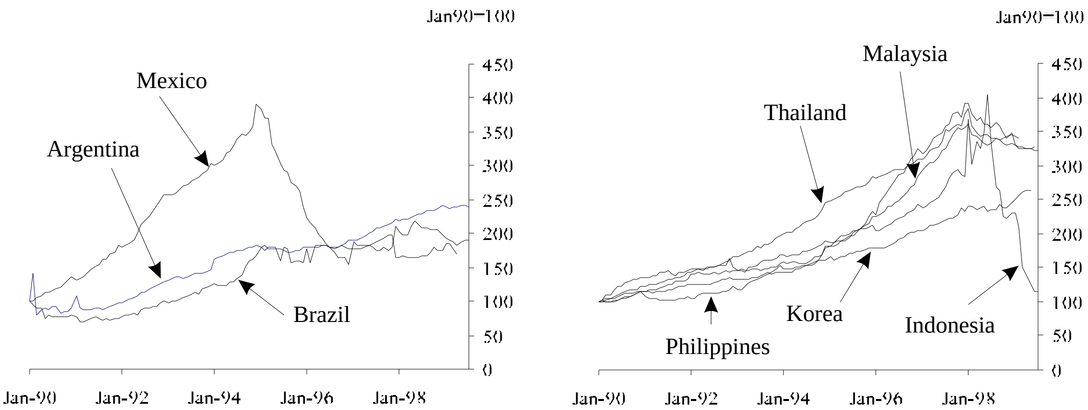
4.2.2 Optimal cut-off

One of the main issues in building a good forecasting model is to balance out two types of error: the number of false alarms (predicted crises that do not materialise) and the number of failures (unanticipated crises). In a discrete choice model, the expected value of crisis, given a set of indicators, is a probability measure. However, the predicted probability (a continuous variable) is clearly not an *admissible* prediction since the dependent variable takes values of only 0 or 1. For an admissible predictor we need a decision rule (normally involving a threshold) which attaches 0 or 1 to these probabilities. A natural choice is to choose 0.5 as the threshold, above which a 1 is assigned. However, if the sample is relatively unbalanced (as in most of the crisis studies that have far more tranquil periods than crises), ie, it has many more zeros than ones and hence the sample mean of the dependent variable much lower than a half, then this decision rule might bias toward predicting a crisis. One can always adjust the threshold accordingly, but in doing so, it will always reduce the probability of missing a crisis while increasing the probability of a false alarm and *vice versa*. Greene (1993) points out that there is no correct answer as to the optimal cut-off level; it all depends on the researchers' subjective criterion function upon which the prediction rule depends. For example, most of the studies conducted by the investment banks aim at predicting the next crisis of a particular country more accurately. Meanwhile, policy-makers and international policy institutions, whose main interest is in preventing crises, could tolerate more false alarms and so might prefer a lower threshold value.

4.2.3 Problems with forecasting

The first objection to forecasting with these models links to the Lucas critique. While theoretical models such as the Krugman-Flood-Garber and the Obstfeld models are free from the Lucas critique, these reduced-form empirical models that are estimated over different policy regimes are not. This is

Chart 5: Private lending



Source: IMF.

because while we can deduce some useful information from the indicators before a crisis, once a crisis occurs, the government and international agents may impose different policy measures such that all the estimated parameters change. For example, if the authorities are aware of a crisis in waiting, they may adopt some emergency policy actions to prevent the problems developing into a full-blown crisis. In that case, a signal might be registered as an out-of-sample false alarm.

Furthermore, the structural parameters might change due to changing demand and supply conditions, rendering the estimates of some of these models (especially those that are built around a particular crisis) no longer appropriate.[34] Chart 5 shows real private lending for three Latin American and the five Asian countries.[35] We can see that growth in private lending is very strong in both sets of countries before the Mexican and Asian crises respectively, so a positive relationship is expected between the lending boom and crisis. However, after the crisis, the lending boom was moderate, and even negative in Indonesia where financial risks remained considerable. This was partly due to the shrinking credit supply post-crisis.

How to choose the most appropriate forecast horizon poses another problem. In the signalling and discrete choice models, a 'good' call is usually defined as a signal issued that is followed by a crisis within a certain period of time, say 24 months. So far, there is very little discussion on this issue, and most investigators arbitrarily define this period as 24 months (see Edison (2000, page 14)). But given that the number of good calls can be very sensitive to this decision, certainly more research is needed to help choosing this forecast horizon.

[34] One may argue that most econometric models will suffer from the same problem, but it is more problematic for most of these indicator models as they were built around a particular crisis.

[35] We follow STV's definition to calculate real private lending by taking out the claims on government from the total domestic credit, then dividing the difference by the consumer price index.

The other problem, which only applies to the discrete-choice models, relates to the probabilistic nature of the method. In most other disciplines, the principal purpose of these discrete-choice models is to obtain results that can be generalised to larger aggregates rather than predicting the probability of an individual event.(36) Therefore, it would be unsurprising to see that the predicted probability of a particular country at a particular time given a set of indicators is quite different from the actual one. Cramer was extremely pessimistic about predicting individual outcomes:

> 'Predicting the state that will obtain at a given regressor vector **x** is tantamount to predicting the outcome of a single statistical experiment like the throw of a die, and almost as futile;'
>
> —Cramer (1990, page 90).

Nevertheless, even some of the authors of these models adopted a relatively guarded tone on the forecasting ability of their models. For example, Bussiére and Mulder (1999) warn against the use of structural models: "as with investing in stock market funds, crisis models require a clear warning: 'past performance is no guarantee for future performance'". In Kaminsky's (1999) words, 'while forecasting the exact timing of crises is likely to continue to remain an elusive goal, ... we can construct a warning system that helps to monitor whether a country may be slipping into a situation that is bound to end up in a crisis.'

4.3 Other issues

The availability of quality data, especially in emerging market economies, poses another big obstacle to more detailed studies. When Berg and Pattillo (1998) re-estimated KLR's work, they found only 8 of the indicators were useful, instead of the 13 reported by KLR. The authors suggested that revisions of data by the IMF was one of the reasons for the difference. But this underlies how sensitive some of these studies are to data quality.

Lack of international comparable data also hinder the development of these models. One specific example is data on non-performing loans (NPLs). Different countries have different criteria of defining NPL status, for example, 90 days in Argentina and 180 days in Malaysia. In addition, countries also have different minimum initial provisioning for NPLs, ranging from 0%–1% in Malaysia to 50%–60% in Chile.(37) Data provided by national sources sometimes show big discrepancies from those cited by

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(36)A discussion of the difference between aggregate forecasting and individual forecasting is beyond the scope of this paper, see Cramer (1990) and Ben-Akiva and Lerman (1985) for details.
(37)See Caprio (1998) for detailed analysis on banking supervision.

the Bank of International Settlements.[38] Another example occurred in June 2000 when the Bank of Thailand released a new series of external liabilities, and the total external debt was revised up from around US$70 billion to above US$90 billion.

The decision on data frequency is also very important. The speed which financial crisis can spread leads researchers to use higher frequency (monthly) data in their models. However, most macroeconomic data (eg, GDP) are only available on a quarterly basis at best. Moreover, in order to justify as leading indicator models, some researchers use the lags of the indicators rather than the contemporaneous levels in their discrete-choice models. Again, the decision of the lag depends on the frequency of the data and lacks any objective judgment. For example, Esquivel and Larrain (1998) adopt annual data with one lag (ie, one year) in their indicators. As mentioned above, the FR model, which is using annual data, fails to recognise an actual crisis in 1997.

One other issue affecting out-of-sample prediction is causality. Unlike time series analysis, where one can include lags and/or leads to test for Granger causality, the nature of the signalling and discrete-choice approaches offers very little scope for tackling these issues. In selecting the indicators, the researchers have already implicitly imposed some causal-relations. However, if the causal-relations assumed were actually in the opposite direction, the changes in the indicators would be caused by the crisis itself instead.

Despite all these limitations, one has to bear in mind that the empirical literature is relatively young and there is still room for improvement. So far, the focus of these models is mainly on their predictive power and relatively little has been said about the estimated coefficients (apart from being summarised in tables). But one should be careful when reading these discrete-choice results. Unlike time series models, one cannot directly read the individual influence of variables from the coefficient. This is because the probability on the left-hand side is obtained by mapping a particular probability density on to a linear combination of variables, so that any change in a variable will affect the probability by the margin of the coefficient while keeping other variables constant. Let $\Phi(\cdot)$ and $\phi(\cdot)$ be the normal distribution and density functions respectively, then

$$P = \Phi(\beta'\mathbf{x})$$

and

$$\frac{\partial P}{\partial x_i} = \phi(\beta'\mathbf{x})\beta_i \qquad \textbf{(7)}$$

[38] Since 1997, the IMF has been promoting the Special Standards for Data Dissemination (SDDS) which encourages countries to follow a particular standard in data reporting. Consequently, some national authorities have recalculated some of their old data on the basis of new international standards.

The right-hand side of equation (**7**) is sometimes called the quasi-elasticity of x_i, which can be read as the change in the likelihood of a crisis with respect to a change of a particular indicator given that it was evaluated at a particular value.[39]

Meanwhile, we also need to improve the estimation method. At present, most models are estimated with panel data using ordinary LOGIT or PROBIT which fails to take into account the serial correlation within the data. But only if the observations are independent both over the countries and over time, the panel data discrete-choice model will not pose any problem.[40] Special estimation methods are therefore needed to tackle the serial correlation problem (see Amemiya (1985) for other estimation methods) and hence to improve the predictive power of the models.

5 Conclusions

This paper surveys the theoretical models and empirical evidence on currency crises. Theoretical models suggest that weak economic fundamentals, such as large fiscal debt and private agents' expectations of government's policy or a mixture of both, are the main causes of financial crisis. Financial and corporate sector problems, moral hazard, and contagion could also play a part. Based on these theoretical underpinnings, researchers have identified a large number of variables, ranging from the standard macro and financial variables such as GDP growth and real interest rates to political stability indices, as potential indicators of crisis.

Most empirical studies, partly because of the relatively low ratio of crisis to tranquil periods in any single country, have to rely on pooling data from a group of countries. There are broadly three different empirical approaches to using these indicators—signalling, discrete choice and structural. While the structural models are built around a particular crisis and hence possibly more suitable for monitoring/early warning purposes, the discrete-choice and signalling models are used for forecasting future crises as well. Most studies claimed to be successful in identifying leading indicators, although the accuracy of their prediction deteriorates out of sample. The poor predictive power can be for several reasons: the difficulties in defining the dependent variable (or a crisis), changes in the structural relationships in an economy, overemphasis on some crisis-specific indicators, and other technical problems such as data quality and revision.

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(39) This interpretation becomes more complicated when a particular variable appears more than once in the right-hand side, eg, the GDP term appears in output growth, reserves/GDP ratio.

(40) While the exchange rate pressure index is constructed as a weighted average of reserves and exchange rate, and the latter variables are also included as indicator variables, thus the problem of endogeneity is obvious.

Nonetheless, whichever approach the research is based on, an interesting fact is that a particular set of indicators always emerges as informative in predicting an impending crisis. This includes indicators of real exchange rate overvaluation, liquidity problems, lending growth/boom and contagion. Focusing on the evolution of these indicators might usefully complement the whole set of indicators currently monitored for surveillance purposes.

Appendix

A First-generation model

We describe the basic Flood and Garber (1984) model here to show how bad fundamentals can lead to balance-of-payments crisis. First, we will show that under a fixed exchange rate regime, continuous credit expansion will dry up the reserves in finite time, and then we will examine the exact timing of the speculative attack on the currency.

A.1 Assumptions

Money demand:

$$\frac{M(t)}{P(t)} = a_0 - a_1 i(t) \tag{A.1}$$

where M, P, and i represent nominal money stock, price level, and interest rate respectively.

Money supply:

$$M(t) = R(t) + D(t) \tag{A.2}$$

where R and D are book value of foreign reserves and domestic credit.

Assuming credit expansion at a (positive) fixed rate μ,

$$\dot{D}(t) = \mu \tag{A.3}$$

Finally, we assume PPP and UIP hold, ie,

$$P(t) = P^*(t)S(t), \tag{A.4}$$

$$i(t) = i^*(t) + \left[\frac{\dot{S}(t)}{S(t)}\right] \tag{A.5}$$

where S is the spot exchange rate defined as the domestic price of foreign currency. We use an asterisk $(*)$ to denote foreign variables, which are assumed exogenous for the small country case.

A.2 Money market equilibrium under fixed exchange rate

With PPP and UIP, ie, substitute (**A.4**) and (**A.5**) into (**A.1**), money demand becomes

$$\begin{aligned} M(t) &= [a_0 P^*(t) - a_1 i^*(t) P^*(t)] S(t) - a_1 P^*(t) \dot{S}(t) \\ &= \beta S(t) - \alpha \dot{S}(t) \end{aligned}$$

where $\beta = [a_0 P^*(t) - a_1 i^*(t) P^*(t)]$ and $\alpha = a_1 P^*$. Thus, money market equilibrium gives

$$R(t) + D(t) = \beta S(t) - \alpha \dot{S}(t) \tag{A.6}$$

Under a fixed exchange rate system, $S(t) = \bar{S}$, $\dot{S}(t) = 0$, and foreign reserves are then equal to,

$$R(t) = \beta \bar{S} - D(t) \tag{A.7}$$

It is obvious that under the fixed rate system, continuous domestic expansion will dry up the reserves in finite time as,

$$\dot{R}(t) = -\dot{D}(t) = -\mu \tag{A.8}$$

A.3 Timing of the attack

One of the interesting implications of the first-generation model is the timing of the attack. Assuming the post-attack exchange rate is free floating, we can find out the relationship between that rate and domestic money supply. Let z be the time at which the reserves were exhausted, and z_+ and z_- and be the instant right after and before the attacks respectively. Take for instance, at $t = z_+$, we have

$$M(z_+) = \beta S(z_+) - \alpha \dot{S}(z_+) \tag{A.9}$$

Equation (**A.9**) is a first-order differential equation, which we can be solved as follows. First we conjecture the solution to be $S(t) = \lambda_0 + \lambda_1 M(t)$. But at the instant right after the attack reserves will be depleted completely, $R(z_+) = 0$, so $M(z_+) = D(z_+)$, and hence $\dot{M}(t) = \dot{D}(t) = \mu$. Therefore, $\dot{S}(t) = \lambda_1 \mu$. Combining this with (**A.9**) we have

$$S(t) = \frac{\alpha \lambda_1 \mu}{\beta} + \frac{1}{\beta} M(t) \tag{A.10}$$

By comparing (**A.10**) with our conjectured solution, we find $\lambda_1 = 1/\beta$ and $\lambda_0 = \alpha\mu/\beta^2$. Therefore, the 'shadow exchange rate' equals

$$S(t) = \frac{\alpha\mu}{\beta^2} + \frac{M(t)}{\beta}, \qquad t \geq z \tag{A.11}$$

To deduce the exact timing of the attack, we need to find out the level of the exchange rate at the moment of an anticipated attack on foreign reserves, $S(z_+)$. Consider the case of discrete currency depreciation, $S(z_+) > \bar{S}$, in which a speculator who launch an attack will profit by an amount $[S(z_+) - \bar{S}]R(z_-)$. So whenever an agent expects a discrete exchange rate increase he will have an incentive to pre-empt his competitors by purchasing all the reserves an instant before z. Therefore launching an attack at z and a discrete exchange increase at z is contradictory. On the other hand, if

$S(z_-) > \bar{S}$, agents who attack the currency will result in a loss of $[S(z_+) - \bar{S}]R(z_-) < 0$, and hence have no incentive to attack. Under this no-arbitrage condition, we can conclude that at the moment of an anticipated attack on foreign exchange reserves, the shadow exchange rate must be equal to the fixed rate, ie, $S(z_+) = \bar{S}$. Substituting this condition and the fact that $M(t) = D(t) = D(0) + \mu t$ into (**A.10**), we have

$$z = \left[\frac{\beta\bar{S} - D(0)}{\mu}\right] - \frac{\alpha}{\beta} = \frac{R(0)}{\mu} - \frac{\alpha}{\beta} \qquad \textbf{(A.12)}$$

From (**A.12**), we see that the larger the initial reserves, the later will the agents attack the fixed rate. Also, a decrease in credit expansion (smaller μ) will put off the attack.

B Second-generation model

The Obstfeld (1996) 'second-generation' crisis model provides a framework for evaluating the exit strategies. The basic framework of the model follows the Barro-Gordon approach, with the additional assumption that PPP holds and foreign price being normalised at zero, then domestic inflation reads exchange rate depreciation. The standard time-inconsistency problem follows from the government's resolve to keep the exchange rate peg. In the case when the government needs to invoke the 'escape-clause' and leave the fixed exchange rate system, a punishment cost will be incurred.

B.1 The model

Assume that the government minimises the following loss function:

$$\mathcal{L} = (y_t - \tilde{y})^2 + \psi\pi_t^2 + C(\pi_t) \quad \textbf{(B.1)}$$

where y_t and $\tilde{y}_t$ are real and target output, π is rate of inflation, $\psi(1 > \psi > 0)$ weights the cost of inflation relative to that of suboptimal output, and $C(\cdot)$ is included to temper with the credibility problems.

Assuming that PPP holds with the foreign price being normalised to one, then the log of exchange rate e will be equal to the log of price, p. Thus $\pi_t = e_t - e_{t-1}$, or the inflation rate corresponds to the realised rate of currency depreciation. We further assume that the government has adopted a 'fixed-but-adjustable' exchange rate such that any upward change in e (a devaluation, implying $\pi_t > 0$) will lead to an extra cost to the government of $C(\pi_t) = \overline{c}$. Similarly, any downward change in e leads to a cost of $C(\pi_t) = \underline{c}$. If there is no change in exchange rate, $C(0) = 0$.

Output is described by an expectations-augmented Phillips curve

$$y = \overline{y} + (\pi - \pi^e) - \varepsilon \quad \textbf{(B.2)}$$

where ε is a conditional i.i.d. output supply shock with zero mean, and superscript e represents an expectation variable. We further assume that there is a wedge, k, between the output targeted by the authorities and the natural level of output so that

$$\tilde{y} - \overline{y} = k > 0 \quad \textbf{(B.3)}$$

B.2 Equilibria

Ignoring the fixed cost term C, the government (with discretion) will then choose π so as to minimise (**B.1**) subject to (**B.2**):

$$\frac{\partial \mathcal{L}}{\partial \pi} = 0 \qquad \Rightarrow \pi = \frac{k + \varepsilon + \pi^e}{1 + \psi} \tag{B.4}$$

Substituting (**B.4**) back into (**B.2**), we obtain the output level,

$$y = \bar{y} + \frac{k - \psi\pi^e - \psi\varepsilon}{1 + \psi} \tag{B.5}$$

and the corresponding *ex post* policy loss

$$\mathcal{L}^D = \frac{\psi}{1 + \psi}(k + \pi^e + \varepsilon)^2 \tag{B.6}$$

However, under strict policy rule not to devalue, that is not to devalue under any circumstances, the *ex post* policy loss is

$$\mathcal{L}^R = (k + \pi^e + \varepsilon)^2 \tag{B.7}$$

Comparing (**B.6**) and (**B.7**), it is obvious that $\mathcal{L}^R > \mathcal{L}^D$. Absent a mechanism for enforcing a promise of no devaluation, a monetary authority whose promise is believed will never find $\pi = 0$ optimal *ex post*.

Now take into account the fixed costs of currency alignment, $C(\pi)$. Given those costs, the authorities will change the exchange rate only when ε (the supply shock) is large enough to make $\mathcal{L}^R - \mathcal{L}^D > \bar{c}$, in which case the government will devalue the currency. Similarly, the government will revalue the currency if ε is low enough to make $\mathcal{L}^R - \mathcal{L}^D > \underline{c}$. Thus devaluation occurs when $\varepsilon > \bar{\varepsilon}$, where

$$\bar{\varepsilon} = \sqrt{\bar{c}(1 + \psi)} - k - \pi^e \tag{B.8}$$

and revaluation when $\varepsilon < \underline{\varepsilon}$, where

$$\underline{\varepsilon} = \sqrt{\underline{c}(1 + \psi)} - k - \pi^e \tag{B.9}$$

For shock realisations $\varepsilon \in [\underline{\varepsilon}, \bar{\varepsilon}]$, the fixed exchange rate is maintained.

To summarise, the monetary authorities defend the fixed exchange rate against all but very large (in absolute value) shocks, in which case they pay the fixed costs of devaluation/revaluation in order to use monetary policy for output stabilisation.

The rational expectation of inflation (depreciation) π in the next period, given wage setters' expectations π^e, is

$$E\pi = E[\pi|\varepsilon < \underline{\varepsilon}]\Pr(\varepsilon < \underline{\varepsilon}) + E[\pi|\varepsilon > \overline{\varepsilon}]\Pr(\varepsilon > \overline{\varepsilon}) \qquad \textbf{(B.10)}$$

where E is the expectational operator and $\Pr(\cdot)$ is the probability.

Notice that both $\overline{\varepsilon}$ and $\underline{\varepsilon}$ are functions of expected inflation, so expected inflation enters here both in determining the inflation rate the government chooses conditional on choosing to realign, and and in determining the probability of a realignment. The fact that *ex post* inflation depends on π^e in a potentially very complicated way gives rise to the possibility that there are **multiple equilibria** expected inflation rates under the 'fixed but adjustable' exchange rate scheme.

B.3 Parametric example

The existence of multiple equilibria can be easily shown if we assume ε is uniformly distributed on $[-Z, Z]$, then we have the following:

$$\begin{aligned} \Pr(\varepsilon > \overline{\varepsilon}) &= \frac{Z-\overline{\varepsilon}}{2Z}, \qquad E[\varepsilon|\varepsilon > \overline{\varepsilon}] = \frac{Z+\overline{\varepsilon}}{2}, \\ \Pr(\varepsilon < \underline{\varepsilon}) &= \frac{Z-\underline{\varepsilon}}{2Z}, \qquad E[\varepsilon|\varepsilon < \underline{\varepsilon}] = \frac{-(Z-\underline{\varepsilon})}{2} \end{aligned} \qquad \textbf{(B.11)}$$

Combining **(B.4)**, **(B.8)–(B.11)**, we have

$$E\pi = \frac{1}{1+\psi}\left[(k+\pi^e)\left(1-\frac{\overline{\varepsilon}-\underline{\varepsilon}}{2Z}\right) - \frac{\overline{\varepsilon}^2-\underline{\varepsilon}^2}{4Z}\right] \qquad \textbf{(B.12)}$$

It is obvious that the solution of **(B.12)** involves multiple equilibria.

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