**Financial measures and banking crisis**

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**Abstract:** This paper assesses the predictive power of calibrating financial cycle measures on the probability of a banking crisis. Data are at a yearly frequency, span the period 1980–2020, and cover 196 countries. The standardized cumulative credit-to-GDP ratio is important for advanced economies (AEs) and to a lesser extent for low-income developing countries (LIDCs), but it is not for emerging economies (EEs). IMF and World Bank policymakers and analysts need to take a more comprehensive approach to evaluating financial stability and systemic vulnerabilities in EEs and LIDCs because of their deep informal banking sector.

**Keywords:** Banking crisis, financial measures, logit, forecasting

**JEL classification:** E50; G32; C58; G17

1. **Introduction**

2007–08 when the world economy painfully experienced a convergence of financial imbalances and economic downturn, studying became a major preoccupation for theorists and policymakersThe COVID-19 pandemic focused discussions about policy normalization on financial vulnerabilities. The exceptional support that mitigated the consequences of the pandemic also increased debt, which was already exceedingly high in the wake of the GFC. Today’s most pressing policy dilemma is how to balance measures to prevent future financial crises with those that promote growth in the still unstable post-pandemic, post-high-inflation era.

Drehmann et al. (2012), Aikman et al. (2015), Schuler et al. (2015), and Chen and Svirydzenka (2021) see financial and systemic banking crises as correlated. Financial authorities estimate the countercyclical capital buffer (CCyB) required for their banking systems on the basis of extracting data for long-term credit cycles (Basel Committee on Banking Supervision, 2010). Sohn and Park (2016) suggest that credit growth is more indicative for predicting a banking crisis than the credit-to-GDP gap. According to Carrodo and Schuler (2019), the best way to stop a bubble from expanding is to implement a macroprudential rule that responds to the credit-to-GDP imbalance.

Decisionmakers have to consider diverse perspectives on how to quantify the scale of any banking crisis, how to select the appropriate metrics, and how to detect overheating in real time. Our study uses logistic regression analysis to assess three groups of 196 countries—advanced economies (AEs), emerging economies (EEs), and low-income developing economies (LIDCs)—and two measures for calibrating credit booms: Cumulative two years credit/GDP growth; and standardized cumulative two years credit/GDP growth. The logit regression performed did not incorporate any other variable with potential utility for predicting banking crises. We included the M2 money supply measure (% of reserves, m2\_res), general government gross debt (%GDP, ggDebtGr\_gdp), and real annual percentage GDP growth (gdp\_ncconstgr).

We demonstrate that, contrary to conventional belief, the probability of a banking crisis appears to be higher for AEs (7.5%) and, thus, volatility is higher than in LIDCs and EEs. The heterogeneity of financial development implies a wide dispersion of the level of credit-to-GDP growth. Cumulative credit-to-GDP is a better indicator of a credit boom. To minimize this asymmetry, we standardized cumulative GDP-to-growth. It is more appropriate to use standardized two years credit/GDP as the crisis variable is either 0 or 1. If M2 and credit both increase, the probability of a banking crisis is higher. If GDP growth is higher, however, the probability of decreases. The logit regressions confirmed each country’s heterogeneity in terms of credit-to-GDP. Standardized cumulative credit-to-GDP is significant for AEs and, to a lesser extent, LIDCs, but not for EEs.

The following sections outline: The data and methodology used to extract banking cycles and presents stylized facts about their behavior; our results for the empirical relationship between banking cycles and financial measurements; and our conclusions.

1. **Data and Methodology**

Our objective is to assess credit growth’s capacity for predicting banking crises. We use a database that assesses a binary variable on the banking crisis: A crisis either exists (1) or it does not (0). Our quarterly data for the period 1980–2020 cover 196 countries. Given our binary conception of a crisis, using limited dependent-variable approaches like logit or probit makes sense. Probit models have been used in many previous empirical research projects that have used discrete choice models (e.g., Eichengreen et al. 1996; Frankel and Rose 1996; Berg and Patillo 1999). We used a logit structure, the sole distinctive feature of our model being that, in both logit and probit models, the basic latent variable supposed to produce the discrete event has a slightly different distribution. In the logit instance, it is more fat-tailed.

The focus of our interest in predicting stress or crises is on the tail of a distribution. Tail risk is the risk that future realizations lie in the tail of the distribution. Tail-risk realizations occur with small probability but entail large losses (stress events, crises). Stress or crisis realizations are coded as binary variables. The 0 or 1 classification may be based on pre-determined criteria: The falling short or superseding of a variable’s threshold, the assumed extreme event; the occurrence of certain events (e.g., defaults); and both events and superseding of multiple thresholds together. Different thresholds produce different timings for tail-risk realizations (stress, crises). Events are often difficult to precisely define.

The variable to forecast is therefore

)

Assuming that there is an underlying response variable

What we observe is

The probit model is the cumulative distribution function (cdf) of the standard normal distribution

 (1)

where the logit model is the cdf of the logistic distribution

 (2)

where is a vector of explanatory variables and is a vector of parameters.

In the probit model, is replaced with where is the standard normal cumulative distribution function.

Interpretation of the estimated coefficients is not straightforward because the model is not linear: The slope of the function depends on the values of the explanatory variables and assessing the impact of the explanatory variables on the dependent variable requires using F(.). For both probit/logit: Predicted values can be interpreted as probabilities; predicted probabilities are either 0 or 1; and logit tends to better encounter fat tail and then extreme events. The difference between logit and probit is small.

1. **Results**

Our findings reveal the banking crisis frequency in the three country groups and which group is more often affected by a banking crisis and why.

**Table 1: Frequency of banking crises in AEs, EEs, and LIDCs**

|  |  |
| --- | --- |
|   | **AEs** |
| Value | Count | Percentage | Cumulative count | Cumulative percentage |
| 0 | 1,555 | 92.50 | 1,555 | 92.50 |
| 1 | 126 | 7.50 | 1,681 | 100 |
| Total | 1,681 | 100.00 | 1,681 | 100 |
|  |  |  |  |  |
|  | **EEs** |
| Value | Count | Percentage | Cumulative count | Cumulative percentage |
| 0 | 3,795 | 95.42 | 3,795 | 95.42 |
| 1 | 182 | 4.58 | 3,977 | 100 |
| Total | 3,977 | 100.00 | 3,977 | 100 |
|  |  |  |  |  |
|  | **LIDCs** |
| Value | Count | Percentage | Cumulative count | Cumulative percentage |
| 0 | 2,233 | 93.90 | 2,233 | 93.90 |
| 1 | 145 | 6.10 | 2,378 | 100 |
| Total | 2,378 | 100.00 | 2,378 | 100 |
|   |   |   |   |   |

*Source: Authors’ calculations*

Table 1 shows that banking crises appear to be more frequent for AEs (7.5%) than EEs (4.6%) and LIDCs (6.1%). This is a stylized fact supported in many other papers, the reasons being that the size of the financial market is more important in AEs, leading banks to take more risks and, therefore, create a greater likelihood of crises, and the fact that advanced countries can borrow much more due to their deemed creditworthiness. Banking markets are much less developed in low-income countries, meaning those countries are less prone to such crises.

Examining the simple statistics, means and standard deviations, of credit-to-GDP for the three income groups also reveals that AEs have the largest mean (32.78) and a standard deviation of 922.71, while EEs have 3.33 and 15.43 and LIDCs 5.28 and 33.50 respectively. The mean is much higher for AEs than the median, driven by a strong asymmetry: More observation on the right tail of the distribution can prove the maximum value. The asymmetry is also important but less so for LIDCs and EEs. This implies great asymmetries and outliers in the data.

To minimize this asymmetry, we placed the data into groups, truncated the sample, and either smoothed or standardized the data. Cumulative credit-to-GDP is a better indicator for a credit boom. To minimize this asymmetry, we standardized the cumulative GDP-to-growth by removing the mean and dividing by the standard error. Therefore, the standardized variable has zero mean and 1 variance. As a consequence, volatility is high, in particular for AEs. The heterogeneity of financial development implies a huge dispersion of the level of credit-to-GDP growth.

We regressed the banking crisis variable on both measures of credit booms: Cumulative two years credit/GDP growth; and standardized cumulative two years credit/GDP growth.

**Table 2: Banking crisis regression using ML – binary logit**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Variable | Coefficient | Std. Error | z-Statistic | Prob.  |
|  | Standardized cumulative two years CREDIT/GDP growth |
| SCRED\_GDPG2 | 0.3603 | 0.1011 | 3.5652 | 0.0004 |
| C | -2.7799 | 0.1070 | -25.9887 | 0.0000 |
|  |  |  |  |  |
|  | Standardized cumulative two years CREDIT/GDP growth |
| CRED\_GDPG2 | 0.0025 | 0.0010 | 2.3518 | 0.0187 |
| C | -2.9834 | 0.1577 | -18.9196 | 0.0000 |
|  |  |  |  |  |

*Source: Authors’ calculations*

Table 2 shows that cumulative credit-to-GDP significantly explains the occurrence of a banking crisis on a yearly basis. This result is robust for standardized and non-standardized variables, the only difference being that the value of the coefficient 0.36 for the standardized and 0.0025 for the non-standardized. The first one is more suitable and is easier to interpret as the crisis variable is either 0 or 1.

The logit regression performed in Table 2 does not include any other variable that may have predictive power for banking crises. We now add: M2 (% of reserves, m2\_res), general government gross debt (% of GDP, ggDebtGr\_GDP), and real annual percentage GDP growth. (GDP\_ncconstgr).

**Table 3:** **Banking crisis with M2, general government gross debt, and real GDP growth**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Variable | Coefficient | Std. Error | z-Statistic | Prob.  |
| SCRED\_GDPG2 | 0.5339 | 0.2015 | 2.6498 | 0.0081 |
| M2\_RES | 0.0092 | 0.0039 | 2.3824 | 0.0172 |
| GGDEBTGR\_GDP | -0.0013 | 0.0042 | -0.3037 | 0.7614 |
| GDP\_NCCONSTGR | -0.0825 | 0.0233 | -3.5401 | 0.0004 |
| C | -3.3640 | 0.3329 | -10.1065 | 0.0000 |

*Source: Authors’ calculations*

Note: M2 (% of reserves), general government gross debt (% of GDP), and real GDP growth (percent, annual).

The variables in Table 3 have all the expected signs and are all significant, except debt/GDP. If M2 increases as well as the credit, the probability of a banking crisis is higher. On the contrary, if GDP growth is higher, the probability of a banking crisis decreases. Table 3 reveals that a 1% increase in standardized cumulative two years of credit/GDP growth explains 53.39% of the banking crisis. The M2 explains only 0.92% of the banking crisis probability, while a 1% increase in real GDP decreases the banking crisis probability by -8.25%.

**Table 4:** **Banking crisis for the three different income groups**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Variable | Coefficient | Std. Error | z-Statistic | Prob.  |
|  | **AEs** |
| SCRED\_GDPG2 | 1.0948 | 0.5064 | 2.1617 | 0.0306 |
| M2\_RES | 0.0180 | 0.0133 | 1.3532 | 0.1760 |
| GGDEBTGR\_GDP | 0.0013 | 0.0076 | 0.1759 | 0.8604 |
| GDP\_NCCONSTGR | -0.1000 | 0.0521 | -1.9175 | 0.0552 |
| C | -3.2413 | 0.6840 | -4.7390 | 0.0000 |
|  |  |  |  |  |
|  | **EEs** |
| SCRED\_GDPG2 | 0.1047 | 0.2933 | 0.3570 | 0.7211 |
| M2\_RES | -0.0418 | 0.0419 | -0.9990 | 0.3178 |
| GGDEBTGR\_GDP | 0.0053 | 0.0069 | 0.7672 | 0.4429 |
| GDP\_NCCONSTGR | -0.1393 | 0.0537 | -2.5939 | 0.0095 |
| C | -3.4445 | 0.5731 | -6.0103 | 0.0000 |
|  |  |  |  |  |
|  | **LIDCs** |
| SCRED\_GDPG2 | 0.2685 | 0.1324 | 2.0273 | 0.0426 |
| M2\_RES | 0.0165 | 0.0107 | 1.5479 | 0.1216 |
| GGDEBTGR\_GDP | -0.0230 | 0.0127 | -1.8165 | 0.0693 |
| GDP\_NCCONSTGR | -0.0153 | 0.0123 | -1.2454 | 0.2130 |
| C | -2.9488 | 0.4597 | -6.4146 | 0.0000 |
|  |  |  |  |  |

*Source: Authors’ calculations*

The three regressions confirm the countries’ heterogeneity in terms of credit-to-GDP. For AEs and, to a lesser extent, LIDCs, the standardized cumulative credit-to-GDP is significant, but it is not for EEs. The fit of the regression is the highest for AEs, again due to their higher dependency on financial markets.

Table 4 shows that the standardized cumulative two years of credit/GDP growth in AEs has the largest impact, 109.48%, on the banking crisis relative to the EEs and LIDCs. In LIDCs, the impact is much lower: 26.85%. Higher levels of leverage and risk-taking, more accurate data reporting, significant market expectations and confidence dynamics, regulatory and institutional factors, and the service-oriented nature of their economies are all contributing factors to the higher impact of standardized cumulative two years of credit/GDP growth on banking crises in AEs than on LIDCs. All of these elements combine to increase the impact of and potential instability of credit booms in developed countries.

Real GDP affects the banking crisis probability negatively and significantly for both AEs and EEs: -10% and -13.93% respectively. A higher GDP growth rate reduces defaults and financial distress by enhancing the financial health of both enterprises and consumers. Economic expansion increases corporate earnings and investor confidence in both AEs and EEs, strengthening banking industry stability. Moreover, stable fiscal policies and higher government income levels enable the financial system to be effectively regulated and supervised. Financial innovation and economic diversification lower systemic risks and increase financial inclusion.

General government debt decreases the banking crisis in LIDCs by -2.3%. Even though high government debt is typically viewed as a risk factor, there are circumstances in which it reduces the chance of financial crises in such nations. For banks, government debt may offer stability as a safe asset. Effective and efficient fiscal policies and public investments financed by government debt can promote economic stability in LIDCs. Moreover, the banking industry may benefit from improved governance and institutional strengthening and financial inclusion initiatives financed by government debt can broaden and stabilize the financial system. Such positive effects largely depend on the government in question’s ability to manage its debt prudently, maintain investor confidence, and ensure that borrowed funds are used effectively to support economic and financial stability.

Figure 1 plots the banking crisis in-sample forecasts for the income groups. The model can predict very well the period of crisis for AEs: See Panel (a). The actual (orange) and the fitted (green) lines have a co-movement. Although some aspects remain unexplained by the model, it assesses, forecasts, and signals the timing of the crisis accurately. Because credit-to-GDP ratios can indicate excessive loan growth, rising leverage, declining credit quality, financial system vulnerabilities, and macro-financial links, they are an important predictor of banking crises in industrialized nations. Using this link, policymakers can create regulatory and supervisory policies that effectively avoid financial instability and guarantee the stability of the banking industry.

**Figure 1: In-sample forecasts by country group**

 *Source: Authors’ calculations*

Panel (b) of Figure 1 forecasts the position for EEs. The model predicts most of the crises, though some remain uncaptured, such as Brazil’s in 2007 and that of the Maldives in 2017. Improving data collection and quality, adding more variables and non-linear models, and understanding the distinct economic dynamics of EEs are all necessary to improve the quality of the outputs here. This could lower residuals and increase the accuracy of such econometric models. These factors can lead to larger or more variable residuals compared to those in more stable and developed economies.

Panel (c) of Figure 1 shows that the model can predict banking crises in LIDCs to a certain extent. Several factors—including poor data quality, economic volatility, the importance of the informal economy, difficulties with model specification, external shocks, weak institutions, and structural limitations—contribute to the huge residuals in models for LIDCs.

1. **Conclusions**

The predictive power of the financial cycle measures on the probability of a banking crisis is variable across the three income groups. Standardized cumulative credit-to-GDP ratio is an important indicator for AEs and, to a lesser extent, for LIDCs, but not for EEs. Higher levels of regulatory and institutional factors, more accurate data reporting, significant market expectations and confidence dynamics, and higher levels of risk-taking heighten the effect and possible instability of credit booms in industrialized nations.

Higher government debt could reduce the chance of banking crises in emerging nations with low incomes. Economic stability in LIDCs can be supported by effective and efficient fiscal policies as well as public investments funded by debt issued by the government. Institutional strengthening and better governance practices could be advantageous to the banking sector. Initiatives for financial inclusion funded by public debt can also stabilize and expand the financial system.

The significance of the standardized cumulative credit-to-GDP ratio may be constrained by the specific characteristics and difficulties that EEs have, even though it can still offer insights on credit patterns and possible hazards in these regions. In the context of emerging markets, IMF and World Bank policymakers and analysts may need to take a more comprehensive approach when evaluating financial stability and systemic vulnerabilities. Their informal lending practices, still developing financial infrastructure, and deeper informal sector contribute to the credit-to-GDP ratio’s lack of reflection of actual credit risks.

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