Credit Booms in Emerging Market Economies: A Recipe for Banking Crises?

Daniel Ottens, Edwin Lambregts and Steven Poelhekke*

* Views expressed are those of the individual authors and do not necessarily reflect official positions of De Nederlandsche Bank.
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Abstract

This paper investigates whether credit booms are an important warning signal for banking crises in Asian and Latin American emerging market economies. Based on a signalling leading indicator model, the results suggest that credit booms are indeed a prelude for banking crises, especially in Latin America. To minimise a policymaker’s loss-function, it is optimal to take precautionary actions in the event credit growth rises substantially above its trend.

JEL Codes: E44, G10, G21  
Keywords: emerging markets, credit booms and banking crises

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1. Introduction

Economic growth in emerging markets as a whole surged to more than 7 percent in 2004, the highest level in the past decade. This fast expansion is increasingly driven by buoyant domestic demand, underpinned by strong private credit growth. Although rapid credit growth may reflect improved economic fundamentals and financial deepening, it also raises concerns since credit booms are often seen as a prelude for a banking crisis. In this paper, we assess whether banking crises are driven by credit booms. To address this question we construct an empirical indicator of a credit boom, and then apply this indicator to a signalling model for banking crises. Our analysis is based on annual data for Asian and Latin American emerging markets between 1980 and 2003. The results indicate that lending booms are an important leading indicator for banking crises in emerging markets, especially in Latin America. If we assume that the cost of a banking crisis is 5 times the cost of taking preventive action, it seems optimal for the Latin American policymaker to intervene when the credit-to-GDP ratio is more than 5 percent above its trend for two consecutive years.

The outline of the paper is as follows. Based on the economic literature, the next section discusses the driving factors behind excessive credit growth and why a credit boom can trigger a banking crisis. Section 3 lays out the paper’s methodology and provides an empirical definition of credit booms, a banking crisis and a description of the data. In Section 4 the results are presented. Finally, Section 5 presents some conclusions and policy implications.

2. Conceptual background: what is a credit boom, and how could it cause a banking crisis?

Not all episodes in which private credit grows more rapidly than nominal GDP can be qualified as a credit boom. One important reason why credit can temporarily expand faster than GDP is because companies’ investment in working capital – funds needed to pay in advance for inputs into production – often fluctuates ahead of the business cycle. The resulting deviation between credit and GDP is therefore not unusual (IMF, 2004). Credit growth can also exceed GDP growth for a longer period of time due to financial deepening, reflecting the growing importance of financial intermediation. Rapid lending may thus represent a permanent deepening of the financial system and an improvement of investment opportunities that are beneficial for the economy. As empirical evidence indeed suggests, a deeper financial system contributes to economic growth (Mishkin, 2001 and Demirgüç-Kunt
and Levine, 2001). By contrast, a credit boom is an episode of excessive credit expansion that is unsustainable and eventually collapses of its own accord (IMF, 2004).

Credit booms have various roots. In some cases they originate from financial deregulation which increases banks’ access to new credit markets. These reforms are often accompanied by a reduction in banks’ reserve requirements and by poorly regulated capital account liberalisation, providing ample liquidity to fund lending booms (Cottarelli, Dell’Ariccia and Vladkova-Hollar, 2003). In addition, credit booms may arise from a surge of capital inflows driven by external factors (such as low interest rates in advanced economies), or from periods of strong disinflation (Gourinchas, Valdés and Landerretche, 2001). The latter can boost favourable real lending conditions, higher asset prices and more optimistic risk assessments.

Several econometric studies have investigated the relation between rapid credit growth and banking sector fragility. Borio and Lowe (2002), Eichengreen and Arteta (2000) and Kaminsky and Reinhart (1999) find evidence that credit booms increase the likelihood of banking crises. Triggered by these empirical findings, a number of recent theoretical models also examined the link between credit booms and banking crises. These models usually incorporate the financial accelerator mechanism, where shocks are amplified by balance sheet effects (Bernanke, Gertler and Girlchrist, 1999). Over-optimism about future returns can provide an extraordinary boost to asset prices and thus companies’ net worth, creating a self-reinforcing rise in borrowing, investment, asset prices and further borrowing. In the context of the sheer volume of lending, banks might find it harder to screen and monitor projects properly. Furthermore, the rise in borrowers’ net worth may reduce banks’ incentives to monitor adequately. The “excessive” pace of credit growth thus leads to a deterioration of the quality of bank portfolios. When it becomes clear that the optimistic expectations are unjustified, the whole process is reversed. The failure of a large number of the “bad” projects funded during a credit boom could then set off downward spiral. Borrowers unable to repay their debt (credit risk) see their collateral seized and sold by banks, which could trigger asset price declines, lower net worth and further loan recalls. If loan losses exceed a bank’s reserves

3 However, the pace of financial deepening may later subside as the private sector increasingly gains access to other sources of finance, such as from financial markets (equity and bonds).

4 Credit booms are also invigorated by the bailout expectations mechanism. Bailout guarantees encourage banks to undertake not only too many investments projects, but also projects that are more risky than may be socially efficient (moral hazard). Apart from explicit guarantees, such as deposit insurance schemes, these safeguards frequently involve implicit or systemic guarantees of which the government is not always aware (Tornell and Westermann, 2002). Examples of implicit guarantees in emerging markets are policies aimed at exchange rate stabilisation. Under these circumstances lenders may take on more risk than they would in case of more exchange rate volatility. The story usually ends up in tears if projects fail to deliver and the authorities are unable to fully provide the expected bail-out.
and equity cushion, the bank is technically insolvent. Even in the absence of a rise in loan losses, banks are exposed to higher solvency risk if asset price declines set off falls in the value of their marketable investments (*market risk*).

Problems within banks may not surface immediately. Once a bank is in trouble, it has an incentive to conceal losses by raising new deposits or stretching its balance sheet, to increase its bet with current clients and to invest in new high-risk and high-return investment projects in an effort to make up for losses on assets (Caprio and Klingebiel, 1996)\(^5\). The opacity of banking business, associated with the complexity of intertemporal contracting, makes it hard for outsiders such as shareholders and depositors to see through the veil surrounding the bank’s balance sheet until it is too late. This asymmetric information problem, together with banks’ demandable liabilities, makes banks vulnerable to runs: an indication of problems can prompt depositors to withdraw their funds (*liquidity risk*). As problems at one bank easily spill over to other banks, this could trigger a crisis of confidence and widespread bank failure to the detriment of financial intermediation and overall economic activity.

While a credit boom seems a key determinant of banking crises, it remains difficult to judge when credit growth can exactly be considered excessive. Empirical research is therefore needed to distinguish between “healthy” credit expansions, including financial deepening, and unsustainable ones associated with worsening bank balance sheets.

### 3 The signalling approach

This section outlines our empirical definition of a credit boom, describes the methodology of the signalling model and classifies a banking crisis. The approach taken draws on the work of Borio and Lowe (2002), Gourinchas, Valdés and Landerretche (2001) and Kaminsky and Reinhart (1999). As in their studies, the idea is to define threshold values for credit growth. When credit growth exceeds the threshold, it is defined as a credit boom, which is supposed to signal that a banking crisis is imminent.

#### 3.1 Credit booms, signals and a policymaker’s loss-function

As indicated before, lending booms must take into account that credit usually follows a business cycle and a trend, of which the latter reflects financial deepening. In this paper, we

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\(^5\) Especially when depositors have explicit protection, banks can attract new depositors with the promise of higher interest rates.
empirically define a lending boom episode as two consecutive periods in which the ratio of nominal private credit to nominal GDP deviates from trend by a certain threshold. This threshold varies from 2 to 10 percentage points of GDP (credit gap). The trend is calculated by using a country-specific and backward-looking rolling Hodrick-Prescott filter for the entire sample period (1980-2003), with a smoothing factor of 100 for annual data. By calculating a backward-looking trend, we only use information that would have been available to the policy maker when he was assessing whether or not there was a credit boom. Appendix A gives the credit gaps for each country, defined as the credit-to-GDP ratio in deviation from its backward-looking trend. A group unit root test on all series indicated that the sample observations are stationary (the null-hypothesis of a unit root is rejected for the group).

Since fragilities may linger in the financial system for a couple of years before a crisis erupts, we look at multiple time-horizons from 0-3 years. For each threshold value and for multiple time-horizons, we then compute: i) the noise-to-signal ratio (the fit of the indicator); ii) the percentage of correctly predicted crises and iii) the conditional probability of a banking crisis occurring after a signal of a lending boom has been given (the accuracy of signals). We can classify all observations in the two-by-two matrix below (following Kaminsky and Reinhart, 1999). A perfect indicator would only have entries in cells A and D. The noise-to-signal ratio is given by: \( \frac{B}{(B+D)} / \frac{A}{(A+C)} \). Hence, a lower ratio represents a better fit of the indicator. Subsequently, we can derive the percentage correctly predicted crises and the (in-sample) conditional probability of a banking crisis occurring after a signal of a lending boom has been given. The first is calculated by \( \frac{A}{(A+C)} \), and the second by \( \frac{A}{(A+B)} \).

<table>
<thead>
<tr>
<th></th>
<th>Banking crisis occurs in next 0-3 years</th>
<th>No banking crisis occurs in next 0-3 years</th>
</tr>
</thead>
<tbody>
<tr>
<td>Indicator issues a signal</td>
<td>A</td>
<td>B</td>
</tr>
<tr>
<td>Indicator does not issue a signal</td>
<td>C</td>
<td>D</td>
</tr>
</tbody>
</table>

We then need to select an appropriate threshold which gives the policymaker an idea when a large credit gap is considered a relevant signal of a banking crisis and when not. The criterion typically adopted under the signalling approach, is to select the threshold that minimises the noise-to-signal ratio. Choosing the optimal threshold involves a trade-off. While increasing the threshold reduces the amount of false signals (in which credit booms are not followed by

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6 By using two consecutive periods rather than one, we limit the number of false signals while losing a few good signals. Apparently, credit booms tend to last longer than one year.
banking crises), it also lowers the number of correctly predicted banking crises. This trade-off also applies to the policymaker who is concerned about financial stability. By acting on all warning signals, policymakers may prevent all credit booms from turning into a banking crisis. However, this comes at the cost of overreacting in cases where the signal turns out to be false (although it is impossible to check this ex-post).

As Demirgüç-Kunt and Detragiache (2000) rightly point out, choosing the optimal threshold also depends on: i) the relative costs of policy errors and ii) the frequency of crisis events. On the first point, if the authorities judge type I errors (the probability of missing a crisis) more important, they will select a threshold that is reducing type I errors and accepting more type II errors (the probability of falsely identifying a crisis). Clearly, the higher the cost of missing a crisis relative to the cost of taking preventive action, the more inclined the policymaker will be to reduce type I errors and thus lower the threshold associated with a warning signal. On the second point, if crises tend to be rare events, then the overall likelihood of making a type I error is relatively small (opposite, if crises tend to be frequent events, the policymaker will place more weight on reducing type I errors). Empirically, the incidence of crises (the unconditional probability) is typically based on the in-sample frequency of crisis observations. All these three factors (noise-to-signal ratio, relative costs and frequency of crisis events) affect how policymakers proceed.

Based on Bell (2000), we can express the policymaker’s decision making process (involving these 3 factors) in a formal analysis. Let \( p(T) \) denote the probability the model will issue a warning signal for a given threshold \( T \) of the credit gap, and let \( e(T) \) be the probability that a crisis will occur and the model does not issue a warning signal. In addition, \( c_1 \) stands for the costs of taking preventive action, and \( c_2 \) stands for the costs of an unanticipated banking crisis. We then define a simple linear loss-function for the policymaker:

\[
L(T) = p(T)c_1 + e(T)c_2
\]

From Bayes’ theorem we know that \( e(T) \) equals the conditional probability of the model not issuing a warning signal given that a crisis will occur multiplied by the unconditional probability of a crisis occurring. The latter term is written as \( v \), which is independent of time.

\[7\] For a warning system to be useful, we assume that banking crises can be prevented by policymakers or that their cost can be substantially reduced.
Thus, \( e(T) \) equals the probability of a type I error, \( p_1(T) \), multiplied by \( v \). We interpret \( e(T) \) as the likelihood that the policy maker incurs a ‘surprise crisis’ cost \( c_2 \) and \( p(T) \) as the likelihood that the policymaker incurs a ‘preventive’ cost \( c_1 \) (or similarly the probability of both correctly and incorrectly predicting a banking crisis). This equals one minus the probability of a type I error multiplied by the unconditional probability of a banking crisis occurring \((1 - p_1(T)v)\) plus the probability of a type II error, multiplied by the unconditional probability of a crisis not occurring \((p_2(T)(1-v))\). The loss function of the policymaker in equation (1) can then be rewritten (2) as:

\[
(2) \quad L(T) = vc_1[1 + p_1(T)(c_2 - c_1)/c_1 + p_2(T)(1-v)/v]
\]

From equation 2 it is evident that the larger the cost differential between \( c_2 \) and \( c_1 \), the more concerned the policymaker will be about type I errors (missing a crisis). To minimise its loss function, the policymaker will thus try to lower the threshold of the credit gap \( T \), which will lower the chance of type I errors at the cost of increasing type II errors. In short, the policymaker must weigh up the underlying likelihood of a banking crisis as well as the cost of action and inaction in deciding if and when to intervene. In principle, we could minimize equation (2) and derive the optimal threshold for a given distribution of \( p_1(T) \) and \( p_2(T) \). Because these variables do not follow standard distributions in our sample we derive the optimal threshold numerically in section 4.

3.2 Sample Data

Most empirical research on the interaction between credit and investment booms and banking crises focuses on advanced economies or on samples including both advanced and emerging economies. However, there are important differences between advanced economies and emerging markets. According to the IMF (2004), credit booms in the former are less frequent, and if they occur, less costly, largely reflecting stronger institutional frameworks. Our paper exclusively concentrates on emerging markets. By selecting countries with a comparable state of development in South-East Asia and Latin America, we obtain a more homogenous sample. A list of the countries included in the sample can be found in Appendix B.

In the economic literature there is no generally accepted definition of a banking crisis, as it is often difficult to determine its starting point, duration and costs. In defining the dates of banking crises, we have used the recently updated list of Caprio and Klingebiel (2003). Since
we only try to determine whether our indicator signals the start of a banking crisis, we just consider the starting dates relevant and disregard their duration. Table 1 in Appendix B lists the 37 banking crises.

4. Results

Based on the methodology described above, this section examines whether credit booms provide a useful signal of banking crises. The following tables report results on the interaction of credit gap indicators and banking crises, using a horizon of 0-3 years. Each indicator shows a range of thresholds/credit gaps (percentage point deviation of actual credit ratio from trend), the number of correctly signalled banking crises, the associated noise-to-signal ratio and the conditional probability of a crisis. After looking at the credit gaps for emerging markets as a group, we consider Latin America and Asia separately.

Table 2 starts with the link between credit gaps and banking crises for the entire sample. Two conclusions can be drawn. First, Table 2 shows the trade-off when choosing a threshold. A higher threshold raises the conditional probability of a banking crisis (and lowers the noise), but also reduces the percentage of correctly signalled banking crises. This makes sense intuitively; the larger the credit gap, the higher the likelihood a signal is followed by a crisis. However, a higher threshold also increases the risk of missing a crisis by ignoring many warning signals. Second, lengthening the horizon up to three years before the crisis improves the early warning model’s performance. This is not surprising as lengthening the horizon allows the model to give more ‘good’ signals than with a horizon of just 1 or 2 years. For example, given a 1-year horizon and a credit gap of 5 percentage points above trend, roughly 20 percent of the crises are signalled correctly, producing a noise-to-signal ratio of 0.49 percent. Instead, if we use a 3-year horizon, almost 30 percent of the banking crises are signalled correctly and the noise-to-signal ratio is more than 10 points lower than with the 1-year horizon. The accuracy of the credit boom signal itself improves as well when lengthening the horizon up to 3 years. Under a 5 percentage point threshold, almost 60 percent of all credit gap signals correctly predict banking crises, roughly doubling the number under a 1-year horizon. These results support the hypothesis that banking sector problems usually take a couple of years before they erupt.
Dividing the sample into Latin America and Asia yields some interesting results. First, it is encouraging to see that the general findings for the entire sample also hold for the sub-samples taken separately. This suggests that our broad observations are robust across sub-samples. Second, Tables 3 and 4 illustrate that the credit gap indicator performs better in Latin America than in Asia. For example, given a 3-year horizon and a threshold of 5 percentage points, the share of correctly signalled crisis in Asia is 21 percent and 35 percent in Latin America. The accuracy of the signal itself is also higher in Latin America than in Asia. Based on the same horizon and threshold, the noise-to-signal ratio and conditional probability in Asia are respectively 0.30 and 0.53 percentage points, whereas for Latin America these percentages are 0.27 and 0.59 percentage points. So, the credit gap indicator in Latin America not only signals banking crises more frequently, it also signals more banking crises correctly relative to Asia. This suggests that banking crises in Asia are more frequently associated with other factors than excessive credit growth only. These results are consistent with Gourinchas, Vaklé and Landerretche (2001), and Gavin and Hausmann (1996), who find that lending booms in Latin America are more frequently followed by financial turmoil than in the rest of the world. In forthcoming work, we attempt to further substantiate this finding on the basis of a logit analysis.
On the basis of these results, the question remains which threshold the policymaker should choose to take preventive action. On the basis of the policymakers’ loss-function discussed in Section 3, we can choose the optimal threshold. To illustrate, we compute loss functions for three configurations of the policymaker’s cost parameters on a 3-year horizon. For the unconditional probability ($v$), we use our in-sample frequency of 0.07 (based on the entire sample). Following Demirgüç-Kunt and Detragiache (2000), we then normalise $c_1$ in Equation (2) to 1 in all three scenarios and calculate the loss function for three somewhat arbitrarily chosen values of $c_2 - c_1$, namely 10, 5 and 3. Consequently, the threshold values that minimise the loss functions are respectively, 0.03, 0.075 and 0.14 (Graph 1). In other words, a risk-neutral policymaker whose cost of minimising a crisis is, for example, 6 times the cost of taking precautionary measures will take preventive action if the credit gap is approximately 7.5 percentage points above its trend for two consecutive years.
Next, it is interesting to know at which threshold the Asian and Latin American policymakers would respond. Given the in-sample frequency for Latin America of 0.08, and the cost differential of $c_2 - c_1 = 5$, the Latin American policymaker would take precautionary measures if the credit gap exceeds a level of more than 5 percentage point above trend for two successive years (Graph 2). Using an identical cost differential ($c_2 - c_1 = 5$), the policymaker in Asia would minimise its loss when he or she intervenes at a credit gap level of 8 percentage points above trend (Graph 3). The relatively higher intervention level in Asia relative to Latin America reflects the lower incidence of banking crisis (in-sample frequency of 0.06) and the poorer quality of the credit gap signal in Asia. Note that in this exercise we assume policymakers to act risk-neutral. Risk-averse policymakers would place greater weight on minimising type I errors than on minimising type II errors, since type I errors are more costly (and more easily observable for the general public). This implies that it could be optimal for these policymakers to intervene at even lower thresholds than the ones mentioned above.

5. Conclusions

Our empirical results indicate that excessive credit growth, defined as positive deviations from its long-term trend, significantly increases the likelihood of banking crises in Asian and Latin American emerging markets. The credit gap indicator performs better in signalling banking crises in Latin America than in Asia. When a policymaker has to take action to prevent a banking crisis depends not only on the likelihood of a banking crisis but also on the cost differential between action and inaction. If, for example, the cost of failing to anticipate a crisis are 5 times as high as the cost of taking preventive action, the Latin American
policymaker would optimally issue a warning if the credit-to-GDP ratio is more than 5 percentage points above trend for two consecutive years. In Asia, the alarm bells could be raised somewhat later: the policymaker would optimally intervene at a threshold of 8 percent points above trend. Nevertheless, interpreting these results merit caution for the following reasons: i) our study leaves open the question of how sensitive the results are to different aspects of the methodology; ii) in reality banking crises are driven by a myriad of factors next to credit booms alone and iii) new crises may be of different nature than those experienced in the past. These issues deserve to be addressed more completely in future work.
References


12. IMF World Economic Outlook, April 2004 “Are credit booms in emerging markets a concern?”. 


Appendix A

Asia: Credit Gap
Latin America: Credit Gap

Argentina

Bolivia

Brazil

Chile

Colombia

Costa Rica

Ecuador

Mexico

Panama

Paraguay

Peru

Uruguay

Venezuela
Appendix B

List of Countries
As explained in the text, we have selected only Asian and Latin American emerging market economies. Our list includes 24 countries: Argentina, Bangladesh, Bolivia, Brazil, Chile, China, Colombia, Costa Rica, Ecuador, India, Indonesia, Korea, Malaysia, Mexico, Pakistan, Panama, Paraguay, Peru, Philippines, Sri Lanka, Thailand, Uruguay, Vietnam and Venezuela.

Dependent Variable
The banking crises dates are obtained from the updated Caprio and Klingebiel study (2003). Table 1 gives an overview of the banking crises’ starting dates.

<table>
<thead>
<tr>
<th>Country</th>
<th>Dates</th>
<th>Country</th>
<th>Dates</th>
<th>Country</th>
<th>Dates</th>
</tr>
</thead>
<tbody>
<tr>
<td>Argentina</td>
<td>1989,</td>
<td>Ecuador</td>
<td>1981,</td>
<td>Paraguay</td>
<td>1995,</td>
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<td></td>
<td>1995,</td>
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<td>1996,</td>
<td></td>
<td>2001,</td>
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<td></td>
<td>2001</td>
<td></td>
<td>1998</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bangladesh</td>
<td>1987</td>
<td>India</td>
<td>1993</td>
<td>Peru</td>
<td>1983</td>
</tr>
<tr>
<td>Bolivia</td>
<td>1986,</td>
<td>Indonesia</td>
<td>1994,</td>
<td>Philippines</td>
<td>1981,</td>
</tr>
<tr>
<td>Brazil</td>
<td>1990,</td>
<td>Korea</td>
<td>1997</td>
<td>Sri Lanka</td>
<td>1989</td>
</tr>
<tr>
<td></td>
<td>1994</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Chile</td>
<td>1981,</td>
<td>Malaysia</td>
<td>1985,</td>
<td>Thailand</td>
<td>1983</td>
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<td></td>
<td>1997</td>
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<td></td>
<td></td>
<td></td>
<td>1994</td>
<td></td>
<td>2002</td>
</tr>
<tr>
<td>Colombia</td>
<td>1982</td>
<td>Panama</td>
<td>1988</td>
<td>Venezuela</td>
<td>1994</td>
</tr>
<tr>
<td>Costa Rica</td>
<td>1987,</td>
<td>Pakistan</td>
<td>None</td>
<td>Vietnam</td>
<td>1997</td>
</tr>
<tr>
<td></td>
<td>1994</td>
<td></td>
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</table>

Explanatory Variable
International Financial Statistics (IFS) is used for the annual data (1980-2003) on credit to the private sector (IFS lines 22d and 42d) and nominal GDP (line 99b). Graph 4 gives an impression of the Asian acceleration in credit growth in terms of GDP since the early eighties, indicating the process of financial deepening. In Latin America on the other hand this process stagnates: the credit ratio remains roughly at the same level since the early eighties. In both
areas one also distinguishes the periods of financial turmoil: i.e. the Latin American debt crisis in the eighties and the Asian financial crisis in 1997-98.

Graph 4 Credit to private sector (%GDP)
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