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Robust Signals for Banking Crises

Ons Jedidi
CREM-CNRS

Jean Sébastien Pentecote
CREM-CNRS, University of Caen - Low Normandy

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Contact: Ons Jedidi - ons.jedidi@univ-rennes1.fr, Jean Sébastien Pentecote - jean-sebastien.pentecote@unicaen.fr.
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Robust Signals for Banking Crises

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CREM-SHOS

Abstract

We develop an Early Warning System framework for predicting banking crises in 49 countries from 1977 to 2010. We deal with the problem of model uncertainty and omitted variables bias using Bayesian Model Averaging. Consistent with previous literature, we find that GDP growth, credit growth, financial liberalization and central bank assets to GDP are decisive in explaining the occurrence of banking crises. By minimizing a predictive loss function, we find an optimal rate of of false signals and missed crises. The robustness analysis shows that our results remain broadly stable when using different income groups of countries.

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1. Introduction

The last two decades have been marked by severe episodes of banking crises in developed countries as well as emerging economies. According to Caprio and Klingebiel (1996), the bail-costs of banking crises amounted to 10% of GDP on average. This has called for additional efforts to search for factors of banking vulnerability and to design Early Warning Systems (EWS) to predict financial distress.

Early Warning Systems rely primarily on macroeconomic and financial indicators that are able to measure the systemic risk in the banking sector (see Frankel and Saravelos (2012), Laeven and Valencia (2013) and Manasse et al. (2013) among others). We rely on Cummins and Weiss (2012) to define systemic risk as "the risk that an event will trigger a loss of economic value or confidence in a substantial segment of the financial system that is serious enough to have significant adverse effects on the real economy with a high probability".

The aim of this study is to introduce a new EWS to prevent systemic banking crises for 48 countries with various levels of per capita income from 1977 to 2010. Our paper develops a different empirical methodology which address the issue of both model and parameter uncertainties, namely Bayesian Model Averaging (BMA) (see Babecky et al., 2013 and Feldkircher, 2014). This technique has the advantage of minimizing the selection bias in determining the optimal set of early warning indicators. This study is, to the best of our knowledge, the first one that implements Bayesian Model Averaging for a large set of countries and over a long period in order to find robust signals of systemic banking crises. We consider 30 financial and macroeconomic indicators which were usually found useful in predicting banking crises in previous studies. We check for the relevance of our results through out of sample forecasts over 2006-2010. The predictive power of our model is based on a policy maker's loss function making a tradeoff between missed crises and false alarms.

We find that: (1) financial liberalization, GDP and credit growths and external total debt are decisive leading indicators of banking crises; (2) our model would have missed at most 2% of the crises over 2006-2010, though it would have send around 27% of false alarms; (3) the decisive signals found do not depend on the average level of per capita income of countries.

The paper is structured as follows. Section 2 gives an overview of the crisis events and the Bayesian Model Averaging technique. Section 3 describes the data. Section 4 discusses the results, the robustness of crisis signals and the forecasting performance. Section 5 concludes.

2. Methodology

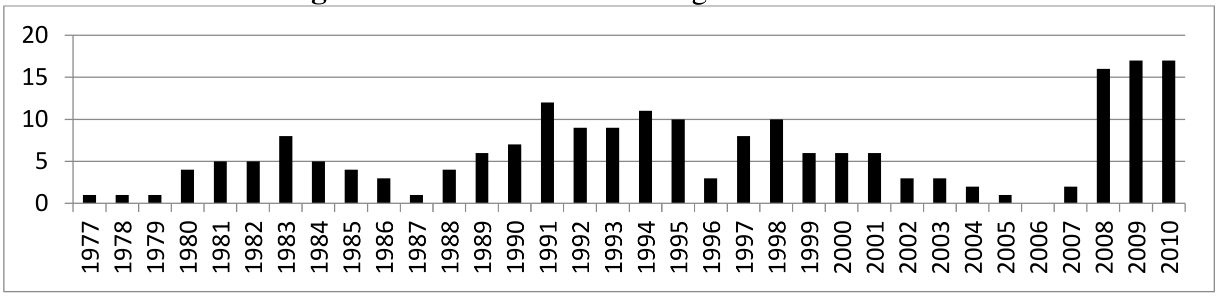
2.1 Banking Crisis events

Laeven and Valencia (2013) provide a dating procedure of banking crises effects by taking into account significant policy interventions. Moreover, their dataset includes banking crises in a large number of countries especially for those since 2008. Therefore, we adopt in the remainder of our analysis their classification. A banking event requires two conditions to be satisfied: first, the appearance of clear signs of financial distress in the banking system (i.e. bank runs, capital losses); second, significant policy interventions as a response of the losses in the banking system. Thus, at least three of the following six conditions must be met:

(1) A substantial liquidity support (5 % of deposits and liabilities to non-residents).
(2) A significant nationalization of the banking sector.
(3) Important guarantees (depending on the size of the economy).
(4) Bank restructuring costs of at least 3 % of GDP.
(5) Assets purchases amounting to a minimum of 5 % of GDP.
(6) Deposit freezes and/or bank holidays.

So the variable to be explained in our analysis is the binary Y_{it}. It takes the value of 1 if a banking crisis occurs during the year *t* and 0 otherwise:

Figure 1: Occurrence of banking crises 1977-2010



Source: Authors' calculations from Laeven and Valencia (2013).

Stylized facts on systemic banking crises in our sample are shown in figure 1. We observe four peaks in the number of banking crises. The first happened in the early 1980s when most Latin American countries and several African countries experienced episodes of financial distress as a result of credit expansion during the 1970s. The second peak corresponds to a rise in banking failures in the early 1990s in the advanced as well as in the developing world. A third peak occurred in the end of that decade as many emerging market countries and those in transition were hit by systemic bank runs. The early 2000s were a period of relative calm with few crises (Argentina in 2001 or Uruguay in 2002). The fourth wave followed the worldwide financial earthquake in the US economy in 2007.
In addition, given Laeven & Valencia's (2013) dataset, the average length of a banking crisis is 5 years in the advanced economies, 3 years in the emerging countries, and 2 years in the less developed economies. This can be explained by the fact that a large shock to a country could increase the duration of the crisis and its magnitude depending on its level of development. It can lead to contagion effects due to the global interdependence between domestic banking systems.

2.2 Bayesian Model Averaging

In a simple linear regression model for predicting banking crises with numerous explanatory variables we may write:

$$Y = \alpha_r + X_r\beta_r + \epsilon \qquad (1)$$

Where Y is a dummy variable indicating the onset of a banking crisis, α_r is a constant, β_r is a vector of coefficients, denotes a given subset of the candidate explanatory variables and ε is a white noise error term. Babecky et al. (2012) warn against two problems with doing a simple regression. First, an unsatisfactory approach is to put all potential variables together in one regression. This tends to decrease the estimation accuracy and might inflate the standard errors (parameters uncertainty). Second, the traditional approach - based on a sequence of tests to get the "best" model - could produce irrelevant results. In other words, an error can be made in each step since relevant variables can be excluded by rejecting a good model (model uncertainty).
Fortunately, Bayesian model averaging (BMA) is a suitable way to deal with both model and parameter uncertainties. This approach takes into account all possible models by averaging their posterior probabilities in order to get the most efficient model (see Hoeting et al., 1999). The

K number of potential explanatory variables yields 2^K potential different models. Thus, an exhaustive BMA analysis is virtually impossible. We employ Markov Chain Monte Carlo Comparisons (MC^3) first developed by Madigan et al. (1995) to deal with this problem. Information from the estimated models is then averaged using the posterior model probabilities that are implied by Bayes' theorem:

$$P(M_r|Y,X) \propto P(Y|M_r,X) \times P(M_r) \quad (2)$$

The posterior probability of model r, $P(M_r|Y,X)$, is proportional to the marginal likelihood of the model $P(Y|M_r,X)$ times the prior probability $P(M_r)$.
We use Posterior Inclusion Probabilities (PIP) to assess the robustness of each signaling variable. The formers are defined as the probabilities of a variable being in a model given the data. We refer to PIP as the sum of the model posterior probabilities of all models containing the variable β_i:

$$PIP_{\beta_i} = P(\beta_i \in Model|Y) = \sum_{r,\beta_i \in M} P(M_r|Y). \quad (3)$$

The higher the PIP, the more robust is the explanatory variable in the regression equation.
We perform four million iterations to obtain a sufficiently long Markov chain and thus more accurate estimates. We excluded the first million simulations to avoid disturbing the prior and to achieve better convergence (see O'Hagan. 1995). We follow Feldkircher and Zeugner (2009) to choose regressors from the hypergeometric distribution thanks to their BMS package on the ***R*** software.

3. Data and indicators

Our sample covers consists of annual data on 20 high-income countries, 17 upper-middle income ones and 11 lower-middle income others from 1977 to 2010. The selection of variables is driven by the empirics on early warning indicators of banking crises. These are:

1. Measures of solvency that assess a country's ability to honor its commitments such as annual credit growth to GDP, exchange rate depreciation, current account balance to GDP, total external debt to GDP;
2. Measures of liquidity such as the ratio of banking credits to bank deposits, M2 to total reserves and foreign exchange reserves (% GDP);
3. Indicators of the state of domestic affairs such as annual GDP growth and inflation;
4. Indicators of cross-border linkages through foreign direct investment (% GDP), financial liberalization, and trade openness.

Table IV in the appendix gives full details about these variables (definitions and sources).

4. Results

Bayesian Model Averaging yields an EWS with 12 variables out to the 23 variables with a large enough Posterior Inclusion Probability[1]. We exclude from our analysis variables with too many missing values like those for which multicolinearity would be an issue.
The Early Warning System requires the introduction of lagged explanatory variables in order to predict crises and to allow policy makers to act in time to limit the consequences of a systemic banking crisis on the economy. So, to determine the best lag structure, we tried several combinations of explanatory variables with delays of 0 to 3 years. We kept the model with the highest correlation between the Posterior Model Probability (PMP) and that deduced from the

[1] According to Raftery (1995) and Jeffreys (1998), a PIP is considered as weak if between 50% and 70%, positive if between 75 and 95%, strong if between 95% and 99%, and decisive if above 99%.

Markov Chain Monte Carlo procedure. Here, that correlation is 0.9968 suggesting that the algorithm should have converged reasonably well.

Table I: Bayesian Model averaging results

			BMA			OLS	
Decision	***Variables***	***lags***	***PIP***	***Posterior Mean***	***Post.SD***	***Coefficient***	***P.Value***
Decisive	Financial Liberalization index	0	1,00	-4,82E-02	1,13E-02	-4.665e-02	0,00
	GDP Growth (% annual)	1	1,00	-1,73E-02	4,18E-03	-1.917e-02	0,00
	Credit Growth (% du GDP)	0	1,00	2,49E-03	6,54E-04	2.723e-03	0,00
	Total external debt (% GDP)	0	0,99	1,67E-03	5,70E-04	1.888e-03	0,00
strong	Deposit interest rate (%)	3	0,98	8,97E-05	3,10E-05	9.492e-05	0,00
	Deposit money bank assets (% GDP)	1	0,95	1,81E-03	7,35E-04	9.492e-05	0,00
positive	Credit to government and state owned enterprises (% GDP)	0	0,93	-5,24E-03	2,35E-03	-7.139e-03	0,00
	Current Account Balance (% GDP)	3	0,83	-7,00E-03	4,45E-03	-7.833e-03	0,01
	General Government final consumption expenditure (annual % growth)	2	0,79	4,51E-03	3,19E-03	5.916e-03	0,01
	Exchange rate depreciation	3	0,75	6,51E-04	5,08E-04	9.795e-04	0,01
Weak	Trade Openness (% GDP)	3	0,59	-4,98E-04	5,42E-04		
	Net foreign assets to total assets	2	0,50	-7,98E-03	1,09E-02		
Very Weak	Bank credits to bank deposits	3	0,46	3,75E-04	5,50E-04		
	Total public debt (% GDP)	0	0,34	1,65E-04	3,51E-04		
	Foreign Direct Investment (net inflows) (% GDP)	3	0,29	-1,74E-03	4,65E-03		
	Industry value added (% GDP)	3	0,28	-6,55E-04	1,82E-03		
	Gross capital formation (% GDP)	2	0,25	-1,37E-04	4,95E-04		
	Foreign exchange reserves (% GDP)	1	0,24	1,27E-02	1,11E-01		
	Gross savings (% GDP)	3	0,23	-4,39E-05	1,32E-03		
	Final consumption expenditure (% GDP)	1	0,22	1,32E-04	9,49E-04		
	External Balance on goods and services (% GDP)	1	0,22	-1,98E-06	1,40E-03		
	Unemployment (% total labor force)	0	0,22	8,30E-05	1,76E-03		
	Inflation, GDP deflator (% annual)	0	0,21	1,67E-07	1,91E-05		

The right part of the table corresponds to the OLS estimation including only significantly robust variables from BMA. We employed OLS to have clearer interpretation of the coefficients from BMA. These OLS estimates are very similar to the BMA results for variables which are decisive and strong in estimating banking crises.

Furthermore, in complex models, it is difficult to work with posterior densities of the variables of interest especially when they are all included in the same regression. So, it will be not possible to approximate expectations of quantities and to have an informative interpretation. Addition to the posterior inclusion probabilities, it is interesting to look at the posterior distribution of the variables with the highest PIP. In figure 2 in the appendix, the two dashed vertical lines denote the 95 % posterior interval. We can see that GDP growth (% annual) and financial liberalization seem to be negatively associated to the occurrence of banking crises. In contrast, credit growth (% GDP), total external debt (% GDP), deposit interest rate (%) and deposit money bank assets (% GDP) are positively associated to banking crises.

We used the Chinn and Ito (2008) index of a country's degree of capital account openness as a measure of financial liberalization. Our estimates in Table I above show that greater liberalization reduces the likelihood of systemic banking crises. This result is consistent with Rancière et al. (2008) and Levine (2001) who show that a mature and opened domestic financial sector is negatively correlated with banking crises. Indeed, it promotes growth by increasing the stock market liquidity and improves the functioning of the national banking system. In addition, Shehzad and De Haan (2009) show that financial liberalization improves financial sector development which in turn contributes to economic growth. Their sensitivity tests confirm that liberalization is a potential indicator for predicting banking crises. The OLS estimation indicates that an increase by 1% in financial liberalization will generate a decrease in banking crises probability by 4.66%.

According to its posterior inclusion probability, GDP growth is also a decisive signaling factor of banking crises with a one year lag. This supports Kaminsky (1999) who finds that real GDP growth was the best leading indicator of banking crises. Laina et al. (2015) also find that GDP growth is the best indicator of banking crises. Indeed, it would have signaled 77% of the banking crises that 11 European countries witnessed from 1980 to 2015. As they show, lagging this indicator one or two years yields similar signaling properties, though a longer lag would provide additional time for policy reaction. Similarly, Rose and Spiegel (2011) point out GDP growth as the main macroeconomic indicator of banking fragility, though they were unable to find robust signals of financial crises. In our case, low GDP growth raises the probability of a banking crisis next year. In a depressed economy, it becomes more difficult for firms and households to repay their debt. Non-performing loans threatens banks' liquidity and solvency. This is consistent with Kaminsky and Reinhart (1999) who found that a decline in GDP growth is conducive to a banking crisis within 8 months.

Credit growth also plays a major role in explaining banking crises with a posterior inclusion probability near 1. Indeed, a high credit growth may deteriorate the quality of bank assets and cause problems in the banking sector. In addition, the increase in bank loans reduces liquidity and thus makes the banking system more vulnerable to a crisis. According to Frankel and Saravelos (2011), countries with strong credit growth have suffered more than others during banking crises. Credit expansion can cause high volatility in asset prices when the real estate bubbles burst which may lead to more severe banking crises.

The total gross external debt to GDP ratio plays a decisive role in determining banking crises too. This is line with the previous findings on the relationship between banking crises and sovereign debt crises. Reinhart & Rogoff (2008) concludes that government debt increases by 86% on average three years after a systemic event. It is not only the financial bailouts costs that cause this increase. Capital inflows and asset price bubbles also contribute to the increase in the public debt. The two authors argue that the high number of banking crises throughout history is associated with the repeated occurrence of sovereign defaults on external debt.

In this context, we can explain the effect of the accumulation of public debt on banking crises by two phenomena. First, the bailout costs are high and affect the credit risk of bank balance sheets. In this case, the government offers deposit guarantees to prevent bank runs (Ireland in 2009). Second, policymakers can implement recovery and resolution plans to boost domestic demand (see Babecký et al., 2012).

The variable deposit interest rate is considered as strong in explaining banking crises, in our case with a probability of inclusion 0.98. From a Logit model, Kraft and Galac (2007) conclude that a high deposit interest rate is an important indicator in predicting banking crises in Croatia. In addition, our result is consistent with Manasse et al. (2013). The latter authors find also that the deposit interest rate is the most important indicator of bank vulnerability. They view it as a lack of confidence in the banking system from the depositors. This situation may degenerate into a bank run and / or liquidity problems forcing banks to increase their deposit rates in order to avoid bankruptcy. According to the authors, if this indicator exceeds 16.2%, the probability of a crisis in the following year rises to 10.1%. Here, the deposit interest rate may signal systemic risk in the banking system up to three years before it occurs.

The importance of credit to the government and state owned firms is strongly and negatively related to the probability of a banking crisis (its PIP equals 0.96). According to Diamond (1984), banks have an incentive to diversify their portfolios to decrease individual borrows default risk.

One way to diversify risk is to finance government and state owned enterprises especially the small and medium-sized ones that have little access to the financial market.
Current account deficit, as a proportion to GDP, contributes positively to the occurrence of a banking crisis with a PIP equal to 0.80 and a lag equal to 3 years. Our results support Shehzad and De Haan (2009) who found that external imbalances are the most robust indicator of the impact of banking crises. According Berkmen et al. (2012), countries with high current account deficits tend to experience more severe crises since they are more vulnerable to external shocks.
As growth in the State's final consumption expenditure accelerates, there is a higher probability of a banking crisis in the economy. This indicator of the fiscal stance has a strong predictive power on systemic events as its PIP is equal to 0.76.
In addition, the depreciation of the national currency is an important leading indicator of banking crises with a 3 year delay. Also, the ratio of deposit money bank assets to GDP is strongly related to the occurrence of banking crises with one year lag. When the deposit banks are diversifying the default risk in their portfolios, they can be more exposed to liquidity and currency risks as argued by Demirguç-Kunt and Detragiache (1998).

4.1 Out of Sample Prediction

We built predictions on the occurrence of banking crises over 2006-2010. For each country in our sample we use posterior model probabilities obtained from 1977 to 2005 for the best model as weights to establish model averaged predictions of the dependent variable.
According to Manasse et al (2013) the evaluation of the prediction power of a model is sensitive to the choice of the probability threshold. We thus transformed the prediction probabilities into "alarms" above which we can classify an observation as signaling a crisis event. To do this, we perform a signal analysis to assess the quality of models prediction and to try to find a compromise between type I (missed crises) and type II errors (false alarms). We choose the threshold that minimizes the loss function given by Sarlin (2013):

$$L(\mu) = \mu T_1 P_1 + (1-\mu) T_2 P_2, \qquad (4)$$

with T1 represents type I errors which is the probability of not receiving a warning conditional on a crisis occurring (missed crises). T2 represents type II error which is the probability of receiving a warning conditional on no crisis occurring (false alarms). Sarlin and Peltonen (2013) recently call for balancing the type I error rate (type II, respectively) by the marginal probability of a crisis P1 (a quiet period P2, respectively) in the sample.
We calculate the relative usefulness like Sarlin (2013) to classify the performance level of competing models. This allows the policymaker to get the model with best forecasting performance. The relative usefulness is defined as:

$$U_r(\mu) = 1 - \frac{L(\mu)}{\min(\mu P_1, (1-\mu) P_2)} \qquad (5)$$

From expression (5), the relative utility of an Early Warning System is the poorest when U_r reaches 0 and the strongest when U_r tends to 1.

Table II: Out-of Sample Performance 2006-2010

Weight in loss function	*TP*	*FP*	*FN*	*TN*	T_1	T_2	$U_r\ (\mu)$
$\mu = 0.0$	1	0	51	188	98.07%	0%	NA
$\mu = 0.1$	1	0	51	188	98.07%	0%	1.92%
$\mu = 0.2$	1	0	51	188	98.07%	0%	1.92%
$\mu = 0.3$	11	3	41	185	78.84%	1.59%	7.69%
$\mu = 0.4$	11	3	41	185	78.84%	1.59%	12.5%
$\mu = 0.5$	45	29	7	159	13.46%	15.42%	30.76%
$\mu = 0.6$	49	34	3	154	5.76%	18.08%	50.64%
$\mu = 0{,}7$	49	34	3	154	5.76%	18.08%	66.20%
$\mu = 0{,}8$	49	34	3	154	5.76%	18.08%	75.53%
$\mu = 0{,}9$	51	51	1	137	1.92%	27.12%	68.08%
$\mu = 1{,}0$	52	157	0	31	0.00%	83.51%	NA

Note: TP: True positive (crisis), FP: False positive (false alarm), FN: False negative (missed crisis), TN: True negative (tranquil period), T1: Type I error, T2: Type II error.

The sample used for predictions contains 52 (years of) systemic banking crises and 188 (years of) tranquil times. From Table II, a quite high cut off point (μ higher or equal to 0.9 here) can lead to a model that always calls a crisis. At the opposite, a low cutoff point could miss almost all the crises between 2006 and 2010. The parameter μ can be viewed as the cost of missing a crisis whereas $(1 - \mu)$ relates to the cost of saving a healthy banking system. Assigning more weight on missed crises requires choosing a lower cutoff threshold for detecting a crisis. Thus, the predictive model would ignore fewer crises but send more false alarms. Table II shows that relative usefulness reaches its maximum at μ equal to 0.8 reflecting that trade-off: 3 crises are wrongly predicted while 3 others are not signaled. In comparison with previous findings, dealing with model uncertainty strengthens the quality of predictions.

4.2 Robustness Analysis

We split our sample into three subgroups of countries according to their gross national income per capita as it is done by the World Bank: the high, the upper middle, and the lower-middle-income countries. Then, we use BMA to find factors of systemic distress in each group of countries. We further explore whether the preceding early warning indicators remain robust to a change in the sample of countries.

Based on these new estimates, the ten leading indicators with a posterior inclusion probability above 0.5 in the general model still play a significant role in upper middle-income countries. In particular, credit growth, public expenditures, liquidity, GDP growth, deposit interest rate, and external debt are strongly related to the probability of occurrence of banking crises with inclusion probability above 0.9.

As a departure from our benchmark model, financial liberalization becomes less correlated with the occurrence of banking crises. The latter has a probability of inclusion of 0.75. As stressed by Demirguc-Kunt and Detragiache (1998), financial liberalization has less impact on banking sector problems where the institutional environment is strong.

Turning now to high-income countries, nine variables have a PIP greater than 0.5. Credit to government and state owned enterprises, M2 to total reserves, deposit money bank assets over GDP and financial liberalization are the most significant leading factors. An interesting finding is that unemployment has a PIP close to one while it was below 0.5 in the benchmark model. Credit growth is significant for this sub-group but with a 2-year lag. This is consistent with Babecký et al (2012) who argue that it may send a signal 4 years before a crisis.

Finally, only three variables appear robust in predicting banking crises in lower-middle-income countries: deposit money bank assets as a percentage of GDP, credit to government and state owned enterprises as a percentage of GDP and credit growth (% GDP). These poor findings may be due to the small number of countries in this group. All in all, our results do not change much across subsamples of countries: GDP growth, financial liberalization, credit growth are robust predictors of banking crises in our sample.

5. Conclusion

To conclude, this empirical study develops an Early Warning System for banking crises. We consider 48 countries with different income levels during 1977-2010. Our results show that 12 variables from 30 are found to have a predictive power in explaining banking crises.

Four variables are decisive in signaling banking crises: GDP growth, financial liberalization, credit growth (% GDP) and gross external debt (% GDP). In addition, deposit interest rate and credit to government and state owned enterprises help predict banking crises occurrence. Our results are consistent with the literature.

Moreover, the out-of-sample prediction over 2006-2010 has pretty good performances since 3 systemic events were missed out of 52 and only 3 wrong alarms would have been send. Finally, we found little discrepancies between the high-income and the upper-middle income groups results, though lower-middle income countries display strong specificities.

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A Appendix

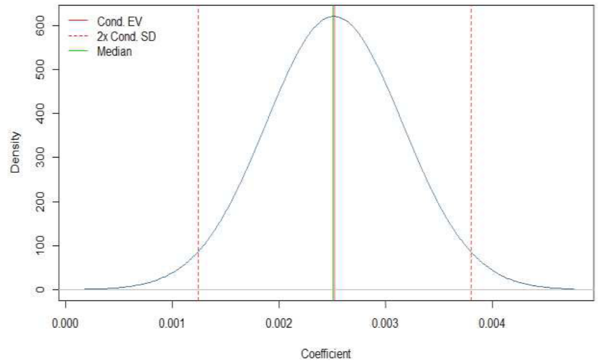
Table III: Banking crises dates according to Laeven and Valencia (2013)

Continents	Countries	Dates of BC	
		Start	End
Africa	Algeria	1990	1994
	Ivory Coast	1988	1992
	Egypt	1980	1980
	Morocco	1980	1984
	Nigeria	1991 2009	1995 2010
	Tunisia	1991	1991
Asia	India	1993	1993
	Indonesia	1997	2001
	Japan	1997	2001
	Korea	1997	1998
	Malaysia	1997	1999
	Philippines	1983 1997	1986 2001
	Sri Lanka	1989	1991
	Thailand	1997	2000
	Austria	2008	2010
	Belgium	2008	2010
	Denmark	2008	2010
	Finland	1991	1995
	France	2008	2010
	Germany	2008	2010
	Greece	2008	2010
	Hungary	1991 2008	1995 2010
	Ireland	2008	2010
	Italy	2008	2010
	Netherlands	2008	2010
	Norway	1991	1993
	Poland	1992	1994
	Russia	1998 2008	1998 2010
	Spain	1977 2008	1981 2010
	Sweden	1991 2008	1995 2010
	Switzerland	2008	2010
	Turkey	1982 2000	1984 2001
	United Kingdom	2007	2010
Latin-America	Argentina	1980 1989 1995	1982 1991 1995
	Bolivia	1986 1994	1986 1994
	Brazil	1990 1994	1994 1998
	Colombia	1982 1998	1982 2000
	Costa Rica	1987 1994	1991 1995
	Dominican Rep	1982 1998	1986 2002
	Ecuador	1982 1998	1986 2002
	El Salvador	1989	1990
	Mexico	1981 1994	1985 1996
	Panama	1988	1989
	Paraguay	1995	1995
	Peru	1983	1983
	Uruguay	1981 2002	1985 2005
	Venezuela	1994	1998
North America	United States	1988 2007	1988 2010

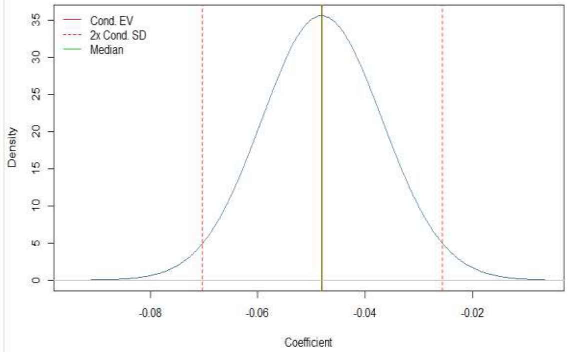
Table IV: Variables and definitions

Variables	Definitions	Sources
Banking credit to bank deposits (%)	Financial resources of the private sector with domestic banks to deposits (demand and savings).	IMF/IFS
Liquid liabilities (M3 as % GDP)	Currency and deposits in the central bank + Transferable deposits and electronic currency + Time and savings deposits, foreign currency transferable deposits, certificates of deposit, and securities repurchase agreements + Travelers checks, foreign currency time deposits, commercial paper, shares of mutual funds or market funds held by residents	World Bank/IFS
GDP growth (annual %)	Annual percentage growth rate of GDP at market prices based on constant local currency. Constant 2005 U.S. dollars.	World Bank
Net foreign assets to total assets (%)	Share of bank assets held by non-resident banks (50% or more of its shares are held by non-residents).	IMF/IFS
Inflation, GDP deflator (annual %)	Annual growth rate of the GDP implicit deflator.	World Bank
Money and quasi money (M2) to total reserves ratio (%)	Currency outside banks + Demand deposits other than those of the central gov. + time savings and foreign currency deposits of resident sectors other than the central gov.	World Bank
Central government debt (% GDP)	Loans to central government institutions net deposits to the gross domestic product.	World Bank
Claims on private sector (annual growth as % broad money)	Gross credit from the financial system to individuals, enterprises, nonfinancial public entities not included under net domestic credit, and financial institutions not included elsewhere.	World Bank
Deposit interest rate (%)	Rate paid by commercial or similar banks for demand, time, or savings deposits.	World Bank
External balance (% GDP)	Exports minus imports of goods and services over GDP	World Bank
Credit Growth (% GDP)	Domestic credit to private sector (loans, purchases of non equity securities, trade credits and other accounts receivable, credit to public enterprises) to GDP	World Bank
Gross savings (% GDP)	Gross savings are calculated as gross national income less total consumption, plus net transfers.	World Bank
Broad money to total reserves ratio	Currency outside banks + demand deposits other than those of the central gov. + time savings and foreign currency deposits of resident sectors other than the central gov. + bank and traveler's checks + other securities	World Bank / SFI
Unemployment, total (% labor force)	Labor force without work but available for and seeking job	World Bank
Current account balance (% of GDP)	Net exports of goods and services + net primary and secondary incomes	World Bank
Financial liberalization index	Composite indicator of restrictions on international financial transactions reported from the International Monetary Fund	http://web.pdx.edu/ito/Chinn-Ito_website.htm
Gross capital formation (% of GDP)	Outlays on additions to the fixed assets of the economy plus net changes in the level of inventories.	World Bank
Final consumption expenditure, etc. (% of GDP)	Household final consumption expenditure + general government final consumption expenditure	World Bank
Foreign exchange reserves (% GDP)	Gold and foreign currency held by the central bank and monetary authoritieies	Euromonitor International Statistics/ IFS
Trade openness (% GDP)	Trade is the sum of exports and imports of goods and services measured as a share of gross domestic product	World Bank
Exchange rate depreciation	Relative change of the official nominal exchange rate at the end of period	Gourinchas and Obstfeld (2012)
Industry, value added (% of GDP)	Added value without excluding consumption of fixed capital	World Bank
Foreign direct investment, net inflows (% GDP)	Equity capital, reinvestment of earnings, other long-term capital, and short-term capital	World Bank
Credit to government and state owned enterprises to GDP (%)	Ratio between credit to domestic money banks to the government and state owned enterprises and GDP	IFS/IMF
Total gross external debt to GDP	Government external debt and private debt issued by domestic private entities in a foreign jurisdiction	Reinhart et Rogoff (2011)
Gross public debt to GDP	Gross debt of Central Government	Reinhart et Rogoff (2011)
Money bank assets to GDP	Total assets held by deposit money banks as a share of GDP	IFS/IMF
Final consumption expenditure (% growth)	Average annual growth of final consumption expenditure based on constant local currency	World Bank
Bank liquid reserves to bank assets ratio (%)	Domestic currency holdings & deposits with monetary authorities over claims on other gov., nonfinancial public enterprises, private sector, and other banking institutions	World Bank
Interest rate spread (%)	Lending minus deposit rate charged by banks or similar banking institutions	World Bank

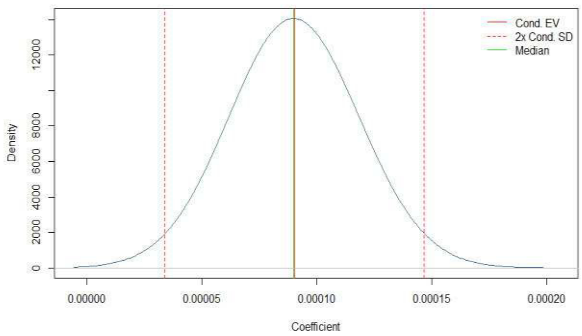
Figure 2: Coefficients Posterior Densities



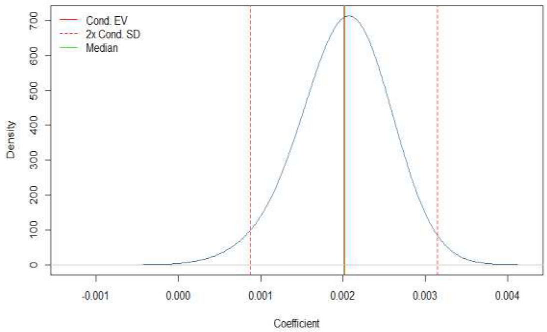
Financial Liberalization index



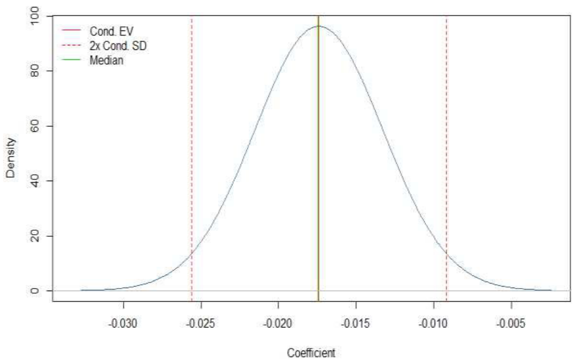
Credit Growth (% GDP)



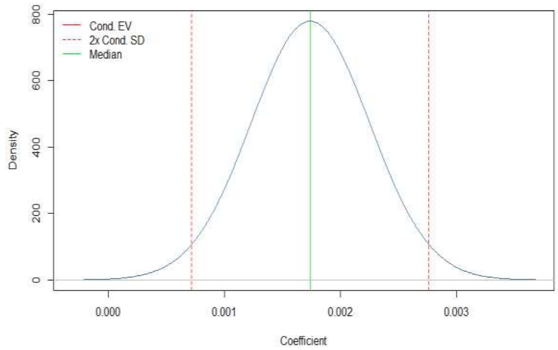
Deposit interest rate (%)



Deposit money bank assets (% GDP)



GDP Growth (% annual)



Total external debt (% GDP)