Working Paper

INTERNATIONAL MONETARY FUND

WP/08/93

IMF Working Paper

The Anatomy of Banking Crises

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 WP/08/93

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Western Hemisphere Department

The Anatomy of Banking Crises

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April 2008

Abstract

This paper uses a Binary Classification Tree (BCT) model to analyze banking crises in 50 emerging market and developing countries during 1990–2005. The BCT identifies key indicators and their threshold values at which vulnerability to banking crisis increases. The three conditions identified as crisis-prone—(i) very high inflation, (ii) highly dollarized bank deposits combined with nominal depreciation or low liquidity, and (iii) low bank profitability—highlight that foreign currency risk, poor financial soundness, and macroeconomic instability are key vulnerabilities triggering banking crises. The main results survive under alternative robustness checks, confirming the importance of the BCT approach for monitoring banking system vulnerabilities.

JEL Classification Numbers: E44, G21

Keywords: Banking crises; binary classification tree; exchange rate; dollarization

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[1] We are grateful to Enrica Detragiache, Herman Kamil, Paolo Manasse, and Montie Mlachila, for their numerous insightful comments. We also thank Jingqing Chai, Mario Mansilla, Adrian Pagan, Catherine Pattillo, Ranjit Teja, participants at a Western Hemisphere Department seminar, Sir Dwight Venner, Jennifer Nero, and participants at an Eastern Caribbean Central Bank seminar, for their helpful suggestions.

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I. INTRODUCTION

The advent of the 1990s witnessed a wave of banking crises in developing countries. These ranged from bank meltdowns in many transition economies in the early 1990s (triggered by macroeconomic instability), to the East Asian crises in 1997–99 (spurred in part by over-lending), and the Dominican Republic crisis of 2003 (reflecting weak balance sheets). Historically, banking crises have imposed a tremendous economic burden, including huge fiscal costs of resolution and/or sharp output losses.[2] Consequently, the plethora of banking crises has sustained the drive for a better understanding of the factors that caused them.

The extensive empirical literature on banking crises has generally used two standard econometric tools.[3] The first is the signals approach, which studies and contrasts behaviors of economic indicators for periods both before and after a crisis, and identifies individual variables that best signal an impending crisis based on over- or under-shooting of specific threshold values (see Kaminsky and Reinhart, 1999). The second approach computes the probability of a banking crisis using a limited dependent variable model (see Demirgüc and Detragiache, 1998; Eichengreen and Rose, 1998). Both these tools consider the significance of individual factors in causing banking crises. In contrast, this paper provides a fresh perspective on banking crises, by demonstrating that such crises are most often underpinned by a combination of weaknesses rather than a single compelling factor.

This paper contributes to the above literature by analyzing banking crises with a binary classification tree (BCT) technique, which to our knowledge has not been previously done.[4] The BCT (described in more detail below) is particularly useful for analyzing banking crises as it recognizes that a combination of vulnerabilities could be more instrumental in triggering crises rather than the deterioration of a unique factor. The model also recognizes that economic indicators may have a nonlinear impact on the probability of crisis, in that any increase or decrease of a key indicator need not make a bank more crisis-prone, unless the value of the indicator crosses an identified threshold. The paper also explicitly considers the role of financial sector conditions and financial soundness indicators (FSI) in triggering banking crisis, which has been little analyzed in the early empirical literature.[5]

The BCT is a data mining technique that sifts the available database of indicators and compares all candidate variables (at all possible threshold values) to identify which variables

[2] See Honohan and Klingebiel (2000).

[3] See Gaytan and Johnson (2002) and Demirgüc and Detragiache (2005) for comprehensive surveys of the recent empirical literature on banking crises. Some authors have also used qualitative approaches that identify stylized patterns of key bank vulnerability indicators prior to a crisis (e.g., Honohan 1997).

[4] See Breiman, Friedman, Olshen, and Stone (1984).

[5] See however, later works by Bongini, Claessens, and Ferri (1998), Gonzalez-Hermosillo (1999), and Rojas-Suarez (1998).

(and at what threshold values) are best able to split the sample into nodes at which the probability of crisis increases and those where it declines. The sample (parent node) is split into child nodes at a particular threshold value of a key splitting variable, and the process repeats itself at each child node until further splitting is stopped. Thus, at each terminal node, the tree reveals a sequence of conditions among key indicators that can be identified as crisis-prone (see Section III for further details).

We analyze banking crises in a sample of 50 emerging market and developing countries during 1990–2005.[6] The set of explanatory variables include: indicators of the overall macroeconomic environment (growth, inflation, nominal depreciation, and government balance); external vulnerability (official foreign exchange reserve (FX) cover of broad money, export growth, and terms of trade (TOT) growth); monetary conditions (credit growth, real deposit rate, foreign interest rate, existence of explicit deposit insurance, and de facto exchange rate regime); and banking sector health (liability dollarization in banks given by FX deposits in total official FX reserves, net FX open position, bank liquidity, equity strength, asset quality, and two proxies for bank profitability).

The baseline model identifies the following five candidate variables (out of the above 19) as most important determinants of banking crises: nominal depreciation, bank profitability, inflation, liability dollarization, and bank liquidity. It also identifies three key crisis-prone conditions:

- ***Macroeconomic instability:*** High annual inflation (greater than 19 percent) combined with relatively low TOT growth (less than 3¼ percent), such that the probability of crisis increases from 5.3 percent to 21.4 percent;

- ***Low bank profitability:*** Low interest profitability (proxied by a spread between lending and deposit rates of less than 3 percent) combined with modest export growth (less than 12 percent), whereby the probability of crisis increases to over 20 percent; and,

- ***High foreign exchange (FX) risk:*** High liability dollarization (FX deposits to official FX reserves more than 140 percent) combined with either (i) relatively high depreciation (greater than 9 percent), where the probability of crisis increases to 25 percent, or (ii) low bank liquidity (private credit to deposits higher than 150 percent), where the probability of crisis increases to 100 percent.

The above results confirm that FX risk—manifested as dollarization-induced liquidity risk—when combined with a trigger such as high nominal depreciation or low bank liquidity, is a leading cause of banking crises. However, even with limited exposure to FX risk, banks can still suffer from crises under high macroeconomic instability (proxied by high inflation) or relatively poor profitability. An alternative model that analyzes “severe” banking crises—defined as banking crises accompanied by recessions—identifies nominal depreciation

[6] The banking crisis data is described in detail in Section IV.

(beyond 10 percent), liability dollarization (beyond 179 percent of official FX reserves) and low bank liquidity (private credit to deposits more than 178 percent) as key precursors to banking crises.

The BCT model performs reasonably well when subject to a number of robustness checks, including: (i) addition of new indicator variables to account for economic volatility, regional contagion pressures, and forward looking information; (ii) assessing out of sample prediction accuracy; and (iii) comparing the consistency of BCT results with those derived from a traditional logit model. These findings confirm the importance of the BCT approach as a key tool for monitoring banking sector vulnerabilities.

The paper is organized as follows. Section II briefly summarizes the existing literature on banking crises. Section III describes the BCT methodology and summarizes a relatively recent crisis literature that uses this approach. Section IV presents the empirical analysis by first describing key stylized facts, followed by the results of the BCT model. Section V discusses many robustness checks on the BCT results, while Section VI concludes.

II. Literature Survey

The empirical literature on banking crises in developing countries is vast, including single country analyses or case studies, surveys, and estimation techniques.[7] With respect to estimation methodologies, two main tools have been used to analyze banking crises: the signals approach, and the limited dependent variable regression approach. This section briefly describes the main results obtained from these two approaches that are relevant for this paper.

The signals approach studies and contrasts behaviors of economic indicators for periods before and after a crisis, and identifies individual variables that most usefully signal an impending crisis based on crossing certain threshold values. This technique was used by Kaminsky and Reinhart (1999) to analyze “twin crises” or the occurrence of both currency and banking crises, in a sample of 20 countries during 1970–95. The authors find that banking crises were frequently related to large exchange rate movements characterizing currency crises. They also show that banking crises were preceded by a decline in output partly reflecting deteriorating terms of trade, rapid financial liberalization characterized by growth of credit and rising cost of credit (i.e., interest rates), decline in the growth of exports and appreciating real exchange rates.

The limited dependent variable technique is a multivariate technique that computes the probability of a banking crisis using a limited dependent variable model as done by Demirgüc and Detragiache (1998) using logits, and extended further in Demirgüc and Detragiache (2005). Using a sample of 31 countries during 1980–94, the authors find that low real GDP growth, high real interest rates, high inflation, low foreign reserve cover of

[7] This section draws heavily from Gaytan and Johnson (2002), Demirguc and Detragiache (2005) and the references therein. See also Eichengreen and Arteta (1999).

broad money, positive credit growth, and an increase in exposure of banks to the private sector raises the probability of a banking crisis. Other variables that are also significantly correlated with banking crises include: real GDP per capita used as a proxy for institutional development (an increase in per capita income lowers the probability of crisis), and the existence of an explicit deposit insurance mechanism (which lowers the probability of crises).

The limited dependent variable model has also been used to analyze banking crises using more micro level data. Bongini, Claessens, and Ferri (1999) analyze banking crises is 193 financial institutions in Indonesia, Korea, Malaysia, the Philippines, and Thailand in 1996. They find that financial soundness indicators such as return on assets, loan loss reserves to capital, loan growth, net interest income, and loans to borrowings were important indicators for predicting bank crises. Gonzalez-Hermosillo (1999) uses bank-specific and macroeconomic data on different regions of the United States, Mexico and Colombia, and finds that nonperforming loans and capital-asset ratios often deteriorate rapidly before banking crises.[8] However, Rojas-Suarez (2001) argues that CAMEL-type variables may not be appropriate for analyzing banking crises in a large panel comprising diverse developing countries, as the differences in the supervisory frameworks across the countries weaken the comparability of these indicators.[9]

As expected, there are some differences in findings across this vast literature with respect to the accepted leading indicators of banking crises. For example, there are conflicting results on the impact of domestic financial liberalization and banking crises. While Kaminsky and Reinhart (1999) and Demirgüc and Detriagiache (1998) find that banking crises are associated with rising interest rates, Rossi (1999) on his analysis of 15 developing countries during 1990-97 finds the opposite result. There is a similar contradiction on the role of rapid credit growth in triggering banking crises. Gavin and Hausman (1996) in their study of Latin America find that lending booms are important precursors to banking crises, while Caprio and Klingebiel (1996) find no such evidence.

Against this background, our paper attempts to take a fresh look at banking crises by analyzing it with a Binary Classification Tree approach, which has not been used before to examine this issue. This approach recognizes the fact that an indicator can become critical in causing banking crises only at a certain threshold value and/or in combination with other conditions, while it could be relatively harmless in other situations. Thus, for instance, our results indicate that while nominal depreciation may not be harmful to banks per se, they become crisis-prone when depreciation exceeds a certain threshold against the background of a high share of banks' FX deposits (relative to the official capacity to withstand FX deposit withdrawals). The specifics of the BCT approach and the literature using it are discussed in more detail in the following section.

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[8] See also Rojas-Suarez (1998) for analysis of bank level data.

[9] CAMEL accounts for main financial soundness indicators such as capital adequacy, asset quality, managerial efficiency, earnings, and liquidity.

III. Binary Classification Tree Methodology[10]

The BCT is a nonparametric statistical technique that is able to identify significant patterns among the available indicator variables to help predict binary outcomes (such as the occurrence of a banking crisis or not). Starting with the whole sample or parent node, the BCT model compares all candidate variables at all possible threshold values and selects an indicator (and a particular threshold) which is best able to split the sample into "purer" sub-samples (or more homogeneous child nodes), where the probability of crises either increases or declines significantly compared with the sample average (see also Figure 2 below). Thus, at the parent node, comprising the entire sample, a primary splitter and its threshold is identified, at which the sample is split into two child nodes. The process repeats itself at each sub-sample or child node until further splitting is stopped or is impossible. The latter occurs when all the cases in that particular node are of the same outcome or there is only one case in the node. In general, however, the tree size is determined in terms of the trade off between the cost of growing (proportional to the number of nodes) and the overall fit of the model (proportional to type I and type II errors); when the former offsets the later, the tree stops growing. The model also computes a score for each variable in terms of its ability to distinguish crisis from noncrisis observations.

The default algorithm used by BCT to select the optimal tree size is called "V-fold cross validation," which determines the tree size by assessing the "out-of-sample" performance of the tree. When there is insufficient data to run a separate test sample (as in the case of this analysis), the BCT technique divides the sample into 10 roughly equal parts, each having a similar distribution for the dependent variable, then constructs the largest possible tree using the first 9/10 parts of the data and then applies the remaining 1/10 part of the data as the test sample for the out of sample performance of this tree. This process is repeated, so that each 1/10 part of the data has been used as a test sample. The out-of-sample results of the 10 test samples are then combined to determine the optimal number of terminal nodes for the full sample. However, we sometimes overrule the optimum tree size chosen by the V-fold algorithm and choose instead a larger or smaller tree—the guiding rule for choosing a tree size different from that given by the default V-fold technique is to ensure that the tree size chosen has a good in-sample fit and that the splits make economic sense.

While the tree shows the splitters and the relationships between them that lead to crisis-proneness, another important piece of information provided by the BCT approach is the ranking of the candidate variables by a "variable importance" index. It is possible for a variable to be slightly outperformed by another as a splitter, and therefore never appear in the final tree, despite the fact that it has more information to analyze crises than other splitters that do appear in subsequent nodes. This is called the "masking problem," which is similar to the problem of one of two strongly collinear variables dropping out in a standard regression

[10] This section draws on Breiman and others (1984). The BCT technique was implemented using the Salford System's CART program (see http://www.salford-system.com). See also Manasse and Roubini (2005) and Chamon, Manasse, and Prati (2007) for succinct summaries of the BCT methodology.

analysis. In the BCT, the "variable importance index" ranks the indicator variables by considering the potential effect of each variable in classifying crises, even when they may be masked by the first choice splitter and never appear in the tree. Hence, besides the classification tree, it is also important to assess the importance of an indicator based on its overall ranking among all available indicators.

The BCT has some distinct advantages over alternative estimation techniques. First, it does not require any assumptions about the underlying functional form of the model, which regression models need to assume despite the fact that well-established relationships between explanatory variables are generally absent, particularly during crises. For the same reason, the BCT approach is also useful when the theoretical foundations of the outcome of interest are not settled, and one can include within the set of candidate indicators variables that are highly correlated with each other. Second, BCTs are very useful in uncovering nonlinearities (for example recognizing the critical information at different ranges of values of an explanatory variable), which is generally much more difficult to establish in standard regression models. Third, as a result of its ability to handle complex relationships, BCTs work very well with datasets that have missing values. Thus, at each node, the BCT considers all possible surrogates to a splitter variable that produce a similar allocation of observations in the child nodes. When the primary splitter has missing observations, the best surrogate is used as a proxy (hence a missing observation of the primary splitter does not lead to deleting that observation as would be the case under standard regression analysis). Similarly, the presence of outliers does not affect BCTs since the splits occur at nonoutlier values, and the outliers are often separated into nodes that no longer affect the rest of the tree. Finally, the model is unaffected by monotonic transformations of the indicator variables.

The BCT method also has a few weaknesses. First, the BCT cannot be used to establish any general relationships that holds through the sample. In fact, as the tree is split into more nodes, the discovery of relationships becomes localized, ignoring sample-wide information. Also, unlike logit/probit regression techniques, BCT is unable to provide the marginal contribution to the overall probability of a particular outcome. Third, as discussed above, some variables may never appear in the tree due to the "masking problem", despite their ability to distinguish crises from noncrises outcomes. Finally, as discussed above, the optimal tree chosen by the V-fold technique can sometimes result in a tree that would have to be pruned or grown further—based on some judgment call—to obtain economically-meaningful results. Despite these limitations, the BCT serves as a good alternative technique to study banking crises, especially given its ability to identify complex nonlinear relationships between existing vulnerabilities in signaling the crisis-proneness of banks.

The BCT has been extensively used in numerous fields (medical diagnosis, engineering, consumer credit).[11] Recent crises studies using the BCT include Ghosh and Ghosh (2002), Frankel and Wei (2004), Manasse, Roubini, and Schimmelpfennig (2003), Manasse and Roubini (2005), and Chamon, Manasse and Prati (2007). Ghosh and Ghosh (2002) use the

[11] References to other relevant studies using the BCT technique can be found in http://www.salford-systems.com.

BCT to assess the role of structural factors such as governance and rule of law relative to macroeconomic variables in explaining currency crises.[12] The authors identify a sequence of complex relationships between macroeconomic imbalances and structural factors underlying currency crises, which a standard logit or probit model would not be able to identify. Manasse and Roubini (2005) study sovereign debt crisis using BCTs and find a combination of vulnerabilities such as debt unsustainability, illiquidity and macroeconomic risks underlying these crises. Chamon, Manasse and Prati (2007) use the BCT to analyze reversals in capital inflows (owing to crises of any type: currency, debt or banking), and confirm with the past literature that crises are underlined by a combination of weaknesses. In particular, the authors find that low FX reserve cover, combined with a high share of external debt to GDP, significantly increases the probability of capital account crises.

IV. Empirical Analysis

A. Stylized Facts

The sample comprises annual observations from 50 emerging market and developing countries during 1990–2005, drawn from Asia, Africa, Europe, Latin America, the Middle East and the Caribbean.[13] The data for banking crisis draws from three sources—Caprio and Klingebiel (2003), Kaminsky and Reinhart (1999), and Carstens, Hardy, and Pazarbasioglu (2004)—whereby a banking crisis is defined as an episode involving banking sector problems that resulted in: exhaustion of much of the capital and closure, merger, large-scale nationalization of banks; or extensive bank runs; or large scale liquidity support by the central bank to avoid a run on deposits.[14] Using this criterion, 127 annual crisis observations are identified, comprising 38 crisis episodes.

Figure 1 and Table 1 provide some stylized facts on the banking crises in the sample. The incidence of banking crises was high in the early 1990s, and declined gradually toward the end of the decade. Among the 50 countries in the sample, 31 experienced at least one banking crisis during the sample period that lasted between 2–3 years, although in some countries the duration of crisis was more than six years (e.g., Ecuador and Jamaica). Only five countries experienced recurring banking crises during the 15-year sample period

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[12] See also Frankel and Wei (2004) for the analysis of currency crises using binary regression trees.

[13] These countries are Antigua and Barbuda, Argentina, The Bahamas, Barbados, Belize, Bolivia, Brazil, Bulgaria, Chile, China, Colombia, Costa Rica, Croatia, Czech Republic, Dominica, Dominican Republic, Ecuador, Egypt, El Salvador, Grenada, Guatemala, Guyana, India, Indonesia, Israel, Jamaica, Jordan, Kenya, Korea, Lebanon, Malaysia, Mexico, Nicaragua, Nigeria, Papua New Guinea, Paraguay, Peru, Philippines, Poland, South Africa, Sri Lanka, St. Kitts and Nevis, St. Lucia, St. Vincent and the Grenadines, Tanzania, Thailand, Trinidad and Tobago, Turkey, Uruguay, and Venezuela.

[14] An alternative criterion for crisis used in the literature is given by a cut off level of nonperforming loans (NPLs), i.e., crisis defined by NPLs exceeding a certain share of total loans (see Demirgüc and Detragiache, 1998), which we do not use because many of the countries in our sample (such as the Eastern Caribbean countries, Antigua and Barbuda, Dominica, Grenada, St. Kitts and Nevis, St. Lucia and St. Vincent and the Grenadines) have very high NPLs but have not experienced any banking crises during the sample period.

(Argentina and Turkey experienced three crises, while Brazil, Indonesia, and Nicaragua experienced two). The sample has a control group of 19 countries that did not experience any systemic banking crisis during the sample period.

Drawing on the existing empirical literature, the following explanatory variables were used in the BCT analysis, proxying for macroeconomic fundamentals, the external environment, monetary conditions, and financial sector health.[15] While the list below is by no means exhaustive, it represents the most comprehensive list that could be obtained—considering data availability—for all the countries in the sample:

Macroeconomic fundamentals: (i) Real GDP growth; (ii) inflation; (iii) nominal exchange rate depreciation; and (iv) fiscal overall balance (ratio to GDP) of the central government.

An economic slowdown (dip in growth) could hurt banks by reducing loan quality and weakening prospects for lending. High inflation, besides causing macroeconomic instability, could decrease the real return on assets and discourage saving while inducing more borrowing. This could also pose the problem of adverse selection as a highly inflationary environment could attract borrowers of relatively low quality.[16] Nominal depreciation can be destabilizing if banks are directly or indirectly exposed to foreign exchange risk. A weak fiscal position would not provide the fiscal space needed to resolve a relatively nonsystemic bank problem. Also, banks in many developing countries are heavily exposed to the government, causing their performances to be vulnerable to fiscal positions.

External liquidity: (i) Growth of exports of goods and services; (ii) terms of trade (TOT) growth; and (iii) official foreign exchange (FX) reserve cover of broad money.

Export and TOT growth affect prospects for overall economic growth and hence banking system performance. Also, to the extent the banking system intermediates credit to exporters, poor export performance can be harmful to banks even if overall economic growth does not decline. The official FX cover of broad money measures the extent to which banking crises are triggered by the inability of monetary authorities to avert a sudden turnaround of capital inflows.

Monetary conditions: (i) Growth of real private credit; (ii) real domestic interest rate; (iii) foreign short-term interest rate given by U.S. one-month LIBOR; (iv) de facto fixed peg exchange rate regime; and (v) existence of explicit deposit insurance.

Excessive credit growth can trigger bank problems by squeezing bank liquidity (see below) and/or by deterioration of asset quality. Rising interest rates can compress bank profitability. The de facto exchange rate regime (which takes a higher value if the regime is more rigid) controls for whether banking system problems stem from an implicit or explicit exchange

[15] The sources of these indicator variables are discussed in Appendix I.

[16] See Boyd and Champ (2003).

rate guarantee provided by the exchange rate regime. The impact of deposit insurance on the probability of crisis is ambiguous (as discussed in Demirgüc and Detragiache, 1998)—on the one hand, deposit insurance should strengthen the capacity to withstand bank runs, on the other hand it can induce moral hazard problems.

Financial soundness indicators: (i) Financial system net open position proxied by the ratio of net foreign assets (NFA) to GDP; (ii) the assumed foreign exchange (FX) risk or extent of liability dollarization of banks measured by the ratio of FX deposits to official FX reserves; (iii) liquidity condition given by the ratio of private credit to banking system deposits; (iv) adequacy of capital given by banking system equity over assets; (v) asset quality given by the share of nonperforming loans in total loans; (vi) and profitability proxied by two separate indicators—interest rate spread (between lending and deposit rates) that is a proxy for interest income, and the pre-tax return over average assets.

NFA positions have information on whether banking crises are caused by large net open FX positions (i.e., negative NFA). However, even if the banking system is well balanced in its FX operations, FX risk may still materialize owing to maturity mismatches, and hence it might be prudent to also monitor the evolution of FX liabilities. Thus, the ratio of FX deposits to official reserves is used as a proxy for the risks posed by FX liabilities, or the dollarization-induced liquidity risk on monetary authorities.[17] The ratio of private credit to deposits measures the domestic currency liquidity in banks—the higher the ratio, the lower the ability of banks to meet deposit withdrawals by liquidating loans. Finally, measures of capital strength, loan quality, and profitability help determine whether banking sector problems are triggered by a deterioration of financial soundness indicators (that may or may not be related to the deterioration of the economic environment or monetary conditions). The behavior of the interest rate spread prior to a banking crisis is, however, ambiguous. On the one hand, bank health may be affected by a decline in bank profitability reflecting a sharp narrowing of interest margins. On the other hand, bank health may also be compromised by a sharp tightening of monetary or credit conditions that increase lending rates beyond deposit rates, thereby widening the interest rate margin.

Table 2 describes how the above indicator variables behave on average before a banking crisis relative to tranquil times. Column (i) gives the average of each variable for the whole sample period. Columns (ii)–(iv) show the average of the variables in the current period “t” given that: there were no banking crisis in period “t” or period “t+1” (column (ii), proxying more tranquil times); or there was no banking crisis in period “t” but there was one in period “t+1” (column (iii), proxying for period before a crisis); or there was a banking crisis in both, periods “t” and “t+1” (column (iv), proxying for an ongoing crisis). Hence column (ii) shows how the variables behave on average during tranquil times, column (iii) shows how they behave prior to a crisis, and column (iv) shows how they behave when the crisis is already underway.

[17] While the share of credit in foreign currency would also be a good proxy for the dollarization risks of the banking system, this variable could not be included due to relatively poor coverage of the data over the sample period.

Table 2 shows that macroeconomic fundamentals perform relatively poorly prior to banking crises relative to tranquil times, i.e., on average, real GDP growth and fiscal balances are lower, while inflation and nominal depreciation higher before a crisis. In the external sector, the official FX cover of broad money, export growth, and TOT growth are lower before a crisis compared with tranquil times.

Both external and domestic monetary conditions tighten before a banking crisis when compared to tranquil times, as shown by higher foreign interest as well as domestic real deposit rates. Also, real credit growth appears to be much higher in the run up to a banking crisis. Banking crises are also associated with a drying up of banking system liquidity, increase in liability dollarization, and a widening of FX open positions. A larger share of countries had explicit deposit insurance before a banking crisis compared to tranquil times, supporting the view that deposit insurance induces moral hazard behavior and weakens the banking system. Contrary to expectations, the average rigidity of de facto exchange rate regimes is actually lower before a banking crisis. Finally, banking sector health is worse before a crisis compared to tranquil times, as shown by relatively lower capital ratios, and lower profitability. However, asset quality, proxied by the NPL ratio, is relatively better before a crisis than under tranquil times (and worsens only when the crisis is well underway, as shown in column (iv)). The latter observation could reflect the dampening effect of rapid credit growth before a crisis on the observed NPL ratio.

B. BCT Results

Baseline specification

Figure 2 shows the results of the baseline model using the Binary Classification Tree (BCT). To avoid any endogeneity issue and to retain the predictive role of the model, the indicator variables are lagged (except foreign interest rate, which is exogenous to the domestic banking system).[18] Also, to avoid a banking crisis from affecting the behavior of the indicators after the crisis is underway, all crisis observations after the first year of crisis are deleted for any given crisis episode, which reduces the sample size from 800 to 711 observations, with 38 crises, implying an unconditional crisis probability of 5.3 percent.

The baseline tree has 8 terminal nodes and a good in-sample fit—it is able to signal all but 1 of the 38 crises (97 percent) and has false signals for 19 percent of the noncrisis

[18] Some indicators have many missing observations for the given sample (e.g., the FSI variables), and so an option whereby the model weighs the contribution of each variable against the number of missing observations is chosen—thus, the final contribution of each variable is given by its contribution multiplied by the proportion of available observations. The other choices that the BCT allows are: (i) assigning different costs for missing crises versus noncrises outcomes; and (ii) a prior crisis probability that is different from that implied by the sample frequency. To avoid any subjective decision about whether missing crises should be more costly than missing noncrisis (hence assigning a higher cost of missing crisis) or if the prior probability of crisis should be higher than the sample frequency, we simply use the default options (i.e., missing crises and noncrises outcomes are equally costly, while the prior probability of crisis is same as the sample frequency of crisis observations). For alternative use and the implication of these options, see Chamon and others (2007).

outcomes.[19] The sample or parent node is first split on the basis of the underlying inflation—if inflation is higher than 19 percent (observations to the right of the parent node), the conditional probability of crisis increases from 5.3 percent to over 16 percent.[20] Conversely, if inflation is lower than 19 percent (observations to the left of the parent node), the conditional probability of crisis declines to 2.8 percent. Consequently, each child node is further split based on values of other key variables. Finally, the following key crisis-prone terminal nodes are identified:

- *Terminal node 1*, which represents a state of macroeconomic instability combined with relatively modest TOT growth (inflation greater than 18.7 percent and TOT growth less than 3.3 percent). This node has a conditional probability of crisis of over 21 percent and comprises 22 crisis episodes, including: Argentina (1990), Brazil (1990, 1994), Bulgaria (1996), Colombia (1999), Ecuador (1996), Guyana (1993), Jamaica (1994), Jordan (1990), Kenya (1992), Lebanon (1990), Mexico (1992), Nicaragua (1990), Nigeria (1993), Peru (1993), Poland (1991), Tanzania (1990), Turkey (1991,1994, 2000), and Venezuela (1993).

- *Terminal node 2*, which represents low interest profitability in banks, combined with relatively modest export growth (interest rate spread less than 3.1 percent and export growth less than 11.8 percent). This node has a conditional crisis probability of 21 percent and comprises the crises in Argentina (1994, 2001), China (1999), Indonesia (1992, 1997), Korea (1997), Sri Lanka (1990), Malaysia (1997), and Thailand (1997).

- *Terminal node 3*, which represents high FX exposure of the banking system combined with high nominal depreciation (FX deposits to official FX reserves more than 140 percent and nominal depreciation more than 9 percent). This node has a conditional crisis probability of 25 percent and contains the crises in Bolivia (1994), Czech Republic (1991), The Dominican Republic (2003), Nicaragua (2000), The Philippines (1998), and Uruguay (2002). The fourth crisis terminal node represents high FX exposure with low banking system liquidity given by a very high share of private credit to deposits (more than 150 percent), and has a conditional crisis probability of 100 percent. However, this node is more like an outlier rather than a key node, since it has only one outcome in it (Croatia, 1996).

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[19] The optimal tree chosen by the V-fold cross-validation technique had 9 terminal nodes and was able to predict all crises and missed only 21 percent of the noncrises. However, we chose a tree with one node less—at the cost of a slightly worse in-sample fit—because the last node did not have any economically-meaningful interpretation.

[20] In the child nodes (or sub-samples) the proportion of observations for each outcome (crisis or noncrisis) gives the conditional probability of that outcome, since it is conditional on meeting a criterion that was used to split the preceding (parent or child) node into subsequent child nodes. Also, at each terminal node, the probability of an outcome is conditional on meeting a sequence of criteria in preceding child-nodes. For example, in the above tree the probability of crisis in either of the first-tier child nodes (immediately following the parent node) is conditional on the value of inflation relative to a threshold of 19 percent.

It is important to consider the BCT results by assessing both the classification tree and the overall ranking of the variables, as shown in Table 3 (first two columns).[21] Out of the 19 candidate indicators, the first five variables are ranked in the following order: nominal depreciation, interest profitability, inflation, liability dollarization, and bank liquidity. These variables also appear as primary splitters in the baseline tree. It is important to note however, that not all splitters in the tree are ranked high in Table 3. For instance, indicators such as TOT and export growth that appear as splitters in the tree are ranked lower than indicators such as real deposit interest rate and FX open position that do not appear in the tree. This reflects the fact that the latter variables are relatively better performers in their ability to classify crises but were possibly "masked" by the first-choice splitter variable, and hence did not appear in the tree.

The inequalities identified by the BCT highlight the role of FX risk in exacerbating banking sector problems. Nominal depreciation increases the probability of crisis when the banking sector suffers from high FX risk—given by a high share of FX deposits relative to the central bank's ability to absorb the deposit withdrawals (terminal node 3). This result sheds light on the nature of "twin crises" analyzed by Kaminsky and Reinhart (1999) who find that the peak of banking crises most often occurs after a currency crisis—our results show that a currency crisis can indeed trigger a banking crisis when banks are highly exposed to foreign currency liabilities and the currency crisis results in a relatively substantial nominal depreciation. The results also support the work of Levy-Yeyati (2005, 2006), who find that financially-dollarized economies are generally more prone to banking crises, and that of Nicolo, Honohan and Ize (2003), who find that financial instability is likely higher in dollarized economies.[22] However, even if exposure to FX risk is relatively low, the banking system can still be crisis-prone if it engages in excessive credit activity (relative to its deposits) resulting in low liquidity or vulnerability to deposit withdrawals (terminal node 4). Other important preconditions of banking crisis include macroeconomic instability (terminal node 1), as well as low bank profitability (terminal node 2).

The tree results emphasize the importance of conditional thresholds in triggering crisis. For instance, financial dollarization, even when it crosses a certain threshold, is not crisis-prone unless also accompanied by nominal depreciation, stressing that the combined effect of economic vulnerabilities have a much more important bearing on banking crises than the deterioration of a unique factor (as noted by Kaminsky, 1999). The importance of conditional thresholds is further noted in Table 4, which shows the median values of the five key indicators at each (crisis and noncrisis) terminal node. It is interesting to assess how the five key variables behave under the different types of crises. For instance, the median value of nominal depreciation under "FX-risk" induced crises is relatively low (12 percent) compared

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[21] The first column shows the ranking, while the second column provides the score or contribution of each variable relative to others (the score of the highest ranking variable is normalized to 100).

[22] Arteta (2003) uses probit estimations to analyze financial crises and finds the opposite result. This could be because the vulnerability from financial dollarization occurs only when both liability dollarization and nominal depreciation exceed certain thresholds as identified by the BCT model, while on average the indicators are not necessarily crisis-prone. This is also confirmed by the results from a logit estimation (see next section).

to that from a "macroeconomic instability" type crisis (35 percent) or noncrisis outcome (28 percent), while the median liability dollarization exposure under "FX risk" induced crises is much higher (over 200 percent) compared to that under "macroeconomic instability" type crises (68 percent). In other words, a 12 percent nominal depreciation can induce banking crises in the presence of high dollarization or FX risk, while a much higher rate of nominal depreciation may not trigger a banking crisis in a relatively low inflation and low dollarization environment.

The BCT results also stress the relative importance of macroeconomic fundamentals—such as inflation and nominal depreciation—rather than "micro" variables, such as FSIs, in explaining crises, supporting the findings by Chamon and others (2007). For instance, more than 50 percent of the crises are accurately classified by just two predictors in the first terminal crisis node—very high inflation, combined with relatively modest terms of trade growth.[23] At the same time, certain nonFSI indicators of bank health that proxy for FX risk, profitability, and liquidity are also identified as key in determining banking crises.

Finally, the results also provide guidance for bank supervision on the combination of conditions that supports resilience to banking crisis. For instance, a relatively low inflation environment (inflation less than 19 percent), combined with relatively high interest profitability (interest rate margin more than 3 percent), and relatively low FX exposure (FX deposits to official FX reserves less than 140 percent) result in a zero probability of banking crisis (Figure 2 and Table 4). These results stress the critical importance of monitoring the key indicators in assessing the health of the banking system.

How different are "severe" banking crises?

An alternative specification is considered, to assess whether "severe" banking crises are associated with conditions different from those under "average" banking crises. While the severity of a crisis is best discerned from the fiscal cost of bank resolution, this data does not exist for all the sample countries. We instead consider a simpler classification of severe crises: banking crises that were associated with a recession or negative real GDP growth. The sample is now reduced to 689 observations with only 16 crisis episodes associated with recessions, yielding an unconditional probability of crisis of a little over 2 percent. All candidate indicators are again considered, except real GDP growth.

Figure 3 shows the classification tree corresponding to severe crises, which correctly classifies all crises but gives false alarms for 35 percent of the noncrises episodes.[24] Again, this specification identifies nominal depreciation, liability dollarization, and bank illiquidity

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[23] See also Manasse and Roubini (2005) who accurately classify a large share of sovereign debt crisis in their sample with only two predictors—share of external debt to GDP and inflation.

[24] The optimal tree size chosen by the V-fold cross-validation technique has two nodes only, but we choose a tree with four nodes to obtain a better model fit (in terms of reducing the type I error) and also to obtain more information about the economic conditions underpinning severe crises.

as primary splitters, although at higher thresholds than the baseline case, given the focus on severe crises. The following three crises-prone inequalities are identified:

- *Terminal node 1*, where a nominal depreciation of over 9.8 percent (in the absence of any accompanying vulnerabilities) almost triples the probability of a severe crisis from 2.3 percent to 6.3 percent. The banking crises in Argentina (1990), Brazil (1990), Colombia (1999), Czech Republic (1991), The Dominican Republic (2003), Jordan (1990), Kenya (1992), Lebanon (1990), Nicaragua (1990), The Philippines (1998), Poland (1991), Turkey (1994), and Uruguay (2002) fall into this crisis node.

- *Terminal node 2*—even if nominal depreciation is lower than 10 percent, the banking system can still be subject to severe crises if exposed to extensive deposit dollarization (with the ratio of FX deposits to official FX reserves over 179 percent), where the conditional probability of crisis is 4 percent. The Argentine (2001) and Bulgaria (1996) crises belong to this node.

- *Terminal node 3,* which represents a crisis condition where the banking system is crisis-prone (with a conditional probability of crisis of 100 percent) owing to high illiquidity (the ratio of private credit to deposits exceeding 178 percent). This node includes the crisis in Thailand (1997).

These results emphasize that the role of currency depreciation and liability dollarization are key to banking crises, in particular when the latter are very severe. Also, low banking system liquidity could trigger a severe crisis if it crosses a certain threshold, even if nominal depreciation and financial dollarization are not excessive. Table 3 (third and fourth columns) shows that nominal depreciation, liability dollarization and liquidity are among the top-ranked variables in their contribution to identifying banking crisis. Inflation, profitability (proxied by both the interest rate spread and return on average assets), and real credit growth are also ranked high in importance, even though they do not appear in the BCT of Figure 3.

V. Robustness Checks

The baseline model was subjected to a number of robustness checks, which are described below.

A. Alternative Indicators

Additional explanatory variables

The following additional explanatory variables are added to the baseline model: (i) *volatility*: real exchange rate volatility, measured by the standard deviation of the CPI-deflated real exchange rate over a four-year period, (ii) *contagion pressures*: a dummy variable that takes the value 1 in a country if there was a banking crisis in the region in the previous year, and (iii) *forward-looking information*: the growth rate of stock market prices (lagged), to assess if the forward-looking nature of equity prices is able to provide information about impending

crises.[25] The ensuing classification tree is almost identical to the baseline model (see Figure 2 again), except that real exchange rate volatility (at an outlier value) replaces illiquidity as a splitter at crisis terminal node 4. The other two variables have no contribution in improving the fit of the model. These results confirm that vulnerabilities in FX exposure, low profitability, and macroeconomic instability are key conditions underpinning banking crises, even when other potentially important triggers are considered.

Does history matter?

Among the 31 countries in the sample that experienced banking crises, 5 were subjected to more than one banking crisis during the sample period (Argentina, Brazil, Indonesia, Nicaragua, and Uruguay). A variable is added to the set of explanatory variables that measures the number of past crises experienced by each country within the sample period. For instance, the variable *past crisis* takes the following values—Argentina: 0 in 1990, 1 from 1991 to 1994, 2 from 1995 to 2001 and 3 from 2002 to 2005. For countries that did not experience banking crises in the sample (e.g., Antigua and Barbuda), the value of this variable is always zero. This additional variable to the baseline does not change the ensuing classification tree (from the baseline model of Figure 2), and the proxy for past crisis does not contribute to the overall fit of the model.

B. Out of Sample Prediction Performance

The predictive power of the baseline model is assessed by performing two kinds of out of sample tests. First, the BCT model is estimated with data up to 2000, 2001, and 2002 to predict crises in 2001, 2002, and 2003, respectively. The out of sample predictions are done after 2000 to provide at least 10 years of data for the BCT model to enable it to gather meaningful information from the data, and is stopped at 2003 (which is the last year with any new crisis episode). While the BCTs are based on new crises only (in that ongoing crises do not enter the sample of observations on which the BCTs are based), the out of sample performance for a particular year considers the model's ability to predict both new and ongoing crises that year.

Second, the BCT is also used to perform an out of sample forecast for the Caribbean banking system. The Caribbean countries have been largely spared from crises of any sort, including banking crises, despite being exposed to a number of vulnerabilities, such as terms of trade shocks, natural disasters, and high exposure to the borrowings of their fiscally-weak governments. Among the 13 Caribbean crises in our sample, only three (Guyana in 1993, Jamaica in 1994, and the Dominican Republic in 2003) experienced a systemic banking crisis during 1990–2005. Hence, the purpose of this exercise is to assess whether the absence of banking crises in the Caribbean countries was a result of strong economic fundamentals or

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[25] This variable has a large number of missing observations for a number of countries (which are dropped from the analysis), and hence is not used in the baseline tree.

plain luck.[26] Two questions are addressed as a part of this exercise: (i) Does the BCT, excluding the Caribbean from the sample, yield a different tree for banking crisis?; and (ii) Can the classification tree predict the three Caribbean crises that actually occurred?

The out of sample performances of the BCT based on the years 2001–03 are mixed. The model is able to predict 3 of the 9 crises in 2001, 4 of the 8 in 2002, and 2 of the 3 in 2003. The out of sample forecast for the Caribbean is good, with the model correctly signaling all the new crises that occurred in the Caribbean during the sample period. The details of these exercises are provided below.

Out of sample prediction of crises in 2001

Figure 4 shows the results of applying the baseline BCT model on 1990–2000 and using this to predict the banking crises in 2001. The classification tree yields three terminal nodes: (i) terminal node 1, representing high inflation combined with modest TOT growth; (ii) terminal node 2, representing low liquidity, and (iii) terminal node 3, representing low interest profitability combined with high real deposit rates. This model correctly classifies only 3 of the 9 ongoing crises in 2001—Ecuador, Korea, Turkey (in bold). The remaining 6 crises—Argentina, Indonesia, Malaysia, Nicaragua, the Philippines, and Thailand—are missed, possibly because most of them were entering the final years of their crises, and their economic environments had already begun to strengthen (except Argentina whose crisis started in 2001 and Nicaragua whose crisis started in 2000). Conversely, the model predicts a crisis in Paraguay in 2001, which ended its banking crisis in 2000, implying that traces of bank weakness continued in Paraguay even in 2001. Finally, the Argentine crisis was narrowly missed in terminal node 3 (the interest rate spread in Argentina was 2.73 percent, slightly above the threshold of 2.7 percent identified by the tree, although the real deposit rate in Argentina in 2001 exceeded 9 percent, well above the cut off identified in the tree).

Out of sample prediction of crises in 2002

Figure 5 shows the BCT model based on 1990–2001 and used to predict the banking crises in 2002. The classification tree produces three terminal crisis nodes similar to the original baseline specification based on the entire sample: (i) terminal node 1 representing high inflation combined with modest TOT growth; (ii) terminal node 2 representing low interest profitability and modest export growth; and (iii) terminal node 3 that combines two measures of high FX risk—high liability dollarization combined with a wide FX open position (as given by a relatively low share of NFA to GDP). This model is able to successfully predict 4 out of the 8 crises in 2002 (Argentina, Ecuador, Korea, and Turkey) and misses the crises in Indonesia, Philippines, Thailand, and Uruguay. Again, the new crisis in Uruguay is marginally missed at terminal node 3, where the NFA to GDP ratio of Uruguay is higher than

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[26] For instance, Chai (2006) relates financial sector stability in Eastern Caribbean countries (that have a fixed exchange rate regime vis-à-vis the U.S. dollar) to price and exchange rate stability, but also argues that the vulnerability of the banking system emanates from extremely high NPL ratios, and high fiscal vulnerability.

the threshold of 3 percent identified by the tree. The tree also signals a banking crisis in Nicaragua, although it had just come out of a banking crisis in 2001.

Out of Sample Prediction of Crises in 2003

Figure 6 shows the BCT model based on 1990–2002 and used to predict the crises in 2003, yielding three terminal nodes: (i) terminal node 1, representing high inflation combined with modest TOT growth, (ii) terminal node 2 representing low interest profitability and modest export growth, and (iii) terminal node 3 that represents high liability dollarization combined with relatively high illiquidity. The model is able to predict 2 of the 3 crises in 2003, the ongoing crisis in Uruguay and the new crisis in the Dominican Republic, but misses the ongoing crisis in the Philippines. The model continues to signal crises in Argentina and Turkey, even though these countries exited their banking crises in 2002.

Out of sample prediction for the Caribbean

Figure 7 shows the BCT based on 1990–2005 but that excludes the 13 Caribbean countries in the sample: Antigua and Barbuda, the Bahamas, Barbados, Belize, Dominica, the Dominican Republic, Grenada, Guyana, Jamaica, St. Kitts and Nevis, St. Lucia, St. Vincent and the Grenadines, and Trinidad and Tobago. The resulting tree provides the following three crisis-prone terminal nodes and is able to correctly forecast the three banking crises in the region: (i) Terminal node 1 reflects a highly inflationary state and predicts the crises in Guyana (1993) and Jamaica (1994); (ii) Terminal node 2 reflects low interest profitability combined with relatively modest export growth. Oddly, this node signals a banking crisis in The Bahamas for the entire sample period; (iii) Finally, terminal node 3 represents a situation with high liability dollarization combined with nominal depreciation, which correctly signals the banking crisis in the Dominican Republic in 2003. The results stress that a key reason underpinning the resilience of Caribbean banking systems is the macroeconomic (price) and exchange rate stability offered by the fixed exchange rate regime.[27]

C. Consistency of BCT Results with Traditional Logit Analysis

Next, we compare and reconcile the results of the BCT model with those from a traditional logit analysis. Table 5 shows the results of estimating banking crises using a logit model. All observations with inflation higher than 100 percent are removed from the sample to exclude economic developments influenced by hyperinflationary conditions.[28] The first two columns of Table 5 show two alternative specifications, one with the sample set of explanatory variables used in the BCT baseline model (column (i)), and another specification where the inequalities corresponding to the primary splitters in the BCT baseline model are also added to the set of explanatory variables in the logit model (column (ii)).

[27] Nine of the 10 Caribbean countries that did not experience a banking crisis have fixed exchange rate regimes that were never adjusted during the sample period. For more details see, Duttagupta and Cashin (2008).

[28] Note that this step, of excluding hyperinflation episodes, was not taken under the BCT analysis, which is robust to outliers among explanatory variables.

Under the baseline logit model (column (i)) the following variables significantly increase the probability of crises: increase in inflation, real domestic interest rate pressure, increase in FX open position, and decline in bank profitability. However, an increase in NPLs appears to reduce the probability of a banking crisis, which could reflect the fact that rapid credit growth in the run up to a crisis masks the asset quality problem by reducing the share of NPLs (this is also confirmed by the average value of NPLs shown in Table 2). The model has a good in-sample fit overall, and is able to correctly classify 82 percent of crises.

The above results do not support the main BCT results, however. Other than inflation, none of the key splitters of the BCT baseline model (including liability dollarization, interest rate spread, and liquidity of the banking system) are significant in the logit analysis, and although interest profitability is significant, it has the opposite sign. These seemingly conflicting results can be reconciled by noting that the logit model identifies key variables by assessing their ability to trigger crises on average, whereas the BCT recognizes that indicators signal crises only after they cross a particular threshold. For instance, nominal depreciation and liability dollarization may not necessarily be harmful on average, but could trigger banking crises when they cross particular limits/thresholds and occur in combination with each other.

The logit specification in column (ii) attempts to reconcile the (column (i)) logit and the BCT results by including dummy variables for the primary splitters at the thresholds identified by the baseline BCT—i.e., inflation > 18.7 percent, nominal depreciation > 9.1 percent, interest rate spread > 3.1 percent, liability dollarization > 140 percent of official FX reserves, liquidity (private credit > 150 percent of deposits), export growth > 11.8 percent, and TOT growth > 3.3 percent. As a result, the logit estimation results (column (ii)) fully support the key BCT results. In particular, the dummies corresponding to an increase in: inflation above 18.7 percent, nominal depreciation beyond 9 percent, FX deposits beyond 140 percent of official FX reserves, and decline in interest rate spread below 3 percent are all statistically significant in increasing the probability of crisis under the logit. This alternative specification also improves the statistical significance of other indicators in signaling banking crises—e.g., official FX reserve cover of broad money, real private credit growth, and equity level—and also has a better in-sample fit, given by its ability to identify 94 percent of the crisis episodes.

The final specification under logit includes only the five key predictors from the BCT analysis and dummy variables corresponding to the crisis terminal nodes (Table 5, column (iii)). This parsimonious specification addresses concerns about strong collinearity in using all the indicator variables of the BCT analysis in the logit estimation and also assesses the statistical significance of the crisis nodes identified by the BCT. As seen in column (iii), all terminal node dummies are statistically significant.[29] However, the five key indicator variables are either not statistically significant or have the wrong sign. These two results show that the predictors of banking crisis are significant only when they cross the identified

[29] Standard *F*-tests confirm the statistical significance of the terminal node dummies, even after considering the linear effects of the predictors. These results are not shown here but are available from the authors upon request.

thresholds, and not at all values, further confirming the importance of the BCT analysis in helping identify the critical thresholds beyond which indicators increase the crisis-proneness of banks.

VI. CONCLUSION

This paper provides a new perspective on banking crises by analyzing them using the Binary Classification Tree (BCT) methodology. While the BCT has recently been used to analyze several types of economic crises, including currency, sovereign debt and capital account crises, to our knowledge this is the first paper that uses the technique to look more closely at banking crises. To investigate the underlying vulnerabilities of a banking crisis we consider not only traditional indicators of macroeconomic fundamentals and external factors, but also monetary conditions and financial soundness vulnerabilities. The BCT results underscore that banking crises are instigated by a combination of "bads" and not any unique vulnerability. The results also stress that unconditional thresholds of variables are not as important in predicting banking crises as conditional thresholds, and that indicators trigger banking sector problems only after crossing these thresholds.

Several indicators of financial market conditions are identified as important predictors of impending banking crises, in particular: nominal depreciation, interest profitability, inflation, liability dollarization and bank illiquidity. However, crises are triggered by complex interactions between financial and macroeconomic variables. The crisis-prone conditions identified by alternative BCT specifications confirm that foreign exchange risk is one of the main vulnerabilities underlying banking crises, in that banks become crisis prone when faced with a nominal depreciation combined with high liability dollarization. This result provides perspective on the nature of twin crises discussed by Kaminsky and Reinhart (1999), who found that the peak of a banking crisis is often preceded by a currency crisis. However, banks can be crisis-prone even when depreciation is limited, owing to the combination of high liability dollarization and low bank liquidity.

As a caveat, our analysis excluded some institutional indicators that have previously been associated with banking crises, such as lack of central bank independence, strength of the supervisory and regulatory framework, and low share of foreign ownership of the banking system, owing to absence of time series data on these indicators.

When dummy variables corresponding to the thresholds of key primary splitters in the BCT analysis are included in a standard logit regression, they are statistically significant. In addition, dummy variables corresponding to the crisis terminal nodes of the BCT are also significant in the logit analysis. These findings confirm that banking crises are caused by a combination of macroeconomic, foreign exchange and financial soundness vulnerabilities acting together, which would have been very difficult to identify in a standard regression analysis. The ability of the BCT approach to identify these nonlinear relationships underlying banking crises makes it a unique and useful tool with which to monitor bank vulnerabilities.

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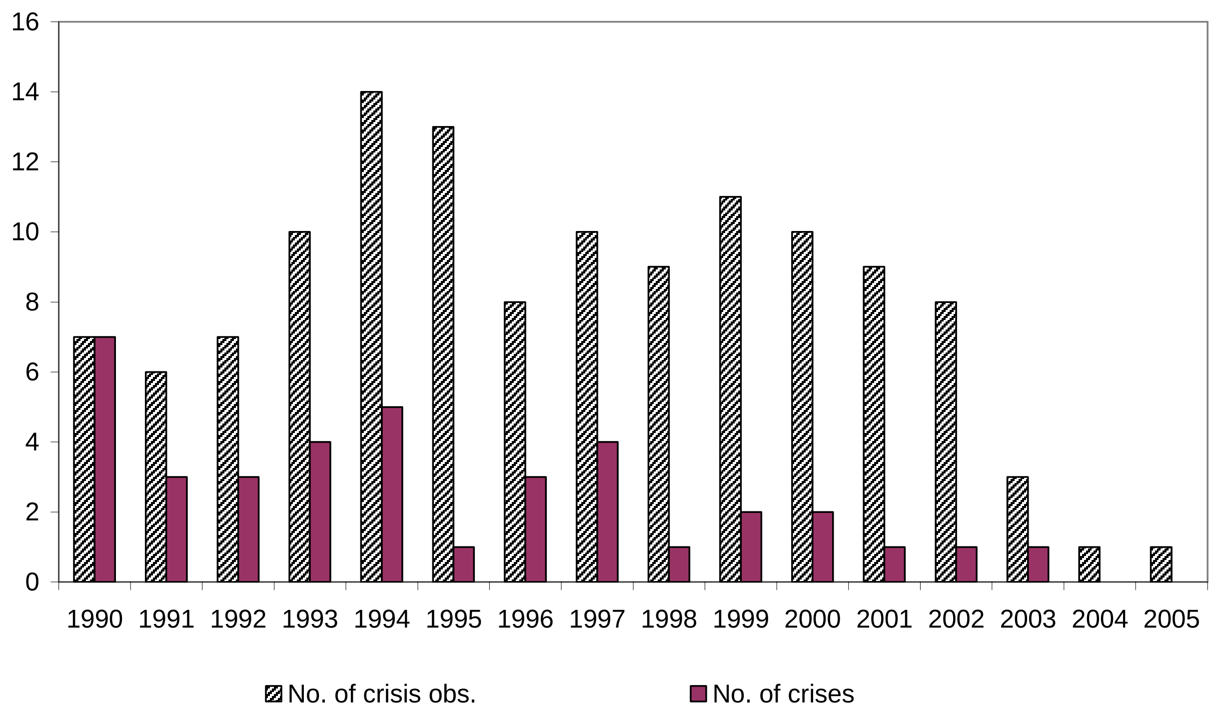
Appendix I. Data Sources

Variable Source	Series Name
1. Real GDP: *World Economic Outlook* (WEO), IMF	NGDP_R
2. Nominal GDP: WEO.	NGDP
3. Inflation: *International Financial Statistics* (IFS), IMF	64.ZF and 64.XZF
4. Nominal exchange rate: IFS	RF.ZF
5. Fiscal overall balance: WEO and IFS	GCB and 80.ZF
6. Export growth: WEO	W.BX
7. TOT growth: WEO	TT
8. Official FX reserves to broad money: IFS	IL.DZ for reserves, (34ZF+35ZF) for broad money, AE.ZF for exchange rate to convert broad money to U.S. dollars
9. Private credit: IFS	32.ZF
10. Deposit rate: IFS (and IMF staff reports, various issues, to fill in missing values)	60.L
11. Interest rate spread (lending rate minus deposit rate): IFS (and IMF staff reports, various issues, to fill in missing values)	60.P and 60.L
12. Net foreign assets: IFS	31.NZF
13. Foreign interest rate: IFS	60. B for U.S. 1 month Libor
14. Dummy for deposit insurance: Demirguc Kunt and Sobaci (2001), and IMF staff reports (various issues)	
15. Dollar deposits in the banking system: Kamil (2006), Levy-Yeyati (2005, 2006).	
16. Capital to asset ratio (equity to asset ratio): Bankscope and Eastern Caribbean Central Bank (ECCB) for the ECCU countries	
17. Nonperforming loans to total loans: Bankscope and ECCB for the ECCU countries	
18. Return over average assets: Bankscope and ECCB for the ECCU countries	
19. De facto exchange rate regime: *Annual Report on Exchange Arrangements and Exchange Restrictions*, various issues (IMF)	

Figure 1. Banking Crises By Year, 1990-2005



Source: Authors' calculations.

Figure 2. Binary Classification Tree, Baseline Model, 1990–2005

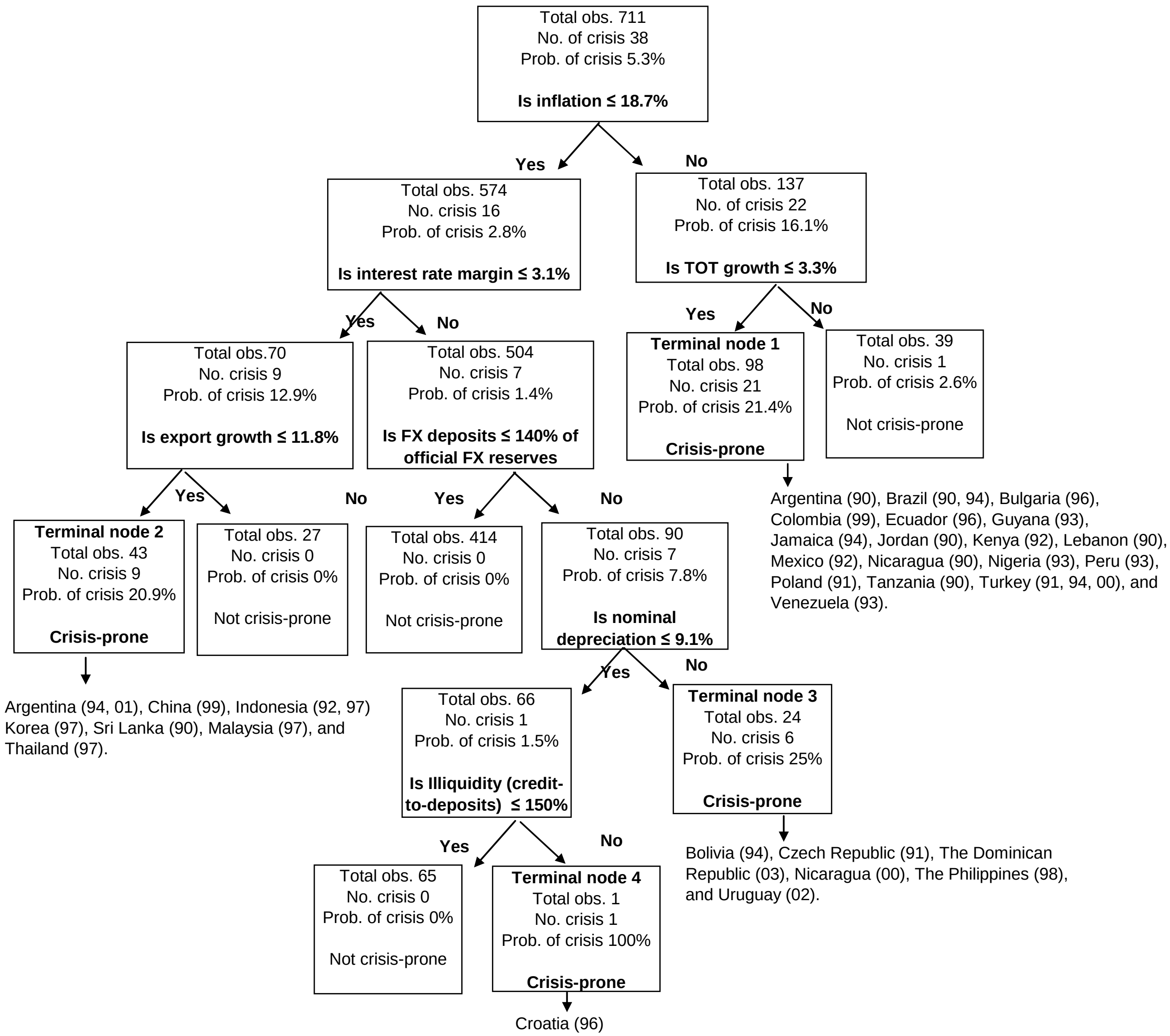


Figure 3. Binary Classification Tree, Alternative Model, 1990–2005
(Classification of “Severe” Banking Crises)

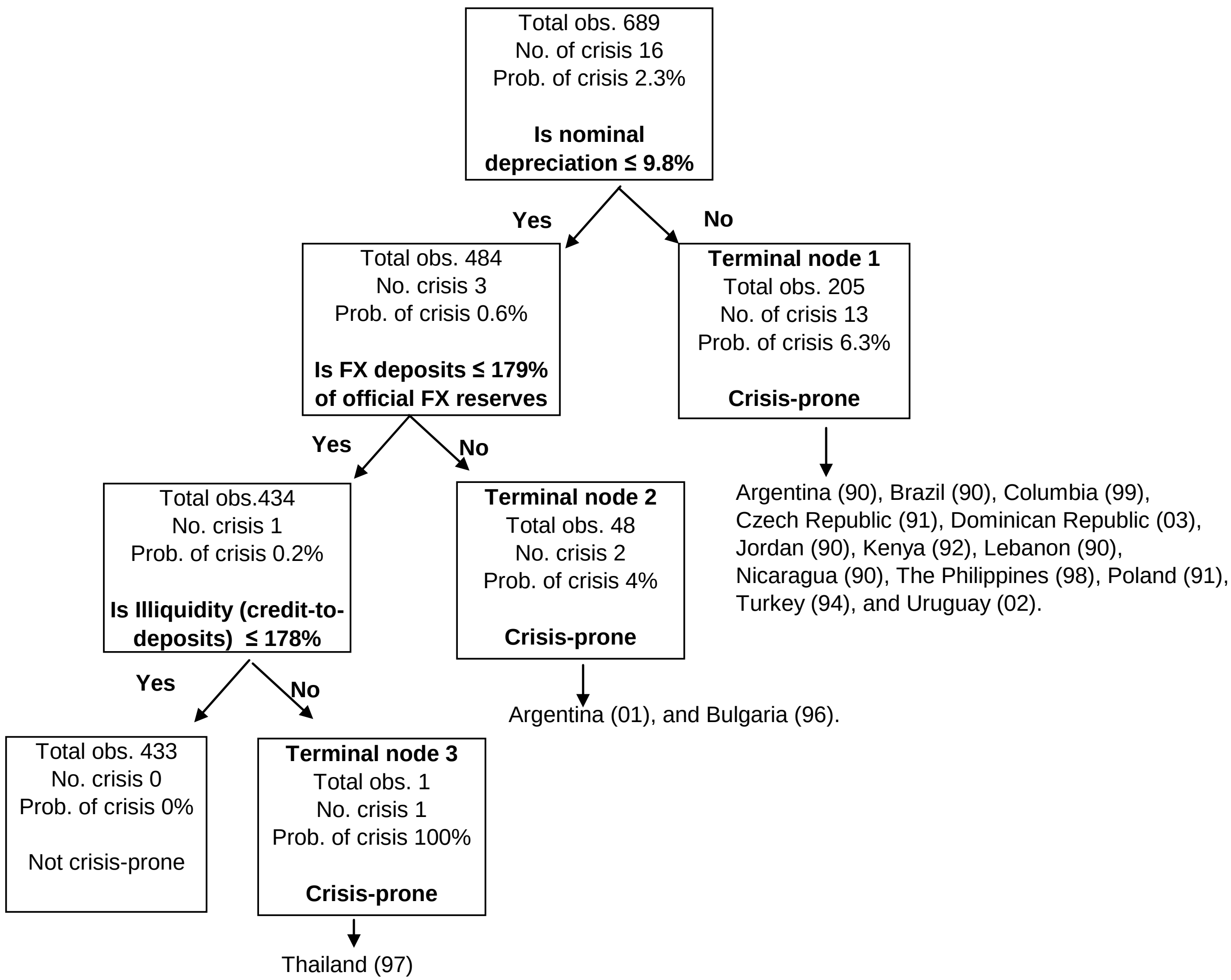


Figure 4. Binary Classification Tree Model on 1990–2000, and Out of Sample Prediction for 2001

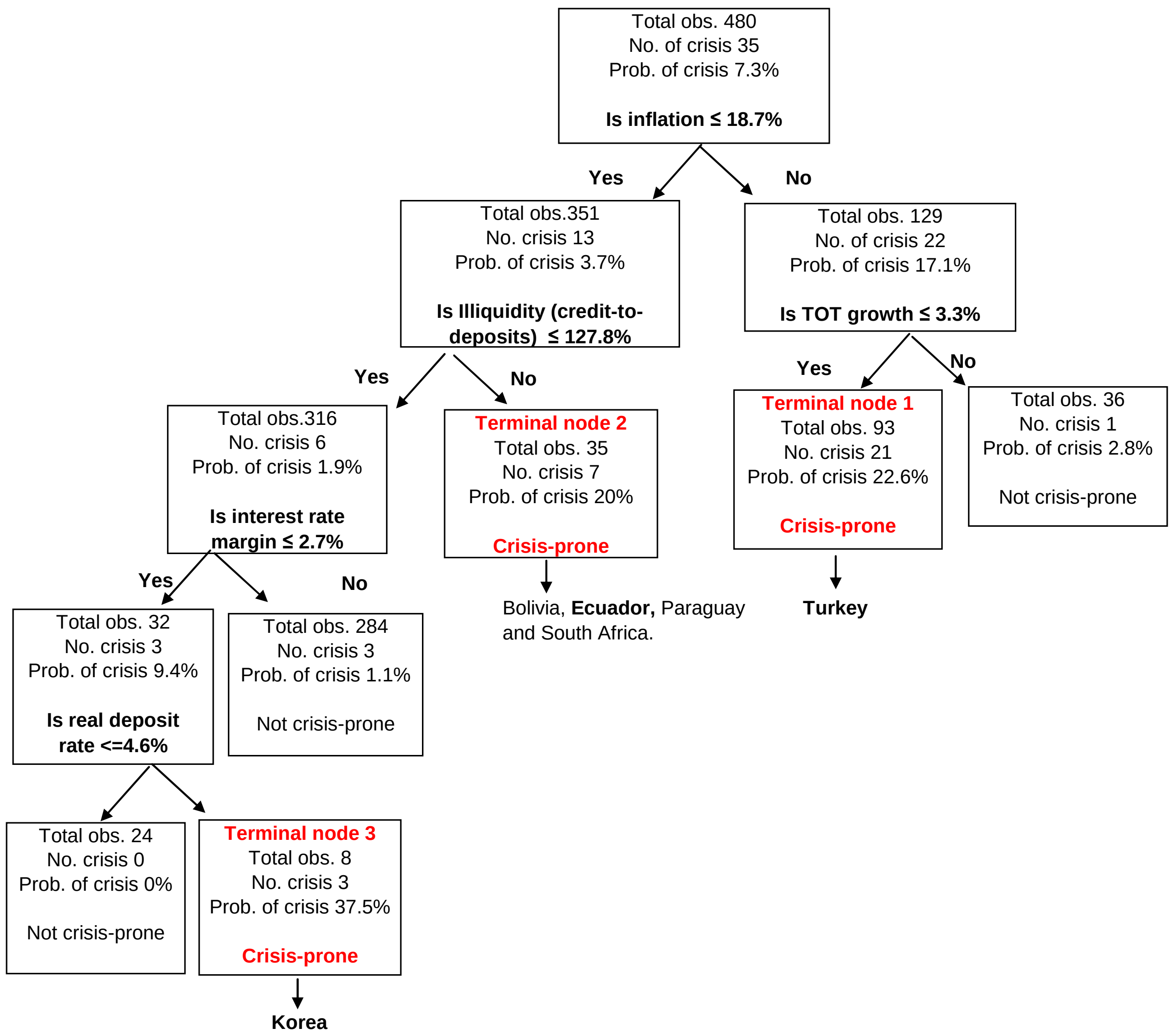


Figure 5. Binary Classification Tree Model on 1990–2001, and Out of Sample Prediction for 2002

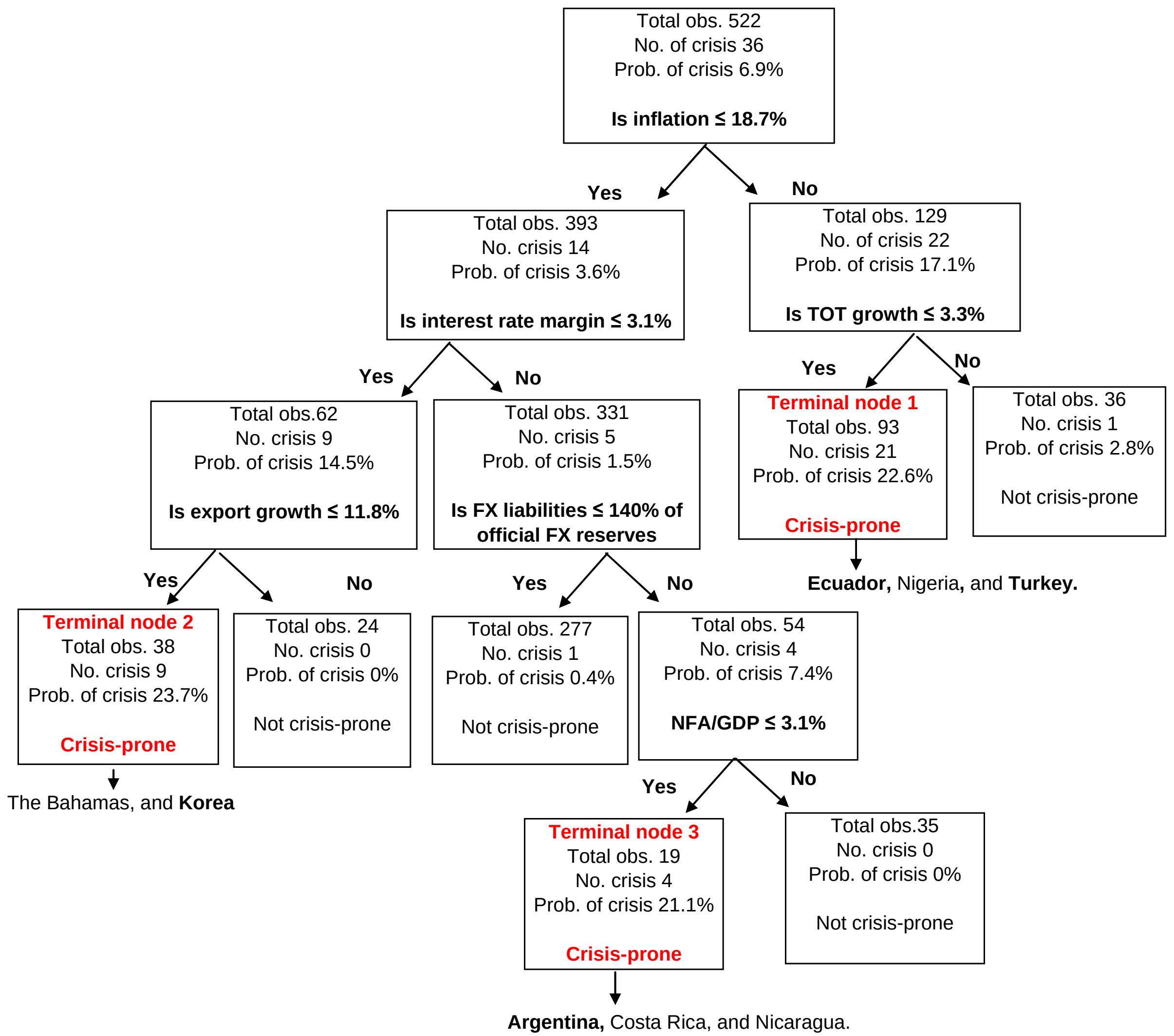


Figure 6. Binary Classification Tree Model on 1990–2002, and Out of Sample Prediction for 2003

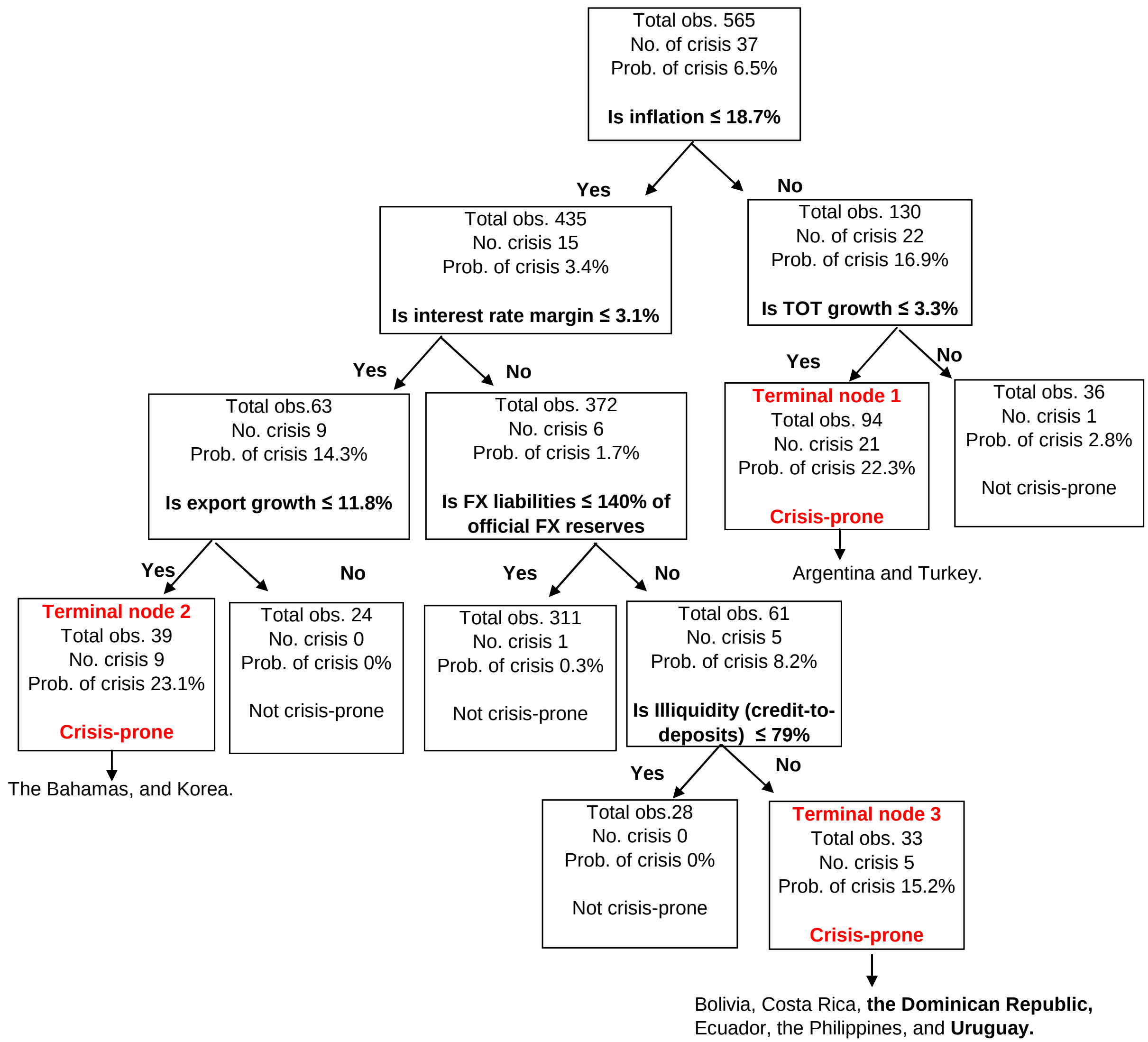


Figure 7. Out of Sample Prediction for the Caribbean Countries, 1990–2005

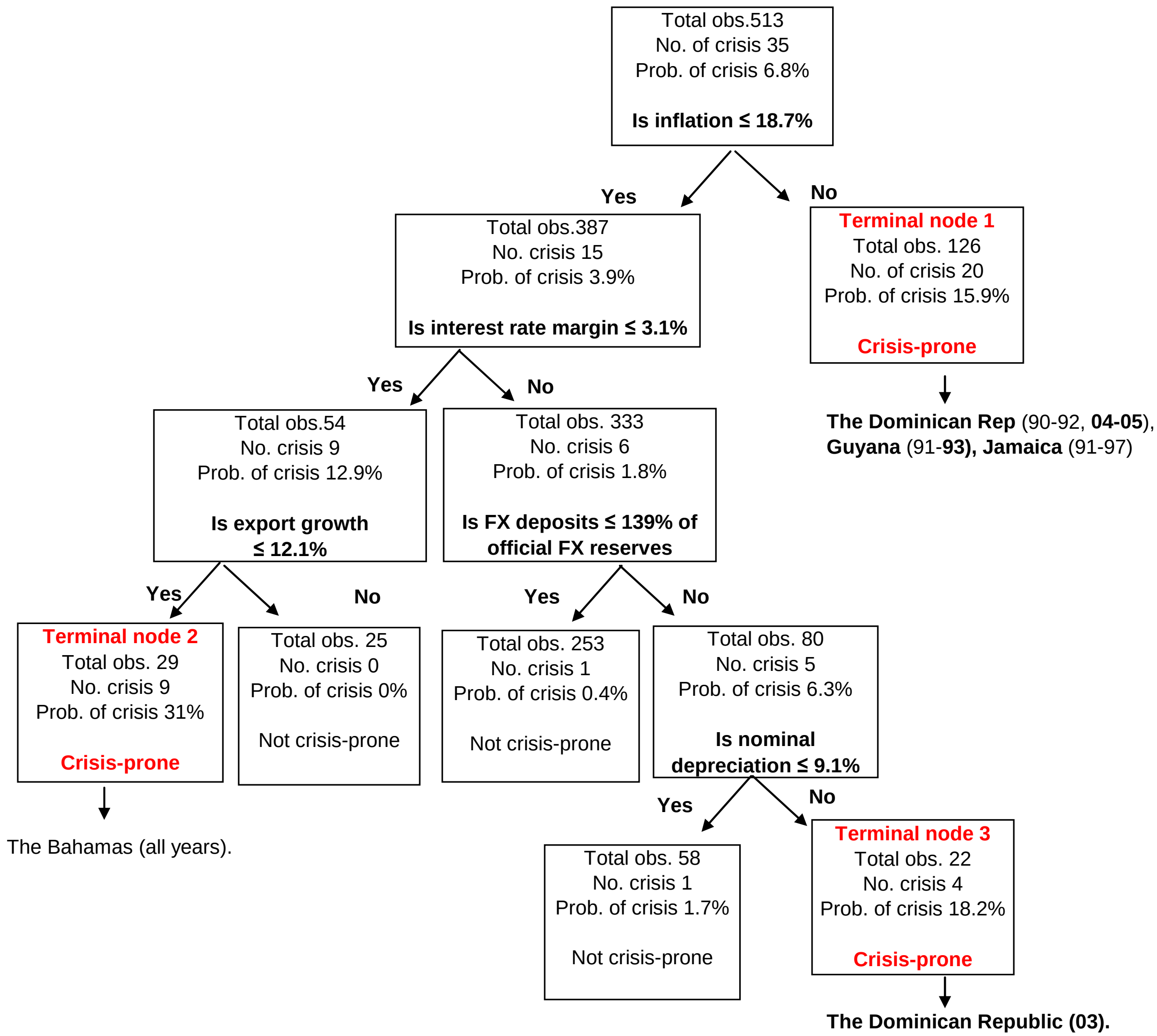


Table 1. Banking Crisis Episodes During 1990–2005

Country	Crisis Episodes	Average Years in Crisis
Argentina	1990, 1994–95, 2001–02	1.7
Bolivia	1994–95	2.0
Brazil	1990, 1994–99	3.5
Bulgaria	1996–97	2.0
China	1999	1.0
Colombia	1999–00	2.0
Croatia	1996	1.0
Czech Republic	1991–95	5.0
Dominican Republic	2003–05	2.0
Ecuador	1996–02	7.0
Guyana	1993–95	3.0
Indonesia	1992,1997–02	3.5
Jamaica	1994–00	7.0
Jordan	1990	1.0
Kenya	1992–95	4.0
Korea	1997–02	6.0
Lebanon	1990	1.0
Malaysia	1997–01	5.0
Mexico	1992–97	6.0
Nicaragua	1990–96, 2000–01	4.5
Nigeria	1993–95	2.0
Paraguay	1995–00	5.0
Peru	1993–94	2.0
Philippines	1998–03	6.0
Poland	1991–95	5.0
Sri Lanka	1990–93	1.0
Tanzania	1990–91	2.0
Thailand	1997–02	6.0
Turkey	1991, 1994, 2000–02	1.7
Uruguay	2002–03	2.0
Venezuela	1993–95	3.0

Countries with no crisis during the sample period—Antigua and Barbuda, The Bahamas, Barbados, Belize, Chile, Costa Rica, Dominica, Egypt, El Salvador, Grenada, Guatemala, India, Israel, Papua New Guinea, South Africa, St. Kitts and Nevis, St. Lucia, St. Vincent and the Grenadines, Trinidad and Tobago.

Sources: Caprio and Klingebiel (2002), Carstens and others (2004), and Kaminsky and Reinhart (1996).

Table 2. Average of Variables Used in the Empirical Analysis, 1990–2005[1]

	(i) Sample Average	(ii) No Crisis in t No Crisis in t+1	(iii) No Crisis in t Crisis in t+1	(iv) Crisis in t Crisis in t+1
		(In percent)		
Macroeconomic fundamentals				
GDP growth	3.4	3.8	1.6	1.2
Inflation	73.9	39.4	330.2	355.3
Nominal depreciation	100.3	77.6	380.2	248.0
Government overall balance (to nominal GDP)	-3.3	-3.2	-3.6	-3.5
External sector				
Official FX reserves (to broad money)	30.9	31.7	26.9	28.4
Terms of trade growth	0.3	0.8	-3.6	-0.7
Export growth	9.4	9.9	7.0	8.1
Monetary conditions				
Growth of real private credit	19.3	-1.1	187.4	268.5
Real deposit rate	6.1	-13.2	438.3	-152.3
Foreign interest rate	4.8	4.8	5.8	5.0
Existence of deposit insurance	44.8	40.3	47.4	55.2
Average rigidity of defacto exchange rate regime 2/	2.0	2.1	1.8	1.6
Banking system financial soundness				
Liquidity: Private sector credit (to deposits) 3/	88.0	85.3	97.5	100.0
Liability dollarization: FX deposits (to official FX reserves)	92.3	87.4	126.5	164.0
FX open position: Net foreign assets (to GDP)	6.1	9.4	-14.3	-24.2
Capital: Equity (to assets)	8.7	9.1	8.1	7.4
Profitability: Return over average asset	1.1	1.4	0.6	0.5
Profitability: Interest rate spread	15.3	17.0	-0.8	3.0
Asset quality: NPLs (to total loans)	8.0	7.4	5.0	8.6

Sources: IMF, International Financial Statistics and WEO; Bankscope; and authors' calculations.

1/ Each column provides the average of the variable in period (t).

2/ The defacto regime can have three values: 1 (for countries with floating regimes), 2 (countries with soft pegs), and 3 (countries with fixed or hard pegs).

3/ Increase implies lower liquidity.

Table 3. Variable Importance Under the BCT Baseline and "Severe Crises" Specifications

Variable Importance	Baseline Rank	Baseline Score	Severe Crises Rank	Severe Crises Score
Nominal depreciation	1	100	1	100
Profitability: Interest rate spread	2	92	6	42
Inflation	3	70	2	68
Liability dollarization (FX deposits to official reserves)	4	54	3	61
Liquidity	5	54	7	40
Real deposit interest rate	6	53	14	0
FX open position (NFA to GDP)	7	42	9	25
Non performing loans	8	28	11	0
Real credit growth	9	20	4	46
De facto exchange rate regime	10	17	16	0
Growth	11	17	...	...
Export growth	12	17	18	0
Government balance	13	16	8	30
Return over average asset	14	14	5	42
Terms of trade growth	15	12	12	0
Official FX reserves to broad money	16	3	13	0
Foreign interest rate	17	0	15	0
Explicit deposit insurance	18	0	17	0
Equity to assets	19	0	10	22

Source: Authors' calculations.

Table 4. Median Values of Key Indicators at Terminal Nodes

	Macroeconomic Instability		Low Bank Profitability		High FX Risk with Nominal Depreciation		High FX Risk with Low Liquidity	
	Crisis	Non-crisis	Crisis	Non-crisis	Crisis	Non-crisis	Crisis	Non-crisis
	Inflation > 18.7% & TOT Growth <= 3.3%	Inflation > 18.7% & TOT Growth > 3.3%	Inflation < 18.7% & Interest Rate Margin <= 3.1% & Export Growth <= 11.8%	Inflation < 18.7% & Interest Rate Margin <= 3.1% & Export Growth > 11.8%	Inflation < 18.7% & Interest Rate Margin > 3.1% & Liability Dollarization > 140% & Nominal Depreciation > 9%	Inflation < 18.7% & Interest Rate Margin > 3.1% & and Liability Dollarization <= 140%	Inflation < 18.7% & Interest Rate Margin > 3.1% & Liability Dollarization > 140% & Nominal Depreciation <= 9% & Iliquidity Index > 150%	Inflation < 18.7% & Interest Rate Margin > 3.1% & Liability Dollarization > 140% & Nominal Depreciation <= 9% & Iliquidity Index <= 150%
Outcome	Crisis	Non-crisis	Crisis	Non-crisis	Crisis	Non-crisis	Crisis	Non-crisis
Conditional probability of crisis (in percent)	21.4	2.6	20.9	0	25	0	100	0
Nominal depreciation	35.2	28.1	0.0	0.0	11.8	0.0	-12.8	0.0
Interest rate spread	13.0	10.8	2.1	2.2	10.6	6.9	14.7	7.7
Inflation	44.7	39.0	5.4	4.5	10.8	4.7	4.0	4.5
Liability dollarization index (increase implies more dollarization)	67.5	69.2	20.0	14.7	201.8	33.6	140.5	221.0
Iliquidity index (increase implies lower liquidity)	74.7	81.7	103.3	115.8	96.0	81.4	158.2	79.1

Source: Authors' calculations.

Table 5. Logit Analysis of Determinants of Banking Crisis, 1990–2005

Explanatory Variables	Coefficients 1/ (i)	(ii)	(iii)
Macro fundamentals			
GDP growth	-0.090	-0.067	
	(0.43)	(0.68)	
Inflation	**0.048**	0.024	0.01
	(0.01)*	(0.61)	(0.44)
Dummy (inflation higher > 18.7%)		**3.992**	
		(0.03)**	
Nominal depreciation	-0.035	**-0.144**	**-0.03**
	(0.17)	**(0.01)****	**(0.03)****
Dummy (nominal depreciation > 9.1%)		**5.130**	
		(0.01)**	
Government overall balance	0.132	0.084	
	(0.23)	(0.63)	
External sector			
Foreign reserves to broad money	-0.026	**-0.078**	
	(0.22)	**(0.08)***	
Export growth	-0.031	-0.049	
	(0.34)	(0.58)	
Dummy (export growth > 11.8%)		-0.204	
		(0.90)	
TOT growth	0.011	0.902	
	(0.74)	(0.45)	
Dummy (TOT growth > 3.3%)		-0.088	
		(0.35)	
Monetary conditions			
Growth of real private credit	0.022	**0.081**	
	(0.27)	**(0.01)****	
Foreign interest rate	0.060	-0.041	
	(0.77)	(0.90)	
Real deposit rate	**0.107**	0.062	
	(0.05)**	(0.32)	
Rigidity of exchange rate regime (de facto)	0.214	-0.575	
	(0.70)	(0.54)	
Existence of deposit insurance (explicit)	0.607	0.586	
	(0.48)	(0.58)	
Banking system financial soundness			
Net FX open position: NFA to GDP	**-0.033**	0.006	
	(0.06)*	(0.82)	
Illiquidity: private sector credit to deposits	0.017	**0.035**	0.01
	(0.12)	**(0.05)****	(0.14)
Illiquidity dummy (private sector credit to deposits>150%)		1.574	
		(0.35)	
Dollarization of liabilities	-0.003	**-0.014**	0.00
	(0.27)	**(0.00)****	(0.68)
Dummy (dollarization of liabilities > 140% of official FX reserves)		**4.462**	
		(0.00)**	
Equity strength: Equity to assets	-0.086	**-0.365**	
	(0.21)	**(0.00)****	
Asset quality: NPLs to total loans	**-0.156**	-0.145	
	(0.02)**	(0.31)	
Profitability: return over average asset	**-0.695**	**-0.640**	
	(0.00)**	**(0.03)****	
Interest profitability: Interest rate spread	**0.056**	0.134	**0.05**
	(0.03)**	(0.61)	**(0.00)****
Profitability dummy (Interest rate spread > 3.1 percent)		**-6.083**	
		(0.00)**	
Dummy corresponding to terminal node 1 in Figure 2 (Inflation > 18.7 percent and TOT growth <= 3.3 percent)			**4.49** **(0.00)****
Dummy corresponding to terminal node 2 in Figure 2 (Inflation <= 18.7 percent and interest rate margin <= 3.1 percent and export growth <= 11.8 percent)			**4.80** **(0.00)****
Dummy corresponding to terminal node 3 in Figure 2 (Inflation <= 18.7 percent and interest rate margin > 3.1 percent, FX deposits > 140 percent of offiicial FX reserves, and private credit > 150 percent of deposits)			**5.03** **(0.00)****
Number of observations	452	452	595
Number of crises	17	17	24
Psuedo R-squared	0.31	0.54	0.40
Significance of the regression (Chi-square)	239.3**	3601.9**	54.14**
Prediction performance			
% of crises predicted correctly	82.4	94.1	91.7
% of non-crises predicted correctly	78.1	89.1	84.6

Source: Authors' calculations.
1/ P values are reported in parentheses. Variables that are significant at the 5 and 10 percent significance level are denoted by ** and * respectively.