Banking Crises of the 1990s and 2000s in Developed Countries: How similar are they?

Thouraya Boudebbous
High School of Business of Tunis, University of Manouba
Tunisia
boudebbous.thouraya@gmail.com

Abstract: *The objective of this study is, on one hand, to determine whether the banking crises occurring in advanced economies in the 1990s and 2000s share the same roots, and on the other hand, whether aggregated accounting indicators are good predictors of crises in these economies. By means of the multivariate logit model, we have identified banking crises indicators for a set of 16 developed countries for the periods 1990-2006 and 2007-2012. Our results show the existence of certain similarities between the crises of the 1990s and 2000s, namely: a private credit boom and a deterioration of banks' balance sheets. In addition, we have tested the robustness of our results through the use of Bayesian averaging models. Our results have allowed us to confirm, in general, the robustness of the estimation results derived from the multivariate logit approach.*

Keywords: *Banking Crises; Multivariate Logit Model; Bayesian Averaging Model*

JEL Classification: *G01, C11*

Article History
Submitted: 17 November 2014
Resubmitted: 21 April 2015
Accepted: 5 May 2015

http://dx.doi.org/10.14706/JECOSS15526

Introduction

The global financial system experienced a serious crisis in July 2007. This crisis, initially affecting the American housing market, gradually spread to the entire global financial system. The crisis not only caused the default of some of the world's largest banking institutions, but was also at the root of a worldwide financial crisis comparable to that of the Great Depression of 1929.

The 2007-2008 banking crises have been the subject of numerous controversies as to their similarities and differences to past banking crises. Some claim that the recent crises are different in every aspect. They are chiefly due to a global savings glut and the absence of shadow banking system regulation (Adrian and Shin, 2009). Others maintain that the recent episodes of banking distress are not so different from the previous ones and that the latter show remarkable similarities to the former. According to Claessens and al. (2010b), these similarities are: First, the price of real and financial assets rising considerably in a number of countries before the crisis, notably in the United States and Europe. These prices reached 60% before the start of the crisis, which strongly recalls the price spike observed during major financial crises of the '90s, notably the Japanese crisis of 1997 (Caballero, 2010). A second similarity is the occurrence, in a number of major economies, of credit booms before the crisis, estimated at over 150% of GDP (Claessens and al., 2010b). Third, international financial integration facilitated large capital inflows, which contributed to the acceleration of GDP growth and massive credit growth, which in turn led to a strong fluctuation of global demand and a strong deterioration of current bank balances during the period preceding the crisis (Cardarelli and al., 2010). Fourth, the inadequacy of the regulation and prudential supervision framework (Bair, 2009).

In light of these findings, the goal of this study is twofold. First, to determine if the banking crises of the 2000s have shared causes with the crises of the 90s, and second, to determine if aggregated accounting indicators are robust banking crisis indicators.

Thus, in this study we propose first to identify banking crisis indicators by means of a limited dependent logit approach for a cross-sectional view of advanced economies during the period preceding the 2007-2008 banking crises, namely 1990-2006, and the period 2007-2012. Second, we propose to test the robustness of the results derived from the multivariate logit approach, by means of Bayesian statistics (BMA). Indeed, according to Cuaresma and Slacik (2009) and Babecký and al. (2012), the BMA approach has the advantage of reviewing different model combinations and of weighting them according to their adjustments in the model.

This paper will be organized as follows: The first section being an introduction, in the second section we briefly present a review of the literature on banking crisis indicators. In the third section, we present our methodology, namely: our country sample and our main data sources, our endogenous and exogenous variables, and our two econometric approaches. In the fourth section, we present a brief descriptive analysis of our data. We describe and discuss in the fifth section our empirical results. The last section is the conclusion.

Financial Crisis Indicators: Review of the Literature

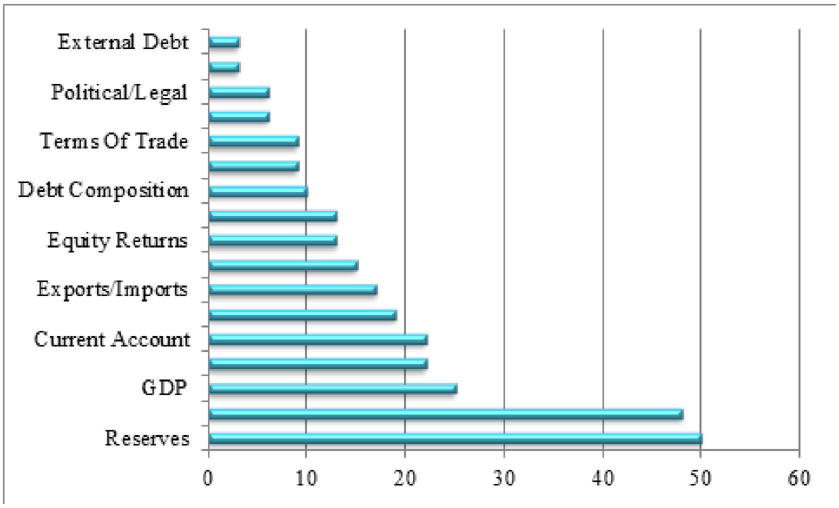
Banking crises are not limited to the 21st century. Indeed, during the past four decades, the global economy was marked by an increase in banking crises. According to Reinhart and Rogoff (2013), banking crises represent a threat to equal opportunity amongst emergent and advanced economies: most countries have had at least one banking crisis during the period of 1945-2008.

The reoccurrence of these crises, their magnitudes and their surprising and unpredictable character, and the financial costs associated with these episodes explain the research communities' interest in these events. They all attempt to define and to identify the risks and vulnerability factors of the banking sector in order to avoid the triggering of new crises, or to find adequate methods for the management and the prevention of this phenomenon before it reaches a catastrophic scale.

The first approaches, used for the detection of turbulence episodes, were based on country risk rating systems (Hawkins and Klau, 2000).Since the seventies, new techniques have been emerging, based on identifying early warning financial crisis indicators. The most commonly used methods for panel data limited dependent probit/logit models. The goal of this approach is to test the statistical significance of different indicators in determining the occurrence probability of a financial crisis across a cross-section of countries (Frankel and Saravelos, 2012).

The indicators commonly used in the empirical literature are: macroeconomic indicators, financial indicators, external indicators, and institutional and structural indicators. The pioneering work done in this field of research is that of Demirguc-Kunt and Detragiache (1998b, 2005), Hardy and Pazarbaşioğlu (1999) and Eichengreen and Arteta (2002). The results of their research suggest that a weak macroeconomic and financial environment marked by small GDP growth, a high increase in real interest rates, excessive credit growth, and strong inflation significantly increase the probability of the occurrence of banking crises at the international level. Recently, Frankel and Saravelos (2012) have conducted a vast review of the literature including over 80 works. The results of this investigation are reported in Figure 1.

Figure 1. Leading Indicators Deemed Relevant Financial Crises in more than 80 Works



Source : Frankel and Saravelos (2012, p.218)

From this figure, we see that the indicators that are most frequently statistically significant are the real exchange rate, foreign exchange reserves, credit growth, GDP, and the measurement of international trade. Nonetheless, the balance of payments, the terms of trade, contagion and institutional variables, capital flow variables, and the various measures of external debt do not seem to be robust early warning indicators of financial crises.

Furthermore, few empirical works have tested the relevance of microeconomic indicators linked to the individual situation of banks in the growth of banking distress probability. These indicators generally reflect the health and solidity of banking institutions and are grouped into five groups forming the acronym CAMEL (CAMEL refers to the five main components of the real situation of a banking institution, namely: Capital Adequacy, Asset quality, Management, Earnings and Liquidity). In addition, CAMEL is a tool allowing for the detection of potential risks that could lead to bank failures and, by extension, banking crises. Muhammad (2009) argues that the strength of these factors determines the global solidity of the bank.

The works of Gonzalez-Hermosillo and al. (1997), Männasoo and Mayes (2009) and Barrell and al. (2010) allowed the isolation of several conventional bank strength measures, derived from CAMEL, considered relevant to the detection of potential risks that could lead to serious problems in the banking sector, notably: (i) the ratio of capital to total assets**;** (ii) the ratio of non-performing loans or loan-loss provisions to total loans**;** (iii) the ratio of costs to revenue; (iv) the ratios of return on equity (ROE) and return on assets (ROA); (v) and the ratio of deposits to total assets, etc.

Methodology

Sample and Data Sources

This study considers a sample of 15 advanced countries and covers the period of 1990-2012. Our data is mainly extracted from the following databases: The World Development Indicators (WDI) of the World Bank, the International Financial Statistics (IFS) of the International Monetary Fund (IMF), Bankscope and the work of Laeven and Valencia (2013).

Overview of Study Variables

Definition and Construction of the Endogenous Bank Crisis Variable

A key element in our study is the construction of the binary banking crisis variable for our sample of countries. We have therefore identified and dated the episodes of financial distress during the 1990-2012 period, referring mainly to the list of Laeven and Valencia (2013).

According to them, a banking crisis is considered systemic if the following two conditions are met: "(1) significant signs of financial distress in the banking system and/or bank liquidations; and (2) significant banking policy intervention measures in response to significant losses in the banking system.

Political interventions in the banking sector are considered important if at least three out of six measures have been used: "(1) extensive liquidity support; (2) significant bank restructuring costs; (3) significant bank nationalization; (4) the setting up of important safeguards; (5) significant asset purchases; (6) freeze on deposits and declaration of bank holidays." (P. 228).

Table 1 gives the dates of banking distress episodes identified by this method for each country in our sample.

Table 1. Sample of Countries and Dates of Banking Crisis

Countries	**Dates of the Banking crises**
Germany	2008-2011
Austria	2008-2011
Belgium	2008-2011
Korea	1997-1998
Denmark	2008-2011
United-States	2007-2011
Finland	1991-1995
Greece	2008-2011

Ireland	2008-2011
Italy	2008-2011
Japan	1997-2001
Netherlands	2008-2011
United Kingdom	2007-2011
Spain	2008-2011
Sweden	1991-1995 ; 2008-2011*

Notes: * non-systemic banking crisis
Source: Laeven and Valencia (2013, p. 254-256)

Thus let be the dummy variable for banking crises that takes on a unit value the first year when a banking distress episode is identified in a country i, and a null value otherwise. Indeed, to the extent to which banking distress episodes occur an average of once per four years, Demirguc-Kunt and Detragiache (1998b) thus suggest to keep only the first year of a given crisis.

$$BCI_{it} = \begin{cases} = 1 & if\ crisis \\ = 0 & if\ not \end{cases} \tag{1}$$

Exogenous Banking Crisis Variables

The choice of exogenous variables comes both from the empirical literature and data availability.

We have grouped our explanatory variables in four distinct categories, namely:

The macroeconomic variables, which are: the stock returns of key market indices adjusted by the dividends ($returns_t$), the growth of gross domestic product ($gdpg_t$), real exchange-rate change ($vtcr_t$), and the real exchange rate (rir_t).

Financial variables, which are: private credit ($privcredit_t$), the ratio of credit to bank deposits ($ratiocreditdeposit_t$), and the ratio of deposits to the money supply M2 ($ratiodepositm2_t$).

The aggregated accounting variables (The aggregation and weighting depend on the size of the bank balance sheets for each country in our sample), which are: the ratio of cost to bank revenue ($ratiocostrevenu_t$), the ratio of capital to total bank assets ($ratiocapital_t$), and the ratio of return on equity (roe_t).

As well as the external variables, which are: opening up to international trade ($opness_t$), the ratio of external debt to GDP ($exterdebt_t$), the ratio of money supply M2 to international exchange reserves ($m2res_t$), and the flow of foreign direct invest mean to GDP (dfi_t).

In Table 2, we have presented various financial crisis indicators covered in this study with the sign of the theoretical link expected between each variable and the occurrence probability of a banking crisis and the source of collected data.

Table 2. Sources and Data Descriptions

Categories	Indicators	Descriptions	Sources	Expected Signs
Macroeconomic variables	$return_s$	Returns on equity indices	Bloomberg	-
	$gdpg_t$	Growth pf the gross domestic production	IFS	-
	ver_t	Change in real exchange rate	IFS	+
	rir_t	Real interest rate	IFS	+
Categories	Indicators	Descriptions	Sources	Expected Signs
Financial variables	$privcredit_t$	Growth of the credit to the private sector	WDI	+
	$ratiocredideposit_t$	Ratio of bank lending to bank deposits	IFS	+
	$ratiodepositm2_t$	Ratio of bank deposits to the money supply M2		-
Accounting variables	$ratiocapital_t$	Ratio of capital to total assets	Bankscope	-
	$roet$	Financial profitability ratio	Bankscope	-
	$ratiocostrevenue_t$	Cost to earnings bank ratio	Bankscope	+
External variables	$exterdebt_t$	Ratio of external debt to GDP	IFS	+
	$opness_t$	Trade openness measured by the sum of exports and imports to GDP	WDI	-
	$m2res_t$	Money supply M2 to International exchange reserves	WDI	+
	dfi_t	Foreign direct investment portfolio as a percentage of GDP	WDI	+

Source: Authors' own work

Furthermore, several indicators, such as, for example, the variables reflecting bank asset quality, the budgetary deficit, the current account deficit, and institution quality and judicial system quality, have not been kept in this study because of data unavailability.

Econometric Approaches

The purpose of this study is to determine, on one hand, if the banking crises of 2007-2008 in advanced economies share the same origin as the crisis episodes of the 90s, and, on the other hand, to determine whether aggregated accounting indicators are robust banking crisis indicators in these economies.

To do this, we propose, first, to identify banking crisis indicators by means of a limited dependent variable logit approach. Second, we propose to test the robustness of results derived from this approach by means of Bayesian statistics (BMA).

In the following, we propose to present briefly these two methods.

Limited Dependent Variable Logit Models

Limited dependent variable logit models were introduced by Eichengreen and al. (1994) and Frankel and Rose (1996). Unlike the "signals" approach, the logit/probit limited dependent variable models provide an explanatory probability simultaneously for the group of explanatory variables in question. Similarly, these models allow one to take into account the marginal contribution of each variable to crisis event genesis. In addition, the empirical literature validates the relevance of these models in the identification of financial crises in the case of panel data (Davis and Karim, 2008).

The model is as follows:

$$y_{it} = X_{it}^{'}\beta + \varepsilon_{it} \tag{2}$$

Where i=1,…, N and t=1,…, T

The explanatory variable is a binary variable that has a value of 1 during crises and 0 otherwise; is the vector of N coefficients relative to explanatory variables to estimate; is the matrix of explanatory variables; and is the residual matrix. identically and independently distributed and follows the logistic distribution.

The Cumulative distribution function is given by:

$$Prob\ (y_{it} = 1|X_{it}^{'}) = F(X_{it}^{'}\beta) \tag{3}$$

The likelihood function associated with this model is written as follows:

$$L = \prod_{t=1}^{T}\prod_{i=1}^{N} Prob\,(y_{it} = 1|X_{it}^{'}) \tag{4}$$

$$L = \prod_{t=1}^{T}\prod_{i=1}^{N} F(X_{it}^{'}\beta)\, y_{it}\, [1 - F(X_{it}^{'}\beta)]\,(1 - y_{it}) \tag{5}$$

The logarithm associated with the likelihood function is written as follows:

$$\log L = \sum_{t=1}^{T}\sum_{i=1}^{N}\{y_{it}\; log[F(X_{it}^{'}\beta)] + (1 - y_{it})\; log[1 - F(X_{it}^{'}\beta)]\} \tag{6}$$

The occurrence probability of the crisis is a function that is obtained by the maximum likelihood method.

Formally, the crisis probability is as follows:

$$Prob\,(y_{it} = 1|X_{it}^{'}) = \frac{e^{X_{it}^{'}\beta}}{1 + e^{X_{it}^{'}\beta}} \tag{7}$$

Bayesian Model Averaging

Bayesian Model Averaging (BMA) has the advantage that it takes into account different model combinations, weighting them according to their adjustments in the model. In addition, the BMA approach provides for each variable an estimate of their coefficients as weighted averages of all models included in the model-space (If we have k variables, the model space will consist of 2^k models) . Thus, the weighting coefficients correspond to the posterior probability of inclusion in each model in the model-space.

The only existing works using this approach in the domain of early warning financial crisis indicators are those by Cuaresma and Slacik (2009), Babecký and al. (2012), Boudebbous and Chichti (2013) and Feldkirche (2014).

We use the BMA approach to identify banking crisis indicators in a list of potential k indicators. We consider the following linear regression model:

$$Y = \alpha_\gamma + X_\gamma \beta_\gamma + f_\gamma + \varepsilon \tag{8}$$

Where is a binary financial crisis variable; is the constant; is a coefficient vector; refers to a subset of all the relevant and available explanatory variables, namely, potential early warning indicators X the fixed effects component; and is the white noise error term.

The number K of potential explanatory variables gives 2^K potential models. The indicator γ is used to refer to a specific model among the 2^K models. Thus, an average is then calculated from the information originating from the model, by using the *a posteriori* probabilities of the model implemented by the Bayes Theorem:

$$p(M_\gamma|y,X) \propto p(y|M_\gamma,X)\, p\,(M_\gamma) \tag{9}$$

With is the *posterior* probability of the model, which is proportional to the marginal likelihood of the model . It facilitates the dating of the model's *a priori* probability

The robustness of a variable in the explanation of the dependent variable can be expressed by the probability that a given variable will be included in the regression. It is assimilated to the posterior inclusion probability (PIP), which is calculated as follows:

$$PIP = p(\beta_\gamma \neq 0|y) = \sum p(M_\gamma|y) \tag{10}$$

Only variables with a PIP greater than or equal to 0.5 are considered robust determinants of the dependent variable.

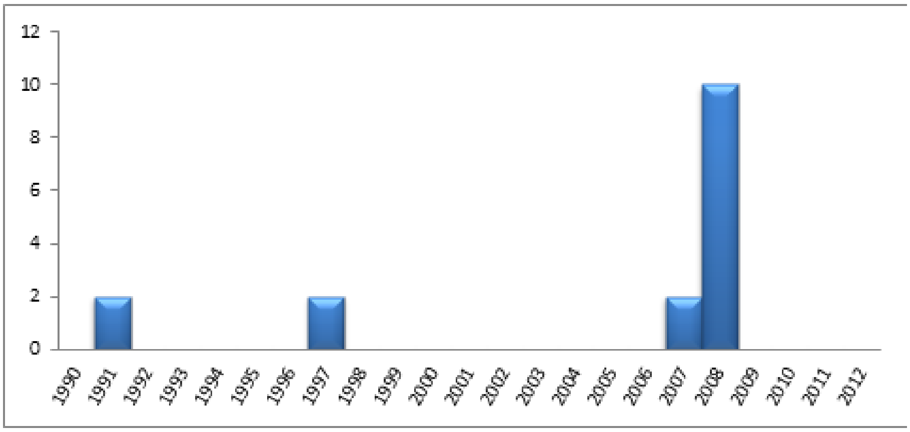
Descriptive Analysis of the Data

Our sample has 15 countries. Our choice was, on one hand, due to data availability and, on the other, to the fact that these countries have had serious banking crises during the past decades.

We use the panel data with annual frequencies relating to the periods 1990-2006 and 2007-2012.

Figure 2 provides a few stylized facts on the banking crises of our sample. We conclude that during the 90s, the frequency of these crises was relatively low, with a maximum of 4 crisis episodes. However, the 2000s were characterized by a higher frequency of banking crises, with a maximum of 16 crisis episodes.

Figure 2. Frequency of Financial Crises in Advanced Economies over the Period 1990-2012



Source: Authors' calculations

In Table 3 are descriptive statistics of the study's set of variables. The analysis of descriptive statistics reveals that for the two periods of the study, certain explanatory variables such as: the market index returns , the exchange rate variation, (), private credit (), the ratio of credit to bank deposits (), the ratio of deposits to the M2 money supply (), the ratio of return on equity (), the ratio of costs to bank revenue (), opening to international trade (), the ratio of external debts to GDP () and the ratio of the M2 money supply to international exchange reserves () on the considered period show very significant fluctuations in comparison to other variables. Furthermore, the number of observations varies from one variable to another because of data unavailability.

Table 3. Descriptive Statistics

Variables	Obs	Mean	Std. Dev.	Min	Max
Period 1990-2006					
BCI_t	255	0.0156863	0.124503	0	1
$Returns_t$	236	6.282372	23.5557	-50.4519	183.365
$gdpg_t$	244	2.079508	2.134638	-7.52457	8.71127
rir_t	245	1.707938	2.321738	-5.46483	10.5684
ver_t	235	0.2941392	12.52485	-18.3922	107.034
$privcredit_t$	252	140.4538	79.90097	48.1827	497.532
$ratiocreditdeposit_t$	224	121.7227	48.81322	50.5599	305.278
ratiodepositm2	175	77.38498	15.84425	38.1715	104.132
$ratiocapital_t$	194	5.925373	2.115559	1	17
roe_t	182	7.593985	13.54288	-2	19

$ratiocostrevenu_t$	188	63.37078	18.55205	12.004	79.056
$m2res_t$	250	28.01272	52.41858	3.54092	630.376
$exterdebt_t$	255	62.84706	31.94798	9	164
$opness_t$	255	71.86413	37.42231	15.924	183.624
dfi_t	242	3.055958	4.71857	-5.89528	26.6532

Period 2007-2012					
BCI_t	90	0.4888889	0.502677	0	1
$Returns_t$	76	3.050686	23.7773	-67.5697	183.365
$gdpg_t$	90	1.511482	2.616534	-8.97498	8.71127
rir_t	68	1.380545	2.252967	-5.46483	10.5684
ver_t	90	0.7454545	12.56793	-18.3922	107.0336
$privcredit_t$	90	139.8145	62.4631	48.1827	346.21
$ratiocreditdeposit_t$	64	124.2889	50.35807	47.2884	313.334
ratiodepositm2	70	74.30398	16.55875	38.1715	104.132
$ratiocapital_t$	71	5.941463	2.035587	1	17
roe_t	75	5.519231	25.38191	-4	19
$ratiocostrevenu_t$	74	61.52309	16.13664	12.004	85.254
$m2res_t$	90	35.09396	67.12172	2.61948	656.961
$exterdebt_t$	72	64.26606	33.69485	9	189
$opness_t$	88	76.88712	39.75442	15.924	192.407
dfi_t	89	3.33932	5.461651	-6.71487	36.4308

Note: Mean, Std. Dev, Max and Min, respectively denote the average, standard deviation, maximum and minimum.

Source: Authors' own work

We have used Pearson's correlation test to detect if there are collinearity problems. The results of these tests are presented in Table 4. Simultaneously, we have included in our regressions all the variables because all the coefficients are less than 50% for the two periods of the study.

Table 4. Correlation Matrices

a. Period 1990-2006							
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1)	1						
(2)	0.4408*	1					
(3)	0.1093	0.0461	1				
(4)	0.1029	-0.0899	0.0177	1			
(5)	-0.1872*	-0.2714*	-0.2547*	-0.0081	1		
(6)	-0.0563	-0.0227	-0.0742	0.1053	-0.0801	1	
(7)	0.0569	0.0144	0.2123*	0.018	0.1098	-0.4110*	1
(8)	0.0668	0.0508	-0.0627	-0.0693	-0.0741	-0.068	0.0796
(9)	0.1447*	0.3914*	-0.0073	-0.0196	-0.0986	0.0468	-0.1506*
(10)	-0.0379	-0.0556	0.4153*	0.1154	0.0029	-0.1229	0.1914*
(11)	-0.0726	-0.0891	-0.2183*	-0.0333	0.2314*	0.1612*	-0.2899*
(12)	0.0165	-0.1769*	-0.0051	-0.0162	0.2112*	-0.4661*	0.3404*
(13)	0.0174	0.0043	-0.2948*	0.0115	-0.1959*	0.2928*	-0.4796*
(14)	-0.0109	0.0575	-0.2293*	0.0439	-0.0598	0.1555*	-0.2211*

Variables	(8)	(9)	(10)	(11)	(13)	(14)	(15)
(8)	1						
(9)	0.1039	1					
(10)	-0.2583*	-0.1667*	1				
(11)	-0.0672	0.0047	-0.3029*	1			
(12)	-0.0182	-0.1495*	0.1746*	-0.1440*	1		
(13)	-0.3886*	-0.0111	-0.2706*	0.2253*	-0.1044	1	
(14)	-0.1816*	-0.0085	-0.2410*	0.3240*	-0.1133*	0.4605*	1
b. Period 2007-2012							
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1)	1						
(2)	0.2846*	1					
(3)	0.0407	-0.0928	1				
(4)	0.2220*	-0.078	0.0722	1			
(5)	-0.0955	-0.3159*	-0.0928	0.0276	1		
(6)	-0.0315	0.036	-0.1176	0.0663	-0.0879	1	
(7)	-0.0118	-0.0286	0.2693*	0.1183	0.2086*	-0.3870*	1

(8)	0.0249	0.1266	-0.0282	-0.0566	-0.0107	-0.0103	0.0732
(9)	0.0897	0.2839*	-0.1236	0.101	-0.0255	0.2810*	-0.2233*
(10)	-0.0102	-0.1479	0.4554*	0.1429	0.094	-0.1538	0.2502*
(11)	0.0464	0.022	-0.2306*	-0.0285	0.1409*	0.048	-0.2848*
(12)	0.1098	-0.1566*	0.0674	0.0307	0.1017	-0.4570*	0.2848*
(13)	0.0864	0.1051	-0.3401*	-0.0358	-0.2637*	0.2227*	-0.4417*
(14)	0.0819	0.1321*	-0.3082*	0.0677	-0.1238	0.1600*	-0.2706*
Variables	(8)	(9)	(10)	(11)	(13)	(14)	(15)
(8)	1						
(9)	0.0579	1					
(10)	-0.2221*	-0.4460*	1				
(11)	-0.0356	0.2037*	-0.2059*	1			
(12)	-0.1034	-0.1138	0.1880*	-0.1383	* 1.0000		
(13)	-0.3437*	0.1446	-0.3210*	0.0977	-0.0333	1	
(14)	-0.1063	0.1011	-0.2132*	0.215	* -0.1388*	0.4721*	1

Notes:(1):$returns_t$; (2): $gdpg_t$; (3): rir_t; (4): ver_t; (5): $privcredit_t$; (6): $ratiocreditdeposit_t$; (7): *ratiodepsiotm2*; (8): $ratiocapital_t$; (9): roe_t; (10): $ratiocostrevenu_t$; (11): $m2res_t$; (12): $exterdebt_t$; (13): $opness_t$; (14): dfi_t; and (*) means that the coefficients of correlations are significant at the threshold of 5%.

Source: Authors' own work

Empirical Results and Discussion

We remember that the objective of this study is to determine, on one hand, whether the banking crises occurring in advanced economies in 2007 and 2008 have shared roots with past crisis episodes, and, on the other hand, to test the contribution of aggregated accounting indicators in explaining these crises.

We have identified, first, by means of multivariate logit models for a set of developed countries during the periods 1990-2006 and 2007-2012, the early warning banking crisis indicators.

Our estimation approach is as follows: First, in model (a) we have included only macroeconomic indicators. Then, in model (b) we have simultaneously integrated our macroeconomic and financial indicators. Finally, in model (c) we have introduced at the same time our macroeconomic, financial, and external indicators. Second, we have reestimated models (b) and (c) by introducing aggregated accounting indicators, namely models (d) and (e).

Model (a): Macroeconomics indicators

$$BCI_{it} = \beta_1 return_{it} + \beta_2 gdpg_{it} + \beta_3 rir_{it} + \beta_4 ver_{it} + \varepsilon_{it} \qquad (11)$$

Model (b): Macroeconomics and financial indicators

$$BCI_{it} = \beta_1 return_{it} + \beta_2 gdpg_{it} + \beta_3 rir_{it} + \beta_4 ver_{it} + \beta_5 privcredit_{it} + \beta_6 creditdeposit_{it} + \beta_7 depositm2_{it} + \varepsilon_{it} \quad (12)$$

Model (c): Macroeconomics, financial and external indicators

$$BCI_{it} = \beta_1 return_{it} + \beta_2 gdpg_{it} + \beta_3 rir_{it} + \beta_4 ver_{it} + \beta_5 privcredit_{it} + \beta_6 creditdeposit_{it} + \beta_7 depositm2_{it} + \beta_8 m2res_{it} + \beta_9 exterdebt_{it} + \beta_{10} opness_{it} + \beta_{11} dfi_{t} + \varepsilon_{it} \quad (13)$$

Model (d): Macroeconomics, Financial and accounting indicators

$$BCI_{it} = \beta_1 return_{it} + \beta_2 gdpg_{it} + \beta_3 rir_{it} + \beta_4 ver_{it} + \beta_5 creditpriv_{it} + \beta_6 creditdeposit_{it} + \beta_7 depositm2_{it} + \beta_{12} ratiocapital_{it} + \beta_{13} roe_{it} + \beta_{14} ratiocostrevenu_{it} + \varepsilon_{it} \quad (14)$$

Model (e): Macroeconomics, financial, accounting and external indicators

$$BCI_{it} = \beta_1 return_{it} + \beta_2 gdpg_{it} + \beta_3 rir_{it} + \beta_4 ver_{it} + \beta_5 creditpriv_{it} + \beta_6 creditdeposit_{it} + \beta_7 depositm2_{it} + \beta_{12} ratiocapital_{it} + \beta_{13} roe_{it} + \beta_{14} ratiocoutaurevenu_{it} + \beta_8 m2res_{it} + \beta_9 exterdebt_{it} + \beta_{10} opness_{it} + \beta_{11} dfi_{it} + \varepsilon_{it} \quad (15)$$

In the first place, we have estimated the set of these models on the two considered periods by means of fixed effects and random effects methods. In the second place, we have used the Hausman test to choose between these two methods. The results of this test validate the relevance of the fixed effects estimation method, since the chi-square probability of the Hausman test is significant at 1%.

The estimation results of models (16) and (17) are given in Tables 5 and 6, respectively. Model (16) concerns the estimation results of the period 1990-2006, while model (17) focuses on estimation results of the period 2007-2012.

Finally, we have evaluated the predictive quality of our set of models. The choice of a critical threshold, namely the critical probability above which the supervisor emits an alert, is inspired by the work of Kaminsky and Reinhart (1999). These authors suggest the use of a critical threshold that minimizes the noise-to-signal ratio, unlike Demirguc-Kunt and Detragiache (2005), who suggest the use of the sample crisis frequency.

The results of the test show that model (16.e) has a greater predictive power than models (16.a), (16.b), (16.c), and (16.d). Indeed, model (16.e) emits fewer false alarms than the other models (namely 37.14 %) and also has a lower noise-to-signal ratio (namely, 0.44). Thus, the specification that brings together the macroeconomic, financial, accountable, and external indicators seems to be the one best suited for the period 1990-2006.

Similarly, the results of this test show that model (17.d) has a better predictive power than models (17.a), (17.b), (17.c), and (17.e). Indeed, model (17.c) emits more accurate alarms (namely 69.00 %) and also has a lower noise-to-signal ratio (namely 0.71). This suggests that a specification that takes into account macroeconomic, financial and accounting indicators would appear to be the most appropriate for the period 1990-2012.

The estimation results of model (16.e) suggest that economic downturn characterized by a growth of real GDP and real interest rates and appreciation of the real exchange rate are robust banking crisis indicators at 1%. This supports the work of Borio and al. (2010) who argue that the banking crises from the 90s in the Nordic countries can be considered twin episodes because they were all found to correspond with simultaneous exchange rate crises. Indeed, in 1992, fears of devaluation of the Swedish krona and the Finnish markka triggered various speculative attacks against these currencies. To deal with these attacks and to defend their respective currencies, these countries significantly raised their interest rates, by more than 60% in Sweden and 15% in Finland, which significantly increased the fragility of the banking sector and the recession (Borio and al., 2010).

Similarly, the estimation results of model (17.e) suggest that a private credit boom, a decrease in the capital ratio and the growth of the ratio of costs to bank revenue are good indicators of banking crises. This suggests that the erosion of banking capital and the growth of banking charges are precursors of banking crises, which is in agreement with the work of Hays and al. (2009), Männasoo and Mayes (2009) and Barrell and al. (2010).

Table 5. Estimation Results of Logit Models of Banking Crises over the Period 1990-2006

Model (16) : Dependent Variable					
Variables	Model (a)	Model (b)	Model (c)	Model (d)	Model (e)
$Returns_t$	-2.05** (-0.029840)	0.45 (0.048122)	0.33 (0.036936)	1.41 (0.062829)	1.41 (0.050549)
$gdpg_t$	-2.48** (-0.622514)	-1.65* (-0.532871)	-1.74* (-0.647875)	-1.67* (-0.546290)	-2.96*** (-0.45918)
rir_t	3.46*** (0.092888)	2.79** (0.086240)	2.82*** (0.142907)	2.55** (0.274048)	3.06 *** (0.336072)
ver_t	1.14 (0.010512)	1.20 (0.028499)	0.41 (0.037164)	0.49 (0.048735)	2.31** (0.068359)
$privcredit_t$		2.82*** (0.072654)	1.93* (0.065686)	1.65* (0.110718)	1.90* (0.087406)

ratiocreditdeposit$_t$		-2.41** (-0.007815)	-1.52 (-0.004154)	-0.20 (-0.003208)	1.34 (0.003546)
ratiodepositm2		-3.43*** (-0.280375)	-2.93*** (-0.47593)	-1.79* (-0.328627)	-0.78 (-0.530227)
ratiocapital$_t$				-0.85 (-0.592645)	-1.98* (-0.603392)
roe$_t$				-0.96 (-0.05384)	0.33 (0.047863)
ratiocostrevenu$_t$				1.75* (0.177059)	2.64*** (0.153894)
m2res$_t$			0.77 (0.02900)		-2.07** (-0.02951)
exterdebt$_t$			1.09 (0.005670)		-0.18 (-0.009407)
opness$_t$			2.34** (0.228135)		2.33** (0.165604)
dfi$_t$			-0.23 (-0.137445)		1.13 (0.125702)
Number of crises	3	3	3	3	3
Observation	158	120	116	104	98
Log-likelihood	-38.99	-26.19	-20.05	-11.01	-9.78
LR chi2	29.10	49.98	60.88	45.07	37.76
chi2 of Hausman test	12.10	19.32	27.85	28.65	33.24
Effect	Fixe	Fixe	Fixe	Fixe	Fixe
Threshold Classification of 20 %					
% correct predictions	57.14	66.67	73.13	78.50	86.79
% crises correctly predicted	55.94	64.08	69.61	77.38	84.34
% flase alerts	72.41	60.66	53.45	50.00	37.14

Ratio Noise/ signal	1.29	0.95	0.77	0.65	0.44

Notes: Ratio noise / signal =% false alarms compared to the % of correct crises ; t-statistic significant at the threshold of (***) 1%, (**) 5% and (*) 10%; () Coefficients.

Source: Authors' own work

Table 6. Estimation Results of Logit Models of Banking Crises over the Period 2007-2012

Model (17) : Dependent Variable					
Variables	Model (a)	Model (b)	Model (c)	Model (d)	Model (e)
$returns_t$	-3.05*** (-0.029013)	-2.18** (-0.030984)	1.81* (0.029756)	1.65* (0.043033)	1.83* (0.064246)
$gdpg_t$	-2.61*** (-0.197041)	-0.50 (-0.162857)	-3.72*** (-0.168214)	-0.35 (-0.173729)	-0.70 (-0.189329)
rir_t	0.82 (0.072584)	2.38** (0.123538)	2.91*** (0.288707)	0.64 (0.213353)	-2.23** (-0.18926)
ver_t	2.77 (0.048038)	2.63*** (0.069458)	1.49 (0.049240)	0.81 (0.052523)	2.20** (0.063600)
$privcredit_t$		4.23*** (0.062747)	2.89*** (0.078891)	2.77*** (0.136620)	2.21** (0.153550)
$ratiocreditdeposit_t$		2.30** (0.002265)	2.35** (0.003617)	0.15 (0.00610)	0.05 (0.003404)
ratiodepositm2		-4.28*** (-0.163423)	-4.92*** (-0.326412)	-2.70*** (-0.402322)	-2.06** (-0.47472)
$ratiocapital_t$				-1.73* (-0.773069)	-1.92* (-0.817551)
roe_t				-1.78* (-0.098542)	-2.19** (-0.087473)
$ratiocostrevenu_t$				2.15** (0.108559)	1.87* (0.112308)

$m2res_t$			0.83 (0.019715)		0.11 (0.015443)
$exterdebt_t$			3.21*** (0.004038)		0.29 (0.007143)
$opness_t$			3.75*** (0.206525)		-1.63 (-0.126561)
dfi_t			-1.88* (-0.147975)		-0.33 (-0.092384)
Number of crises	3	16	16	16	16
Observation	158	186	183	145	138
Log-likelihood	-38.99	-47.80	-37.62	-17.91	-15.38
LR chi2	29.10	75.89	97.50	76.39	78.60
chi2 of Hausman test	12.10	26.85	38.72	42.58	41.75
Effect	Fixe	Fixe	Fixe	Fixe	Fixe
Threshold Classification of 20 %					
% correct predictions	48.30	46.67	60.64	72.66	70.80
% crises correctly predicted	38.46	60.00	50.76	69.00	62.37
% flase alerts	69.36	58.12	58.04	49.21	47.30
Ratio Noise/signal	1.80	0.97	1.14	0.71	0.76

Notes: Ratio noise / signal =% false alarms compared to the % of correct crises ; t-statistic significant at the threshold of (***) 1%, (**) 5% and (*) 10%; () Coefficients.

Source: Authors' own work

Furthermore, the estimation results of model (16.e) show that a drop in the ratio of the money supply to foreign reserves and a higher degree of openness to international trade are good indicators of banking crises. These results contradict the theoretical and empirical literature, notably the work of Caprio and Klingebiel (1996) who show that the majority of countries that were affected by the banking crises suffered declines in their international trading of at least 10%, and a growth in the money-supply-to-foreign-reserve ratio.

The estimation results of model (17.d) show that the growth of market returns is that only macroeconomic variable that is a good predictor of banking crises at 10%. This contradicts the work of Kaminsky and Reinhart (1999), which shows that the period preceding financial crises is generally characterized by fluctuations in equity prices of about 40% compared to those recorded during non-crisis periods. However, these results corroborate those of Caballero (2010) and Claessens and al. (2010b) who found that asset prices in the United States and other advanced countries grew by over 30% before the 2008 crisis to reach a threshold of over 60% just before the onset of the crisis.

Similarly, the estimation results of model (17.d) show that significant bank credit growth and a decrease in the deposit-to-M2-money-supply ratio are robust banking crisis indicators. Indeed, these results are broadly consistent with the work of Davis and Karim (2008) who argue that, working for profit maximization, the banks would lower their requirements for credit granting, offering risky loans to clients who are not necessarily creditworthy. In consequence, with interest rates growing, many borrowers would find themselves unable to meet their obligations. A significant percentage of loans would therefore become doubtful accounts, deteriorating the banks' balance sheets, which in turn would cause investors to lose confidence in the banking system. As a result, a bank-run will follow.

In addition, the estimation results of model (17.d) suggest that a higher ratio of costs to bank revenue, a decrease in the ratio of capital to total bank assets, and a smaller ratio of financial result to equity costs are robust banking crisis result indicators. These results are significantly compatible with the work of Männasoo and Mayes (2009) and Barrell and al. (2008).

In summary, as our results show, it seems that the only points shared between the banking crises of 2008 and those of the 90s in advanced countries are: private credit boom and the deterioration of bank balance quality measured by the decrease of the capital ratio, and the growth of the cost-benefit ratio.

Furthermore, unlike past crises, neither slowed economic activity, nor external shocks seem to have contributed to triggering the 2000s banking crises. Indeed, these crises seem to have been caused by the overvaluation of financial asset prices that had reached dizzyingly high levels.

Our results also validate the relevance of aggregated accounting indicators in the onset of banking crises in advanced economies. Indeed, the insufficiency of net equity leads to an increase in banking institutions' exposure to various sources of risk, such as, for example, credit risk, market risk, and operational risk, which reduces their ability to deal with shocks affecting their balance sheets (Gonzalez-Hermosillo and al., 1997 and Barrell and al., 2008). Similarly, the growth of banking costs relative to operating revenue reflects the ineffectiveness of the operational procedures used by bank directors and, more generally, the inefficient management of banking institutions. This can lead to deterioration of the institutions' profitability (Hays and al., 2009). However, the decrease in the financial profitability ratio, measured by the relation between the financial income and equity, does not seem to be a relevant indicator in cases of past crises. The decline of this ratio is generally a precursor to solvency problems (Grier, 2007).

We have tested, secondly, the robustness of the estimation results of multivariate logit models for the two periods under consideration in this study by means of Bayesian model averaging (BMA).

Indeed, BMA has the advantage of taking into account different model combinations, weighting them according to their adjustments in the model. In addition, the BMA approach allows the estimation of each variable's coefficients as weighted averages of the group of models included in the model space. Thus, if we have 14 variables, the model space will consist of 2^{14} models, meaning 16 384 models. The weighting coefficients correspond to the posterior inclusion probability in each model in the model space.

The estimation results of model (18) more specifically the posterior inclusion probabilities (PIP), the expected posterior parameter values, the conditional posterior sign as well as the posterior variance parameters, are given in Tables 7 and 8. The estimation results of model 18.a that correspond to the 1990-2006 period are given in Table 7. According to table 7, the estimation results of the BMA model are broadly consistent with the results of model (16.e) by the multivariate logit approach (Table 5).

Table 7. Estimation Results of BMA Models of Banking Crises over the Period 1990-2006 (Model 18.b)

Variables	PIP	Post Mean	Post SD	Cond.Pos.Sign
$gdpg_t$	0.9999999	-0.13353645	0.02089559	0
rir_t	0.9999724	0.15534119	0.0269798	1
$opness_t$	0.8992601	0.0159717	0.00849031	1
$privcredit_t$	0.8288625	0.10632599	0.07031128	0.9999322
$ratiocapital_t$	0.8215073	-0.15760263	0.10689843	0.00000031
ver_t	0.6635472	0.02450355	0.02557618	1
$m2res_t$	0.6123305	0.03553483	0.04380036	1
$ratiocostrevenu_t$	0.5005264	0.16522002	0.25460909	1
$ratiocreditdeposit_t$	0.4758206	-0.0023855	0.00419197	0.00015362
$return_t$	0.4744605	-0.02688313	0.05047469	0.01499962
ratiodepositm2	0.4728869	-0.42110641	0.71890055	0.01872499
$exterdebt_t$	0.4341035	0.0042335	0.00830433	0.99952015
dfi_t	0.3947972	0.09860624	0.29774734	0.93293309
roe_t	0.375888	0.01361733	0.08101365	0.8047804

Note: PIP, Post Mean, Cond.Pos.Sign denote subsequently inclusion probability, a posteriori average, a posteriori variance and conditional posterior sign.

Source: Authors' own work

Similarly, the estimation results of model 18.b, which cover the 1990-2006 period are given in Table 8. According to table 8, the estimation results of the BMA model are broadly consistent with the results of model (17.d) by the multivariate logit approach (Table 6). In contrast, contrary to the estimation results of the logit approach, which suggest the non-robustness of real interest rate growth as a banking crisis indicator, the estimation results of the BMA model confirm the relevance of this indicator. Furthermore, for most of the models in the BMA model space, the ratio of credit to banking deposits is significantly positive, unlike the results of the logit model.

Table 8. Estimation Results of the BMA Models of Banking Crises over the Period 2007-2012 (Model 18.b

Variables	PIP	Post Mean	Post SD	Cond.Pos.Sign
$ratiocostrevenu_t$	1	0.17269815	0.02548505	1
ratiodepositm2	1	-0.30048066	0.04172048	0
$privcredit_t$	0.963872	0.09407296	0.03701112	1
roe_t	0.9478391	-0.04140546	0.0178719	0
$return_t$	0.9076954	0.03398578	0.01724719	1
$ratiocapital_t$	0.7594058	-0.18177464	0.14174879	0
rir_t	0.6213379	0.11407877	0.11885064	0.99985226
ver_t	0.4711599	0.01748926	0.02687917	1
$m2res_t$	0.4499	0.02694111	0.04367449	0.98589573
$opness_t$	0.3439876	-0.01128604	0.01347132	0.03099666
$gdpg_t$	0.3426264	-0.09407158	0.26462416	0.00288535
$ratiocreditdeposit_t$	0.3085081	-0.00381585	0.01715114	0.04506733
$exterdebt_t$	0.3025314	0.00124951	0.00903262	0.8971883
dfi_t	0.299575	-0.08117392	1.66181598	0.27757243

Note: PIP, Post Mean, Cond.Pos.Sign denote subsequently inclusion probability, a posterior average, a posterior variance and conditional sign-post.

Source: Authors' own work

We may, in consequence, conclude that the results of the BMA approach, for the two studied periods, are broadly consistent with those obtained by the multivariate logit approach. Indeed, most of the indicators identified as good predictors of banking crises have preserved their sign and significance by means of the BMA approach. We can thus confirm the robustness of the estimation results of the multivariate logit approach. We can also conclude that the BMA approach is robust and can be used as an alternative to limited dependent variable models (logit) as an early warning system for banking crises.

Conclusion

This work provides a new perspective on banking crises by, on one hand, determining if the 2006-2007 banking crises in advanced economies have shared roots with the crises of the 90s, and, on the other hand, testing the relevance of aggregated accounting indicators in explaining these crises.

To this end, we have, first, identified banking crises indicators by means of a logit limited dependent variable approach on a cross-section of advanced economies during the period 1990-2006, which precedes the onset of the banking crises of 2007-2008, and during the period 2007-2012. Our results suggest the presence of certain similarities between the banking crises of 2007-2008 and the crises occurring in advanced economies in the 90s, which are: private credit boom and the deterioration of bank balance sheet strength, measured by a decrease in the capital ratio and a rise in the cost-benefit ratio. Furthermore, neither slowing down of economic activity nor external shocks seems to have contributed to triggering the banking crises of the 2000s, unlike past episodes of crises. Our results also validate the relevance of aggregated accounting indicators in the onset of banking crises in advanced economies.

Second, we have tested the robustness of results derived from the multivariate logit approach through Bayesian model averaging (BMA). In effect, the BMA approach has the advantage of taking into account model uncertainty by considering different model combinations, weighting them according to their adjustments in the model (Crespo Cuaresma and Slacik, 2009; and Babecký and al., 2012).

The results of the BMA approach have allowed confirmation of the robustness of the multivariate logit approach's estimation results, because most of the indicators identified as good predictors of banking crises by the logit approach have preserved their sign and significance through the BMA approach. We can also conclude that the BMA approach is robust and can be used as an alternative to limited dependent variable models (logit) as an early warning system for banking crises.

This study is not exhaustive. A possible extension of this research could be to test the predictive powers of the identified banking crisis indicators beyond our sample.

References

Adrian, T., & Shin, H. S. (2009). The shadow banking system: implications for financial regulation. *Financial Stability Review, 13*, 1-10.

Babecký, J., Havránek, T., Matějů, J., Rusnák, M., Šmídková, K., & Vašíček, B. (2012). *Banking,* Debt, and Currency Crises: Early Warning Indicators for Developed Countries. *Macroprudential Research.* European Central Bank.

Bair, S. C. (2009). Managing the transition to a safer financial system. *Financial Stability Review, 13*, 1-24.

Barrell, R., Davis, E. P., Karim, D., & Liadze, I. (2010). Bank regulation, property prices and early warning systems for banking crises in OECD countries. *Journal of Banking & Finance, 34*, 2255–2264.

Borio, C., Vale, B., & Von Peter, G. (2010). Resolving the financial crisis: are we heeding the lessons from the Nordics? *Working Paper*. Bank for International Settlements.

Boudebbous, T., & Chichti, J. E. (2013). Determinants of systemic banking crises in the Countries of Central and Eastern Europe. *Journal of Business Studies Quarterly 5*(1), 103-124.

Caballero, R. J. (2010). *The* "Other" Imbalance and the Financial Crisis. *Working Paper*. National Bureau of Economic Research.

Caprio, G. Jr., & Klingebiel, D. (1996). *Bank Insolvency: Bad Luck, Bad Policy, or Bad Banking?* In M. Bruno & B. Pleskovic (Ed.), World Bank Conference on Development Economics (pp. 1-29).

Cardarelli, R., Elekdag, S., & Kose, M. A. (2010). Capital inflows: Macroeconomic implications and policy responses. *Economic Systems 34*, 333-356.

Claessens, S., Dell'Ariccia, G., Igan, D., & Laeven, L. (2010b). The Global Financial Crisis: How Similar? How Different? How Costly? *Journal of Asian Economics, 21*(3), 247–264.

Cuaresma, J. C., & Slacik, S. (2009). On the determinants of currency crises: The role of model uncertainty. *Journal of Macroeconomics, 31,* 621-632.

Davis, P. E., & Karim, D. (2008). Comparing early warning systems for banking crises. *Journal of Financial Stability, 4*, 89–120.

Demirgüç-Kunt, A., & Detragiache, E. (1998b). *The Determinants of Banking Crises in Developed and Developing Countries*. IMF Staff Working Papers. International Monetary Fund.

Demirgüç-Kunt, A., & Detragiache, E. (2005). Cross-country empirical studies of systemic bank distress: A survey. *National Institute Economic Review, 192* (1), 68-83.

Edison, H. J. (2003). Do indicators of financial crises work? An evaluation of an early warning system. *International Journal of Finance and Economics, 8*, 11–53.

Eichengreen, B., & Arteta, C. (2002). Banking crises in emerging market: presumptions and evidence. In M. I. Blejer & M. Skreb (Ed.), *Financial Policies in Emerging Markets* (pp. 47-94). MIT Press.

Eichengreen, B., Rose, A. K., & Wyplosz, C. (1994). *Speculative attacks on pegged exchange rates an empirical exploration with special reference to the European Monetary System*. Economic Policy. Working Paper. The National Bureau of Economic Research.

Feldkircher, M. (2014). The determinants of vulnerability to the global financial crisis 2008 to 2009: Credit growth and other sources of risk. *Journal of International Money and Finance, 43,* 19-49.

Frankel, J. A., & Rose, A. K. (1996). Currency crashes in emerging markets: An empirical treatment. *Journal of International Economics, 41*, 351-366.

Frankel, J. A., & Saravelos, G. (2012). Can leading indicators assess country vulnerability? Evidence from the 2008–09 global financial crisis. *Journal of International Economics, 87*, 216–231.

Gonzalez Hermosillo, B., Pazarbaşioğlu, C., & Billings, R. (1997). Determinants of banking system fragility: A case study of Mexico. *IMF Staff papers, 44*(3), 295-314.

Grier, W. A. (2007). *Credit Analysis of Financial Institutions* (2 ed.): Euromoney.

Hardy, D., & Pazarbaşioğlu, C. (1999). Determinants and Leading Indicators of Banking Crises: Further Evidence *IMF Staff Papers, 46*(3), 247-258.

Hawkins, J., & Klau, M. (2000). *Measuring Potential Vulnerabilities in Emerging Market Economies*. Working Paper. Monetary and Economic Bank for International Settlements

Hays, F. H., De Lurgio, S. A., & Gilbert Jr., A. H. (2009). Efficiency ratios and community bank performance. *Journal of Finance & Accountancy, 1*, 1-15.

Kaminsky, G. L., & Reinhart, C. M. (1999). The twin crises: the causes of banking and balance-of-payments problems. *American Economic Review, 89*(3), 473-500.

Laeven, L., & Valencia, F. (2013). Systemic banking crises database. *IMF Economic Review, 61*(2), 225–270.

Männasoo, K, & Mayes, D. G. (2009). Explaining bank distress in Eastern European transition economies. *Journal of Banking and Finance, 33*, 244-253.

Reinhart, C. M., & Rogoff, K. S. (2011). From financial crash to debt crisis. *American Economic Review, 101*(5), 1676-1706.

Reinhart, C. M., & Rogoff, K. S. (2013). Banking crises: An equal opportunity menace. *Journal of Banking & Finance, 37*(11), 4557-4573.