A MACROPRUDENTIAL FRAMEWORK FOR EUROPEAN COMMERCIAL BANKING SECTOR. AN EARLY WARNING SYSTEM WITH LOGIT APPROACH

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Abstract

In the recent years, European commercial banks experienced several periods of banking system instability and turbulence. In this paper we introduce a forward-looking indicator for the banking system turbulence period based on information from the literature. We define a banking turbulence when provision for loan losses on total assets ratio exceeds a certain threshold. The proposed threshold is the value corresponding to the 90th quantile of the distribution of provision for loan losses on total assets ratio. We identify significant macroprudential warning indicators (such as growth, inflation rate, unemployment rate, change in terms of trade, public surplus/deficit and GDP GDP per capita). We use the Logit methodology approach on a panel with 56 commercial banks during the period 2002q1-20011q4 and out of sample estimation for the period 2010q1-2011q4.

Keywords: early warning system, banking crisis and turbulence, Logit approach, panel data

JEL classification:

1. Introduction

There is a quietly large literature on banking crisis prediction via so called early warning systems (EWSs) which use a range of estimators from

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panel Logit (as in Demirgüc-Kunt and Detragiache 2005, Davis and Karim 2008a) to signal extraction (Kaminsky and Reinhart 1999, Borio and Lowe 2002, Borio and Drehmann 2009) to binary recursive trees (Duttagupta and Cashin 2008, Karim 2008, Davis and Karim 2008b).

Financial stability and the identification of macroprudential leading indicators signaling the risks of the banking system are of major importance for commercial banks, central banks and supervisory authorities. The stability of a banking system ensures the optimal allocation of capital resources in an economy, and regulators therefore aim to prevent banking system crises and turbulences and their associated adverse feedback effects on the real economy. Our paper introduces an index for banking system turbulences. We define a banking turbulence when provision for loan losses on total assets ratio exceeds a certain threshold. The proposed threshold is the value corresponding to the 95th quantile of the distribution of provision for loan losses on total assets ratio. Applying the Logit methodology on a panel with 56 European commercial banks we identify significant macroprudential warning indicators (such as growth, inflation rate, unemployment rate and change in terms of trade).

We structure the paper as follows, in Section 2 we outline the specialized literature. In Section 3 we describe the data used in our paper and the panel Logit methodology we have adopted. In Section 4 we provide the results and some analysis of the robustness of our results. Section 5 concludes and makes some suggestions regarding policy implications. We also include Appendices on patterns of marginal effects and on correlation of our right hand side variables.

2. Literature review

Numerous studies have analyzed the early warning systems, as well as currency crises, financial crises or countries crisis and speculative attacks but only a small part focused on banking crises and banking system fragility (Eray Yucel,2011).

Dimas B. Wiranata Kusuma and AbuAsif (2012) analyzed Islamic banking sectors during the period January 2004-December 2006.They build Islamic banking sector fragility index (IBSF) in order to determine the crisis period. IBSF index comprises two main leading indicators of banking crises, namely (i) Islamic bank deposits (DEP), and (ii) domestic credit (DC) and is calculated by: IBSF=(IBSF=(——— ———), where μ is the sample mean and the standard deviation of the IBSF, and m the threshold levels. This paper exercises some threshold levels which are applied by Kaminski (1997), Park (2001), Garcia (1999), and Lestano (2003), namely 3 standard deviation (SD), 1,1 SD, 1,5 SD, and 1.0 SD. The methodology used is signal approach and the independent variables used are the same as in the model of Herrera-Garcia: M2/reserve growth, credit growth, real effective exchange rate and inflation rate. All selected leading indicators indicate the ability for correctly forecasting the crises occurance with at least 24 months before the onset of crises. Kibritcioglu, Aykut (2002) used a similar approach for 22 countries for different periods in 1961-2001.

E. Philip Davis, Dilruba Karim, Iana Liadze (2011) analyzed 20 countries in Latin America and Asia that have emerging financial systems. The banking crisis dependent variable is similar to Demirgu¨c¸-Kunt and Detragiache (2005) model. Authors used explanatory variables used in previous studies: Demirgu¨c¸-Kunt and Detragiache (2005) and Davis and Karim (2008a): real growth (%) (D), real interest rate (%) (RIR), inflation (%) (INFL), fiscal surplus/ (%) (FISCY), M2/foreign exchange reserves (%) (M2RES),real domestic credit growth (%) (DCRED),real GDP per capita (PC),domestic credit/ (%) (DCREDY), depreciation (%) (DEPREC),change in Terms of Trade (%) (DTT). Using Logit methodology and binary tree recognition it is found different crisis determinants across regions, implying inappropriate global samples.

Barrell, R., E.P. Davis, D. Karim and I. Liadze (2010) used Logit methodology on 14 OECD countries during the period 1970-2007. The authors used a similar approach as Demirgüc-Kunt and Detragiache (2005) but they introduced three specific explanatory variables: liquidity ratio (%) (LIQ), unweighted capital adequacy ratio (%) (LEV) and real property price growth (%) (RHPG). It is finding strong effects from capital adequacy and liquidity ratios as well as property prices, and an unsignificant impact from traditional variables.

Dieter Gramlich, Gavin L. Miller , Mikhail V. Oet , Stephen J. Ong (2010) proposed a design principles and a theoretical framework for EWS. Authors proposed five steps in analyzing and determine an early warning systems for banking crises: first it is necessary to establish the objectives and outcome of an EWS, the risk measures,the risk factors, the risk model, and the least step is handling an EWS: treating an EWS as a comprehensive set of elements, use of different models in parallel, running models for different scenarios and running models for different time intervals that are updated frequently.

Davis, E.P. and D. Karim (2008) used multivariate Logit models and signal approach methdology on a global panel with 105 countries. They used two approaches to determine the banking crises period, the first is calculated after the Demirg¨uc¸-Kunt and Detragiache (2005) model and the second is determine after the Caprio and Klingebiel (2003) model, also it is used the Demirg¨uc¸-Kunt and Detragiache (1998) explanatory variables. It is suggested that Logit is the most appropriate approach for global EWS and signal extraction for country-specific EWS. Variables highlighted include terms of trade, growth, the fiscal balance, M2/reserves and credit growth, alone or leveraged with deposit insurance.

Daley J. K. Matthews and K. Whitfield (2005) used binomial Logit models and multiLogit models on total population of banks in Jamaica between 1992 and 1998. A total of 34 banks was assessed, 18 of which were classified as failed. The sample of failed banks was compiled from public data sources, including financial statements and annual reports, the website of the Central Bank, and media reports. The independent variables are financial strength (proxied by capital adequacy, asset quality, earnings and liquidity ratios), the quality of management (proxied by inefficiency ratios), and other variables representing size, audit status, ownership, bank risk and the general macroeconomic state. Several indicators – particularly inefficiency, size and the proxy for the macroeconomic state – discriminate between failed and non-failed banks.

Bongini, P., L. Laeven and G. Majnoni (2002) analyzed a sample that include a total of 29 banks, during the period January 1996-December 1998. Authors used Logit robust estimate.The dependent variable takes the value 1 if the financial institution is experiencing distress (closed, recapitalized suspended or merged), and 0 otherwise. Independent variables comprise the CAMEL specification estimated in Bongini, Claessens and Ferri (2001).Balance sheet indicators, integrated with information about banks' ownership structure, was the most effective predictor of bank distress. Ratings, on the other side showed a much lower predictive.

Demirgüç-Kunt, A. and E. Detragiache (1998) analyzed a panel that include developed and developing economies over the period 1980-1994 using multivariate Logit crisis models. They suggest that there is a banking crises period if at least one of the following conditions is accomplished: the ratio of non-performing assets to total assets in the banking system exceeded 10 percent, the cost of the rescue operation was at least 2 percent of , banking sector problems resulted in a large scale nationalization of banks, and extensive banks rusn place or emergency measures such as deposit freezes,prolonged bank holidays, or generalized deposit guarantees were enacted by the government in response to the crises. Authors used a large number of indicators: real growth, rate of change of the NER, nominal interest rate minus the contemporaneous rate of inflation, rate of change of the deflator, budget surplus/, m2/reserves, domestic credit to private sector/, bank liquid reserves/assets, real domestic credit growth, dummy for an explicit deposit insurance scheme, real GDP per capita, index of the quality of law enforcement. It is found that banking crises tend to appear when the macroeconomic environment is weak, especially when inflation and real interest rate is high and growth is low.

3. Data and methodology

Our dataset covers 56 commercial banks from 5 countries:Denmark, Germany, Greece, Italy and Norway, over the period 2002q1-2009q4. Our variables cover the period 2002q1-2011q4, but we partition the sample into 2002q1-2009q4 for in-sample estimation whilst we use 2010 and 2011 datas for out-of-sample prediction.

Table 1: List of variables (with variable key)

Explanatory Variables List	Estimated Effect	Source
Gowth	-	Eurostat
Unemployment Rate	+	Eurostat
Public Deficit Surplus	-	Eurostat
Inflation Rate Index B2005	+	Eurostat
Change In Terms Of Trade	-	Eurostat
Real GDP per capita from Previous Period	-	Eurostat

Source: authors' calculation

In line with other studies, we define a banking turbulence when provision for loan losses on total assets ratio exceeds a certain threshold. The proposed threshold is the value corresponding to the 90th quantile of the distribution of provision for loan losses on total assets ratio. Thus, the banking turbulence period are the ones that register a ratio above the corresponding value of the 90^{th} quantile.

In order to align our study with previous work, we include the explanatory variables used by Demirgüc-Kunt and Detragiache (2005) and Barrell, R., E.P. Davis, D. Karim and I. Liadze (2010). We construct these variables using the Eurostat database.

The Logit Methdology. In order to detect and predict periods of banking turbulences we rely on Logit regressions. Logit regressions allow us to determine the sign and significance of the influence of each right hand side variable in predicting periods of banking turbulences. In our paper we use the logistic distribution which relates the probability that the dummy takes a value of one when the banking turbulences occurs and zero otherwise.

(1)

where Yit is the banking turbulences dummy for country i at time t, β is the vector of coefficients, Xit is the vector of explanatory variables and F(β Xit) is the cumulative logistic distribution. The log likelihood function which we use to obtain actual parameter estimates is:

(2)

Although we can easily interpret the signs on the coefficients as representing an increasing or decreasing effect on turbulence probability, the values are not as intuitive to interpret. In order to determine the magnitude of the coefficients we calculate marginal effect which is a good approximation to the amount of change in Y that will be produced by a 1unit change in .

The goodness of fit measures for logistic regression used in our paper are: the likelihood statistic L and chi-square tests, pseudo-R-square statistics, Hosmer and Lemeshow test (2000) and classification table.

The likelihood statistic L and Chi-Square Goodness Of Fit Tests and Deviance is used to asses the fitness of the model. The sampling distribution of t he – 2 log L has a chi-square distribution with q degrees of freedom under th e null hypothesis that all regression coefficient s of the model are zero (Fienberg, 1998). A significant p-value provides evidence that at least one of the regression coefficients for an explanatory variable is non zero.

Logistic regression does not have an equivalent to the R-squared that is found in OLS regression; however, many people have tried to come up with one. There are a wide variety of ***pseudo-R-square statistics***.

Cox & Snell's mirrors approach 2 from the list above. The ratio of the likelihoods reflects the improvement of the full model over the intercept model (the smaller the ratio, the greater the improvement).

McFadden's R-squared is a less common pseudo- R-squared variant, based on log-likelihood kernels for the full versus the intercept-only models. The log likelihood of the intercept model is treated as a total sum of squares, and the log likelihood of the full model is treated as the sum of squared errors. The ratio of the likelihoods suggests the level of improvement over the intercept model offered by the full model. If comparing two models on the same data, McFadden's would be higher for the model with the greater likelihood.

McKelvey & Zavoina mirrors approach 1 from the list above, but its calculations are based on predicting a continuous latent variable underlying the observed 0-1 outcomes in the data. The model predictions of the latent variable can be calculated using the model coefficients (NOT the log-odds) and the predictor variables. *(See: http://www.ats.ucla.edu/stat/mult_pkg/faq/general/Psuedo_RSquareds.htm)*

<u>Hosmer and Lemeshow (2000)</u> developed a goodness-of-fit test for logistic regression models with binary responses. They proposed grouping based on the value of the estimated probabilities. This test is obtained by calculating the Pearson chi-square statistic from the 2×g table of observed and expected frequencies, where g is the number of groups. The statistic is written:

where;

is the number of observation in the group.

s the number of event outcomes in the group.

Is the average estimated probability of an event outcome for the group.

The Hosmer and Lemeshow statistic is then compared to a chi-square distribution with (g – 2) degree of freedom. David W. Hosmer,, Stanley Jemeshow and Rodney X. Sturdivant (?:160) suggest that a value that tends to 1 indicates that the model seems to fit well.

The predictive success of the logistic regression can be assessed by looking at the ***classification table***.We can choose a cutoff value on the probability scale and classify all predicted values above that as predicting an event, and all below that cutoff value as not predicting the event. The most commonly used cutoff value is 0.5. Thus, we can create a table as follows:

	+	-
Predicted positive (above cutoff)	a	b
Predicted negative (below cutoff)	c	d

We hope for many results in the a and d boxes, and few in the b and c boxes, indicating a good fit. We can determine the following quantities: and . Higher sensitivity and specificity indicate a better fit of the model.

4. Results and robustness tests

In order to obtain our final model specification, we use a general approach, starting with all the variables listed in Table 2, using the sample period 2002q1-2009q4 and leave the period 2010 and 2011 for forecasting. In order to capture developments in the economy prior to the turbulance period and to avoid endogenous effects of this stress period on the explanatory variables we lag all variables by one, two and three period.

Table 2: Logit model regression - the general and the specific approach

Variable	General form: all variables	
	Coefficient	**z-statistic**
L3.dunemployment	1.058***	-0.24
L3.inflation	1.923***	-0.488
L2.dgowth	-0.447***	-0.092
L2.changeiintermsoftrade	-0.256***	-0.059
L.publicsurplusdeficit	-0.061***	-0.015
L.realppercapita	-0.126***	-0.032
_cons	-3.602***	-0.254
Number of obs.	1211	

Source: authors' calculation

The results in Table 2 clearly show that an increased in growth, change in terms of trade, public surplus and real GDP per capita have a beneficial impact of reducing crisis and turbulence probability and an increased in unemployment rate and inflation rate determine the increase of crisis and turbulence probability.

We complement our statistical results with tests of performance. In terms of such performance, the standard way to assess EWS is in terms of their ability to distinguish crisis and non-crisis periods.we use the likelihood statistic L and chi-square tests, pseudo-R-square statistics, Hosmer and Lemeshow test (2000) and classification table.

Table 3: Goodness of Fit Measures for Logit model

Tests of performance		
Likelihood statistic L and chi-square tests	Log pseudolikelihood	-240.80066
	Prob > chi2	0.0000
Pseudo-R-square statistics	Cox & Snell's	0.138
	McFadden's R-squared	0.271
	McKelvey & Zavoina	0.391
Classification Table	Sensitivity	31,91%
	Specificity	98,03%
	Correctly classified	92,90%
Hosmer and Lemeshow test (2000)	Hosmer-Lemeshow chi2(8)	18.51
	Prob > chi2	0.1177

Source: authors' calculation

The Log pseudolikelihood is -240.80066 and the model Chi-Square statistic determine if the overall model is statistically significant ($p=0.00<0.05$). There are several measures intended to mimic the R-squared analysis. A McFadden's R-squared of 0.271 is considered satisfactory. For Cox & Snell's and McKelvey & Zavoina R –squared it is desired a large value which tends to 1.In our research Cox & Snell's R –squared is 13,8% and McKelvey & Zavoina R –squared is 39,1%. This indicates that the model seems to fit quite well.

The model's classification table is given in the above table (see Table 3). The specificity is, not unexpectedly, high at 98,03%, and sensitivity is quietly good at 31,91% and overall 92,90% correctly classified. A low sensitivity means that 64 of banking turbulences were not recorded even if it actually occurred. This model, besides having good fit, classifies quite well. Table x (Appendix) gives details of the in-sample predictive performances for each baning institution and the relation of any false alarms to the timing of turbulance period. During the period 2002q1-2009q4 it has registered 30 turbulences period. Allied Irish Banks from Irland registered most of the high turbulences period (3), than Diba Bank A/S (Dk:2), Kreditbanken As S (Dk:2), Lollands Bank A/S (Dk:2), Salling Bank A/S(Dk:2), A/S Skjern Bank(Dk:2), Sparbank Vest(Dk:2), Svendborg Sparekasse(Dk:2), Tonder Bank A/S(Dk:2), Totalbanken A/S (Dk:2), and Vestjysk Bank A/S (Dk:2). Total calls highest rate was registered by Melhus Sparebank (Nor:28), Sparebanken Pluss (Nor:28), Sparebanken1 Busker(Nor:28), Totens Sparebank (Nor:28) and Voss Veksel- Og Land (Nor:28).

The value of the Hosmer–Lemeshow goodness of fit statistic computed from the frequencies in Table 5.1 is C=18,51 and the corresponding p-value computed from the chi-square distribution with 8 degrees of freedom is 0.1177. This indicates that the model seems to fit quite well.

Table 4. Marginal effect of a 1 point rise in the variable on turbulance probability

	dy/dx	Std. Err.
L3.dunemployment	0.058018	0.012473
L3.inflation	0.105522	0.028783
L2.dgowth	-0.0245	0.005113
L2.changeiintermsoftrade	-0.01405	0.003272
L.publicsurplusdeficit	-0.00335	0.000843
L.realppercapita	-0.00693	0.001744

Source: authors'calculation

All six leading indicators are significant in the regression model, the inflation rate and unemployment rate consistently causes the highest marginal increasing in banking turbulance likelihood. The implication is that a one point rise in the inflation rate alone could increase crisis probability by at least 0.105% and a one point rise in unemployment rate alone could increase crisis probability by at least 0.05 %.The growth rate rate and change in terms of trade consistently causes the highest marginal decreasing in banking crisis likelihood. The implication is that a one point rise in the growth alone could reduce crisis probability by at least 0.02 % and a one point rise in the change in terms of trade alone could reduce crisis probability by at least 0.01%. Also a one point rise in the public surplus alone could reduce crisis probability by at least 0.003 % and a one point rise in the real GDP per capita alone could reduce crisis probability by at least 0.006%.

To verify our claim, we next turn to out-of-sample prediction to see if our EWS is able to detect the turbulance episode in any of commercial banks. We derive out-of-sample predictions for all the commercial banks in our sample for the years 2010 and 2011. If we call a crisis in any commercial banks we then check the banking turbulence definition (provision for loan losses on total assets ratio exceed the 90th quantile of the distribution of the ratio). We provide the results in Table 5, which indicates any turbulence period called by our EWS in columns 1 and 2 and the corresponding crisis occurrence according to the definitions in columns 3 and 4. In columns 5 and 6 are determineted turbulance probabilities against the EWS fitted values. As can be seen, our EWS is able to call 8 out of 30 turbulences according to the turbulence period definition in 2010 and call 8 out of 34 turbulences according to the turbulence period definition in 2011, and it have a success rate of 23,3% in 2010 and 17,65% in 2011.Moreover, we now go on to show our specification is extremely robust and can therefore be used with confidence.

Table 5: Out-of-sample estimation

Country of origin	**B.ing institution**	**Predicted probability 2010**	**Predicted probability 2011**	**Turbulance period 2010**	**Turbulance period 2011**	**Turbulance probabilities against the EWS fitted values: 2010**	**Turbulance probabilities against the EWS fitted values : 2011**
		1	2	3	4	5	6
DK	DANSKE B. A/S				1		
DK	DIBA			1	1		

	B. A/S						
DK	KREDITB.EN AS			4	3		
DK	LOLLANDS B. A/S			1			
DK	A/S MONS B.			1	2		
DK	NORDJYSKE B. AS				1		
DK	OSTJYDSK B. A/S			4	2		
DK	SALLING B. A/S				1		
DK	A/S SKJERN B.				1		
DK	TONDER B. A/S			2	2		
DK	TOTALB.EN A/S			2	3		
DK	VESTJYSK B. A/S			2	1		
GER	IKB B.			1	1		
GR	ALPHA B. A.E.	2	1		4		1 (Q2)
GR	EFG EUROB. ERGASIA	2	3	4	4	2 (Q2, Q4)	1 (Q2,Q3,Q4)
IR	ALLIED IRISH B.S	2	1	2	2	1 (Q2)	1 (Q4)
IR	B. OF IRELAND	2	1	2	2	1 (Q2)	1 (Q4)
NOR	SANDNES SPAREB.	1		1		1 (Q2)	
NOR	SPAREB.EN VEST	2	2	3	3	2 (Q2, Q4)	2 (Q2, Q4)
Total		8	8	30	34	7	6

Source: authors'calculation

Our conclusions do not change when we thoroughly test our coefficients for robustness. To examine the possibility that variable behaviour in an commercial banks drives our results, we re-estimate the Logit equation by changing the threashold of the dependent variable. The proposed threshold is the value corresponding to the 85^{th} quantile and 95^{th} quantile of the distribution of provision for loan losses on total assets ratio.

Table 6: Logit model regression regression with different dependent variables

Dependent variables	**Turbulance period dummy for 95th quantile of provision for loan losses on total assets ratio**		**Turbulance period dummy for 85th quantile of provision for loan losses on total assets ratio**	
Explanatory variables	Coefficient	z-statistic	Coefficient	z-statistic
L3.dun employment	1.197***	-0.26	0.797***	-0.215
1211 0.273 128.076 0.00	1211 0.258 196.382 0.00	-0.555	1.884***	-0.424
		-0.12	-0.470***	-0.084
		-0.079	-0.215***	-0.053
		-0.017	-0.077***	-0.012
L.realppercapita	-0.114***	-0.038	-0.114***	-0.026
_cons	-4.483***	- 0.335	- 2.935***	-0.209
No. observations	1211		1211	
r2_p	0.273		0.258	
chi2	128.076		196.382	
p	0.00		0.00	

Source: authors'calculation

One of the criticism of our turbulence dummy period could be the proposed threshold of the 90th quantile of the distribution of provision for loan losses on total assets ratio. But as we can see from the above table (Table 6) the impact of the explanatory variables on the likelihood that a turbulence period may occur remain the same even if we change the threashold (we consider turbulance period dummy for 95th quantile distribution of provision for loan losses on total assets ratio, turbulance period dummy for 95th quantile distribution of provision for loan losses on total assets ratio). The results in Table 6clearly show that an increased in growth, change in terms of trade, public surplus and real GDP per capita have a beneficial impact of reducing crisis and turbulence probability and an increased in unemployment rate and inflation rate determine the increase of crisis and turbulence probability.

5. Conclusions

In contrast to the existing literature, we estimate equations for early warning systems for turbulences period in European commercial banks using a new estimation for the dependent variables. We define a banking turbulence when provision for loan losses on total assets ratio exceeds the value corresponding to the 90th quantile of this ratio. These have not been assessed as indicators in extant work. We use only standard indicators for explanatory variables. The results clearly show that an increased in growth, change in terms of trade, public surplus and real GDP per capita have a beneficial impact of reducing crisis and turbulence probability and an increased in unemployment rate and inflation rate determine the increase of crisis and turbulence probability. Moreover, we find that the importance of explanatory variables remains invariant to different robustness tests.

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