Early warning indicators of banking crises: exploring new data and tools[1]

António Antunes[2] | Diana Bonfim[3] | Nuno Monteiro[4] | Paulo M. M. Rodrigues[5]

ABSTRACT

Forecasting rare events is a challenge, especially if these events are driven by many different factors and assume different characteristics. We explore the dynamic dimension of discrete choice models to improve the forecasting accuracy of early warning models of systemic banking crises. Our results show that introducing this dynamic component into the models significantly improves the quality of the results.

1. Introduction

Is it possible to predict the next banking crisis? Almost certainly not. On the one hand, it may be argued that it is econometrically very challenging to predict these very rare events, which in many cases have different causes and consequences. On the other hand, if accurately predicting an emerging banking crisis with some anticipation were feasible, policymakers would ideally be able to take all the necessary measures to avoid its materialization, which would then make the method fail.

The aim of this paper is to contribute to improve the early warning toolkit available to policymakers. Over the last decades, there have been many and diverse contributions to this literature to help understand the main drivers of financial crises, as well as to aid policymakers in forecasting the next crisis. A large part of this literature focuses on currency crises, most notably in emerging market economies (Krugman, 1979, Obstfeld, 1986, Burnside *et al.*, 2004, Chang and Velasco, 2001). Nevertheless, currency crises frequently go hand in hand with banking crises, as noted by Kaminsky and Reinhart (1999). When a financial crisis is characterized by serious disruptions and losses in the banking system, the negative effects on the economy usually last longer and are more pronounced (Cecchetti *et al*., 2009, Jordà et al, 2010, 2012).

Though every crisis seems different and unique (Reinhart and Rogoff, 2011), we explore the commonalities in a dataset of European systemic banking crises. Our main contribution relies on exploring the dynamics embedded in the time series of the dependent and independent variables. We find that using a dynamic probit specification contributes to improve the forecast accuracy of early warning models, both in and out of sample.

This paper is organized as follows. In section 2 we describe the data and introduce the models and the estimation methodology used. In section 3 we discuss our main results, analyze the forecasting accuracy of the models and perform robustness checks. Finally, in section 4 we summarize our main findings.

2. Data and methodology

2.1. Data

This article was initially developed as a contribution to the ECB Workshop on Early Warning Tools and Tools for Supporting Macroprudential Policies. As described in Alessi *et al.* (2014), in this workshop a common set of rules and data were given to all participants. The participants were free to use additional data sources, as long as they were publicly available. Furthermore, the variables contained in the dataset could be rescaled or used to create new variables. The only constraint in this domain was that trend and filter calculations could only consider real-time data, in order to replicate as closely as possible the data available to policymakers in each moment of time. This implies, for instance, using lags of variables to consider the period until data is released or computing one-sided or recursive trend filters.[6]

Though participants were able to use different methodologies and data sources, the list of systemic banking crises episodes was common, in order to ensure the comparability of results. Indeed, as noted by Chaudron and de Haan (2014), there are sizeable differences across the databases of systemic banking crises publicly available. Furthermore, Boyd *et al.* (2009) argue that in many cases crisis dates reflect government actions undertaken in response to bank distress and not the emergence of distress in itself. To ensure the best quality possible for this critical variable, the systemic banking crises database collected by the Czech National Bank (Babecky *et al.,* 2012) was used. This database benefited from the inputs of the Heads of Research of the Eurosystem. The database was recently updated with contributions from the ESRB/IWG Expert Group (for further details, see Detken *et al.*, 2014). This database considers two different definitions of crises: one with actual banking crises and another which also includes episodes of heightened vulnerability which could, *ex-post*, have justified the implementation of macroprudential tools, even if no crisis effectively occurred.[7] While for the exercise presented at the ECB Workshop on Early Warning Tools and Tools for Supporting Macroprudential Policies the former definition was considered, in this paper we use the broader crisis definition.

In the abovementioned workshop there was a horse race between different methodologies, as discussed in Alessi *et al.* (2014). To allow for the comparability of the results achieved with different techniques, all participants were asked to report values for a contingency matrix, as well as for the area under the receiver operating characteristic (AUROC) curves.[8]

The exercise was performed in three different time windows: total, early and late periods. The total period comprises the 20 to 4 quarters prior to a crisis, grouping the early and late periods. The early period, defined as 20 to 12 quarters before a crisis, should work better as an early warning tool, giving enough time for policymakers to act. The late period, defined as 12 to 4 quarters before the crisis, explores the information content immediately before the emergence of a crisis, when signals may be stronger and policy action may need to be prompter. A similar reasoning is presented by Oet *et al.* (2010).

Finally, participants were asked to compare not only the in-sample performance of their methodologies, but also the out-of-sample performance. Two exercises were suggested: one excluding the global financial crisis and the other excluding Denmark, Finland and Sweden, where there was a systemic banking crisis in the late 1980s/early 1990s.

Besides the banking crises data, the dataset provided also included several macroeconomic and financial variables from various data sources: private credit (from BIS and from IMF); house prices (EU, BIS and OECD data); equity prices (EU and IMF); nominal and real GDP (EU, IMF); debt service ratio (BIS, ECB and EUROSTAT; calculations performed by the ECB based on the methodology by Drehmann and Juselius, 2012). In addition, several bank variables were available: net interest income (OECD), net pre-tax income (OECD), capital and reserves (OECD, EU), leverage ratio (EU), total assets (EU). We tried to maximize the information set available. For that purpose, in some cases we combined the series from a given source with data from other sources available in the dataset. Most variables are provided on a quarterly basis. The longest series span from 1970Q1 to 2010Q4. Moreover, the results presented in this paper rely on an updated version of the data-set initially provided by the ECB, using Thomson Reuters. When the data sources were not the same, the series were extended using chain growth rates with data up to 2013Q2.[9] In some cases, the series were also extended back to previous periods.

We implemented a few transformations of the variables provided. First, we computed several ratios, such as credit-to-GDP and total assets of the banking system as a percentage of GDP. Second, we computed year-on-year growth rates for most of the variables. Finally, we estimated deviations from long-term trends, using one-sided Hodrick-Prescott filters with different smoothing parameters.[10]

After these transformations, we obtained 37 possible explanatory variables. In order to select the potentially more relevant variables, we performed an univariate analysis similar to the one described in Bonfim and Monteiro (2013), examining the AUROC of each series. In addition, the availability of information was also considered and the shorter series were not included in this analysis. The best performing variables are equity price indices, the year-on-year growth rate of the debt-to-service ratio, the credit-to-GDP gap with a smoothing parameter of 400 000[11] and the year-on-year growth rate of house prices.

Table 1 presents some descriptive statistics on these variables for the whole sample, while table 2 displays country by country summary statistics. For some countries, there is no information for some of the variables used, thereby implying that these countries are not included in the multivariate analysis (Belgium, Bulgaria, Cyprus, Estonia, Croatia, Hungary, Lithuania, Luxembourg, Latvia, Malta, Poland, Romania, Slovenia and Slovakia). The final sample thus consists of 14 European countries.

Several features are worth highlighting from table 2. Equity prices reached higher values in Portugal and France and were more subdued in Finland, Sweden and Spain. The highest growth in the debt-to-service ratio was observed in Greece and the UK, while in Germany and Finland this ratio did not change much during most of the sample period. The credit-to-GDP gap, which has been found to be one of the best predictors of banking crises (Drehmann *et al.*, 2010), displays relatively low median values in Germany, Netherlands and Austria. The highest median values for this gap are observed in Portugal, Ireland and Italy. Finally, house prices have increased more significantly in Greece, UK, Spain, Ireland and Finland. House price dynamics displayed a smaller magnitude in Germany, Austria, France and Portugal.

2.2. Methodology

Since the seminal work of Estrella and Hardouvelis (1991), binary response models have played an important role in the estimation and forecasting of recessions (see also *e.g*. Wright, 2006, Kauppi and Saikonnen, 2008, and Nyberg, 2009).

In this paper we consider variants of the general dynamic probit model representation,

$$y_{it}^{*} = \alpha + \sum_{k=1}^{p} \sum_{j=1}^{d} \beta_{kj} x_{ij,t-k} + \sum_{k=1}^{p} \gamma_k y_{i,t-k} + u_{it} \tag{1}$$

Table 1 • Summary statistics

	Total sample					
	N	Mean	St. dev.	Min	Median (p50)	Max
Crisis dummy	4816	0.10	0.29	0	0	1
Equity price index	2678	58.5	44.2	1	48.0	265.1
Debt-to-service ratio (yoy)	2827	0.03	0.11	-0.63	0.02	1.24
Credit-to-GDP gap	2285	4.6	12.0	-47.2	2.4	62.5
House price index (yoy)	2834	0.11	0.44	-0.42	0.06	14.42

Sources: Babecky *et al.* (2012), BIS, Detken *et al.* (2014), ECB, Eurostat, IMF, OECD, Thomson Reuters, and authors' calculations.
Notes: yoy - year on year growth rate. The crisis dummy takes the value 1 during banking crises or during periods of heightned vulnerability in which a crisis could be eminent. The equity price index combines data from Eurostat and the IMF, to obtain the longest series possible. The debt-to-service ratio series were provided by the ECB, following the methodology of Drehmann and Juselius (2012). The credit-to-GDP ratio was computed as the ratio between domestic private credit series provided by the BIS (and in some cases extrapolated with IMF data) and nominal GDP. In turn, the credit-to-GDP gap was computed as the deviation from the long-term trend of the credit-to-GDP ratio using a one-sided Hodrick-Prescott filter, using a smoothing parameter of 400.000. The house price index combines data from the BIS and OECD.

Table 2 • Summary statistics by country

	Equity price index		Debt-to-service ratio (yoy)		Credit-to-GDP gap		House price index (yoy)	
	N	median	N	median	N	median	N	median
Austria	177	33.5	167	0.02	169	0.5	132	0.03
Belgium	0	.	127	0.02	129	6.9	161	0.06
Bulgaria	59	49.8	60	0.15	0	.	132	0.03
Cyprus	0	.	75	0.04	0	.	0	.
Czech Republic	84	59.1	66	0.01	80	4.4	80	0.04
Germany	177	54.4	166	0.00	169	-1.4	132	0.03
Dennmark	98	68.8	35	0.02	141	2.9	132	0.05
Estonia	66	54.6	61	0.10	0	.	30	0.07
Spain	177	26.6	167	0.01	169	1.4	132	0.07
Finland	177	24.0	167	0.00	169	2.4	132	0.06
France	105	79.0	167	0.01	169	1.9	132	0.04
Greece	85	63.3	41	0.10	129	1.2	132	0.12
Croatia	61	89.1	3	-0.06	0	.	62	0.03
Hungary	93	43.8	67	0.05	0	.	88	0.09
Ireland	177	32.3	127	0.01	129	8.0	132	0.06
Italy	177	39.7	167	0.01	168	6.1	132	0.05
Lithuania	48	77.4	68	0.14	0	.	55	0.06
Luxembourg	77	59.6	126	-0.01	0	.	141	0.09
Latvia	67	65.9	68	0.20	0	.	26	0.03
Malta	0	.	160	0.03	0	.	0	.
Netherlands	177	35.1	166	0.01	141	0.1	149	0.04
Poland	0	.	27	0.08	84	4.1	96	0.09
Portugal	105	79.7	139	0.01	141	12.5	130	0.04
Romania	0	.	20	-0.04	0	.	89	0.49
Sweden	177	25.0	167	0.01	129	2.4	132	0.05
Slovenia	62	55.2	32	0.08	0	.	22	-0.01
Slovakia	75	44.7	24	0.04	0	.	80	0.07
United Kingdom	177	46.6	167	0.04	169	2.5	173	0.09
Total	2678	48.0	2827	0.02	2285	2.4	2834	0.06

Sources: Babecky *et al.* (2012), BIS, Detken *et al.* (2014), ECB, Eurostat, IMF, OECD, Thomson Reuters, and authors' calculations.
Note: All variables defined in table 1.

where y_{it} is a binary crisis indicator, y_{it}^* is a latent variable such that $y_{it} = 1$ if $y_{it}^* > 0$ and 0 otherwise; $x_{ij,t}, j = 1,..., p$ corresponds to a set of p exogenous covariates, and $y_{i,t-k}$, $k=1,..,p$ corresponds to the kth lag of the crisis indicator.

Hence, based on (1), for empirical purposes two distinct models will be considered: i) a marginal model which results from setting $\gamma_1 = ... = \gamma_p = 0$, *i.e.*, only considers the effects of covariates on the probability outcomes and treats serial dependence as a nuisance which is captured through association parameters; ii) a transitional model which explicitly incorporates the history of the response in the regression for y_{it}^* (complete model (1)). Hence, in this way, each unit specific history can be used to generate forecasts for that unit, as opposed to the marginal model which makes forecasts solely on the basis of the values of the exogenous variables.

Estimation of these models is done by maximum likelihood estimation (MLE). The maximization of the likelihood function is a highly nonlinear problem but can be straightforwardly carried out by standard numerical methods. De Jong and Woutersen (2011) showed, for an univariate time series context, that under appropriate regularity conditions, the conventional large sample theory applies to the MLE estimator of the regression parameter vector.

3. Results

3.1 Main results

The first step in the analysis consisted of the estimation of the models previously indicated. Thus, denoting the endogenous binary response indicator of crisis by y_{it} (taking value 1 if a banking crisis is observed and zero otherwise), multistep ahead projections can be obtained through the pooled panel probit specification, where the probability forecast of observing a crisis at time t, $P(y_{it} = 1)$ is given by $\Phi(y_{it}^*)$. In particular, $\Phi(.)$ is the Gaussian cumulative distribution function and y_{it}^* is thus a latent variable. Defining h as the forecast horizon, we can adjust (1) to produce the necessary forecasts, *i.e.*,

$$y_{it}^* = \alpha + \sum_{k=1}^{p}\sum_{j=1}^{d}\beta_{kj}x_{ij,t-k-h} + \sum_{k=1}^{p}\gamma_k y_{i,t-k-h} + v_{it} \tag{2}$$

The model was estimated with three different lag structures, as discussed above. First we considered 20 to 4 lags of all explanatory variables. This allows us to analyse the determinants of banking crisis 1 to 5 years in advance. In addition, we estimated the model in a so-called "early period", exploring the crisis determinants with a lag between 20 and 12 quarters. This allows us to explore the variables with stronger early warning signals. Finally, we estimate the model in the "late period", using information lagged between 12 and 4 quarters, thus exploring which variables may be more relevant to signal a crisis in the near future.

For all models, we began by estimating the model with all the lags of the four selected explanatory variables (equity price index, the year-on-year growth rate of the debt-to-service ratio, the credit-to-GDP gap, and the year-on-year-growth rate of the house price index). From that estimation, we selected only the variables which were statistically significant at a 10% level, thereby estimating a more parsimonious model. These are the results presented in table 3.

The results regarding equity price indices are not remarkably strong. In the parsimonious representation, the equity price index provides statistically significant signals (10%) at t-6, t-9 and t-10 quarters. The growth of the debt-to-service ratio provides signals with a significant anticipation (at t-16, t-17 and t-20), thereby confirming the results of Drehmann and Juselius (2012). The

Table 3 • Regression results: simple and dynamic probits

	Simple Probit									Dynamic probit								
	Total Period			Early Period [12;20] lags			Late Period [4;12] lags			Total Period			Early Period [12;20] lags			Late Period [4;12] lags		
	Lags	Coef.	P>|z|	Lags	Coef.	P>|z|	Lags	Coef.	P>|z|	Lags	Coef.	P>|z|	Lags	Coef.	P>|z|	Lags	Coef.	P>|z|
Crisis dummy										L4.	6.66	0.00	L12.	1.33	0.00	L4.	7.44	0.00
										L5.	-4.09	0.00	L13.	-0.20	0.27	L5.	-4.66	0.00
										L9.	-0.02	0.98						
										L10.	-0.52	0.22						
										L13.	0.44	0.07						
										L18.	-0.90	0.08						
Equity price index																		
	L5.	0.00	0.44	L12.	0.01	0.06	L5.	-0.01	0.00	L6.	0.02	0.01	L12.	0.01	0.01	L6.	0.01	0.05
	L6.	0.01	0.00	L14.	0.00	0.44	L6.	0.01	0.00	L9.	0.00	0.33	L13.	0.00	0.10	L9.	-0.01	0.22
	L9.	-0.01	0.04	L16.	0.00	0.88	L7.	0.00	0.91	L11.	-0.01	0.02	L16.	0.00	0.34			
	L10.	0.01	0.00	L18.	0.00	0.49	L10.	0.01	0.17	L12.	0.01	0.00	L18.	0.00	0.40			
	L12.	0.00	0.14							L14.	-0.01	0.05						
	L16.	0.00	0.66							L16.	-0.01	0.08						
	L18.	0.00	0.52							L18.	0.01	0.11						
Debt-to--service ratio (yoy)																		
	L9.	0.73	0.66	L16.	4.76	0.00				L5.	9.10	0.00	L12.	5.59	0.00	L4.	4.47	0.01
	L11.	0.88	0.63	L17.	2.18	0.00				L6.	-5.33	0.08	L16.	3.60	0.02	L12.	4.48	0.00
	L16.	8.62	0.00	L20.	2.27	0.11				L9.	4.29	0.02	L17.	2.80	0.11			
	L17.	2.14	0.00							L10.	-0.64	0.73						
	L20.	4.80	0.01							L12.	2.11	0.34						
										L13.	2.65	0.19						
										L16.	3.87	0.02						
										L20.	3.40	0.02						
Credit-to--GDP gap																		
	L4.	-0.03	0.24	L12.	0.06	0.00	L4.	-0.05	0.06	L5.	-0.03	0.29	L14.	0.01	0.78	L12.	0.00	0.63
	L6.	0.03	0.12	L14.	-0.05	0.01	L6.	0.05	0.00	L6.	0.05	0.07	L17.	-0.04	0.00			
	L10.	0.05	0.00	L17.	-0.06	0.00	L11.	0.06	0.00	L14.	-0.06	0.01	L20.	0.05	0.00			
	L11.	0.06	0.02	L20.	0.06	0.00	L12.	-0.03	0.03	L20.	0.04	0.03						
	L14.	-0.07	0.00															
	L15.	-0.02	0.16															
	L16.	-0.08	0.00															
	L17.	-0.02	0.14															
	L20.	0.10	0.00															
House price index (yoy)																		
	L4.	-15.42	0.00				L4.	-12.00	0.00	L4.	-6.37	0.01				L4.	-11.21	0.00
	L5.	2.72	0.07				L5.	6.88	0.01	L16.	-0.54	0.74				L5.	9.35	0.00
	L6.	1.55	0.25							L19.	1.46	0.29						
	L11.	3.27	0.00															
Constant		-1.83	0.00		-1.57	0.00		-1.10	0.00		-2.38	0.00		-1.79	0.00		-2.32	0.00
R2			0.4084			0.1919			0.2275			0.6145			0.2549			0.5723
N			1316			1471			1521			1274			1480			1417

Sources: Babecky *et al.* (2012), BIS, Detken *et al.* (2014), ECB, Eurostat, IMF, OECD, Thomson Reuters, and authors' calculations.
Note: All variables defined in table 1. The total period refers to lags [4;20], the early period [12;20] and the late period [4;12]. Standard errors clustered by country.

credit-to-GDP gap is the variable that displays more statistically significant coefficients, with useful signals many quarters ahead of crisis. However, the signs of these coefficients are not always consistent, i.e., in some quarters the estimated coefficients are positive, whereas in others they turn out to be negative. Finally, the year-on-year growth rate of house prices also displays mixed signals, with a positive coefficient at t-5 and t-11, and a perhaps more counterintuitive negative coefficient at t-4. This may suggest that systemic banking crises are more likely after periods of strong growth in house prices that are followed by sharp declines.

In the early period (t-20 to t-12), the results are somewhat different. House prices growth is never statistically significant, thereby showing that this variable does not have strong early warning properties in a multivariate setting. Debt-to-service ratio growth appears significant at t-16 and t-17, maintaining the positive signs of the total period estimation. Equity price indices display a significant positive signal with a lag of 12 quarters. The credit-to-GDP gap is also significant in several periods.

In the period closer to the crisis (t-12 to t-4), the growth of the debt-to-service ratio is never statistically significant. This means that this variable has strong early warning signalling properties, though not close to the emergence of a crisis. The other three variables continue to provide significant signals.

In the second part of table 3 we present the results for the dynamic models. As discussed before, by exploring the dynamics embedded in a crises time series, we hope to be able to improve the quality of our early warning model. Indeed, including lagged dependent variables in the model specification seems to substantially improve the model fit. Several lags of the dependent variable turn out to be statistically significant in explaining the likelihood of occurrence of a systemic banking crisis, in the three different estimation windows considered. The results concerning the other explanatory variables are broadly consistent. The main exception is the growth of the debt--to-service ratio, which is now significant also in the late period.

All in all, the growth of debt-to-service ratios seems to provide useful guidance for policymakers significantly ahead of crises. The credit-to-GDP gap provides strong signals in all horizons, though not always consistent.

3.2 Model assessment

The main goal of this exercise is to provide useful early warning guidance to policymakers ahead of systemic banking crises. To test how useful the guidance provided by the models may be, several assessment metrics may be considered.

Since the model is a binary response one, we can define a cut-off value for the latent variable. The observation is classified by the model as “crisis” if the latent variable is above the cut-off; otherwise, the observation is “non crisis”. This procedure defines, for each cut-off, a classification for each observation in the sample. Notice that we know, from the data, the actual classification of each observation, that is, what actually happened in each country-quarter pair of the sample. Against this background, it is possible to build a contingency matrix that includes four elements: number of true positives (TP - number of correctly predicted crises by the model), number of true negatives (TN – number of non-crises observations correctly predicted by the model), number of false positives (FP) and number of false negatives (FN).

Naturally, a perfect model would classify correctly all observations. This does not happen in practice. As a matter of fact, a very negative value for the cut-off means that a lot of non crisis observations are going to be classified by the model as crisis (this is the so-called type I error, which we can think of as a false alarm). As we increase the cut-off, more and more non crisis observations are going to be classified as such by the model but some observations that actually are crisis are going to be classified as non crisis (this is the type II error, or a "wolf in a sheep's clothing"). When the cut-off is very high, all observations are classified as non crisis – and so all crisis observations will be wrongly classified as non crisis by the model.

We call specificity to the fraction of non crisis observations that are correctly classified by the model, and sensitivity to the fraction of crisis observations that are correctly classified by the model.

When the cut-off is minus infinity, all observations are classified as crisis by the model; therefore, sensitivity is 1 and specificity is 0. When the cut-off is plus infinity, sensitivity is 0 and specificity is 1. By varying the cut-off we obtain a set of values for these two measures. A possible representation of the model's performance is the Receiver Operating Characteristic curve (or ROC), which we can see in chart 1. This chart illustrates two hypothetical ROC curves. In the horizontal axis we represent 1 minus specificity, that is, the percentage of non crisis observations incorrectly classified as crisis by the model (*i.e.*, type I errors). In the vertical axis we represent sensitivity, that is, the fraction of crisis observations correctly classified as crisis by the model. A given point *(x,y)* in the curve answers the following question: What percentage *x* of non crisis observations will be incorrectly classified by the model in order to classify correctly a percentage *y* of crisis observations? In a perfect model we would be able to correctly classify 100 percent of crisis observations without incorrectly classifying any non crisis observation (0 percent). This means that the perfect model's ROC curve would be the line segment between points (0,1) and (1,1). On the other hand, a model randomly classifying observations will have a ROC curve given by the line segment between points (0,0) and (1,1), *i.e.*, a 45º degree line. In other words, the model would incorrectly classify 25 percent of the non crisis observations to correctly classify 25 percent of the crisis observations. This fact suggests that an adequate measure for the performance of the model is the area under the ROC curve, commonly known as AUROC.

Chart 2 plots the ROC curves for the six specifications presented in table 3, while table 4 presents several indicators to assess the quality of these models.

Examining the model's goodness of fit (evaluated using McFadden R^2) and the AUROC provides consistent results. The best performance is always obtained for the total period estimation. In contrast, the early period estimations provide the weakest results. This is not surprising, as it

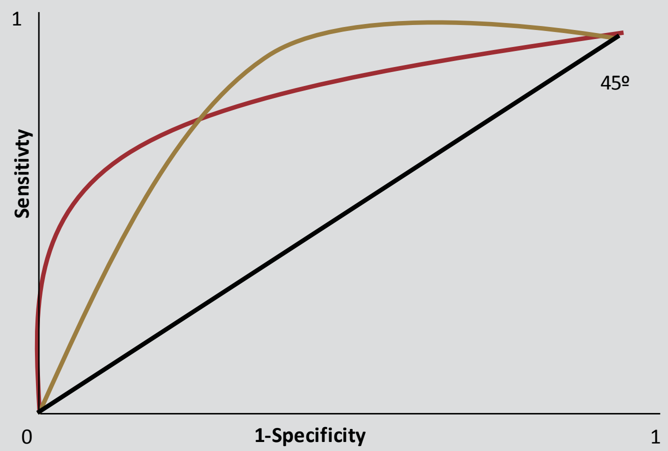


Chart 1 • Examples of ROC curves

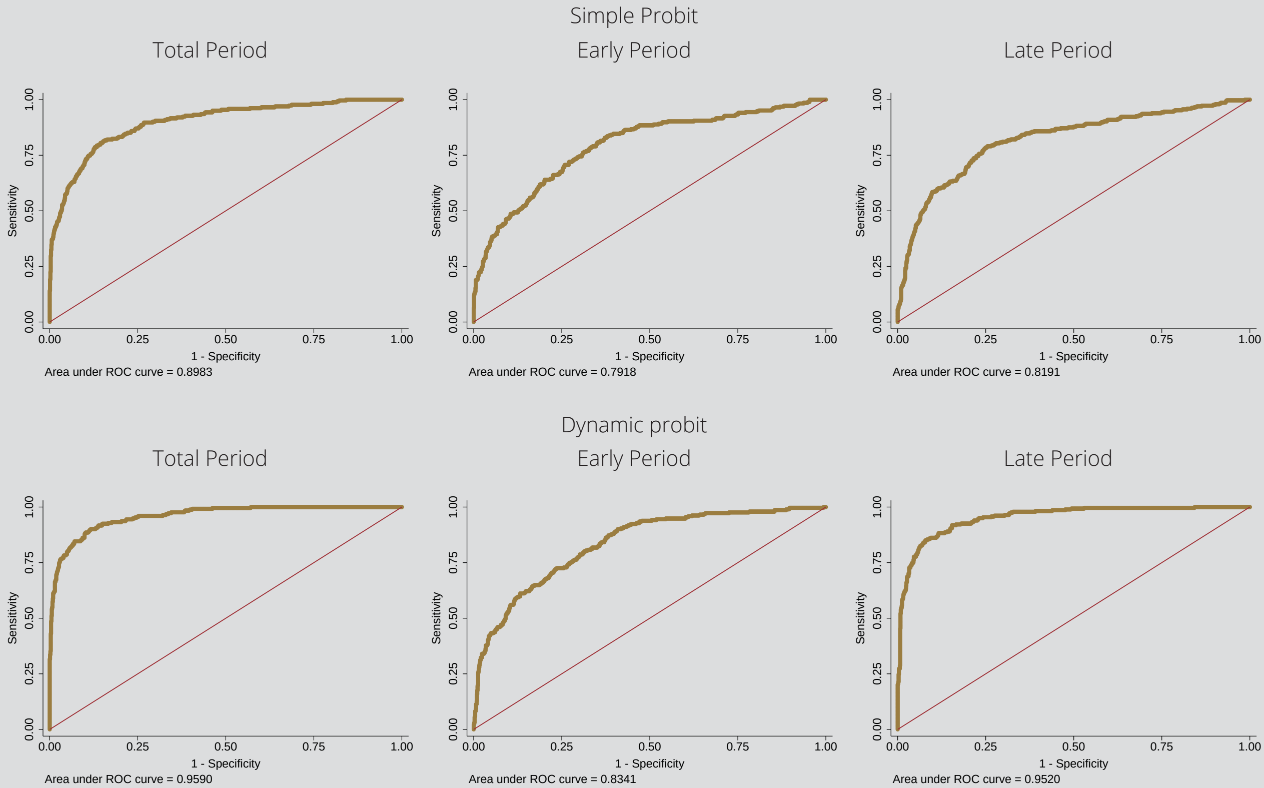
Source: Authors' calculations

Table 4 • Model evaluation

	Simple Probit			Dynamic probit		
	Total Period	**Early Period**	**Late Period**	**Total Period**	**Early Period**	**Late Period**
N	1316	1471	1521	1274	1480	1417
R^2	0.408	0.192	0.228	0.615	0.255	0.572
AUROC	0.898	0.792	0.819	0.959	0.834	0.952
Confusion matrix - full sample						
True positives (TP)	149	79	96	190	106	204
False positives (FP)	46	34	42	29	41	37
False negatives (FN)	113	207	200	63	185	78
True negatives (TN)	1008	1151	1183	992	1148	1098
TOTAL	1316	1471	1521	1274	1480	1417
% false alarms	3.5	2.3	2.8	2.3	2.8	2.6
% missed crises	8.6	14.1	13.1	4.9	12.5	5.5
% correctly predicted	87.9	83.6	84.1	92.8	84.7	91.9
Sensitivity (TP/(TP+FN))	56.9	27.6	32.4	75.1	36.4	72.3
Specificity (TN/(FP+TN))	95.6	97.1	96.6	97.2	96.6	96.7

Sources: Babecky *et al.* (2012), BIS, Detken *et al.* (2014), ECB, Eurostat, IMF, OECD, Thomson Reuters, and authors' calculations.
Notes: the results refer to the regressions presented in table 3. The total period refers to lags [4;20], the early period [20;12] and the late period [4;12].

Chart 2 • ROC curves



Sources: Babecky *et al.* (2012), BIS, Detken *et al.* (2014), ECB, Eurostat, IMF, OECD, Thomson Reuters, and authors' calculations.

would be expected that signals are stronger immediately before the crisis than 3 years before. Nevertheless, looking at information for a long period is relevant, as the total period estimation performs better than the late period (12 to 4 quarters before the crisis).

Regarding the methodology, the model's performance, assessed by the R^2 and the AUROC, is substantially better when we include dynamic effects, using the lagged dependent variable. This shows that exploring the dynamics of the dependent variable helps to significantly improve the performance of the model, in all the estimation horizons considered.

Though the model's goodness of fit and the AUROC are useful summary measures to assess the performance of each model, it is relevant to consider how many crises the model correctly predicts, how many it fails to predict and how many false alarms exist. This is relevant especially in a setting as ours, with potentially relevant implications for decision-making. Indeed, as noted by Alessi and Detken (2011), policymakers are not indifferent between missing a crisis or acting upon false alarms. As there is a trade-off between these two dimensions, which are subsumed in the AUROC, it might be relevant to look at them separately.

Dynamic probits are able to reduce the percentage of false alarms only for the total and late period estimations. Nevertheless, this percentage is very small in all the models, being at most 3.5 per cent (simple probit for the total period estimation). In contrast, dynamic probits significantly reduce the percentage of missed crises (from 8.6 to 4.9 per cent, in the total period estimation). Given that missing a crisis may be costlier than issuing a false alarm (Demirgüç-Kunt and Detragiache, 1999, Borio and Lowe, 2002, and Borio and Drehmann, 2009), this result suggests that dynamic models may be more useful for policymakers. In addition, dynamic models are able to correctly predict a larger percentage of crisis episodes, most notably in the total and late periods.

It is also interesting to see that dynamic probits allow to significantly increase the models' sensitivity. As mentioned above, sensitivity is defined as the number of true positives as a percentage of the total number of crises, thereby being a so-called true positive rate. This confirms that dynamic probits are more helpful in identifying crisis periods than marginal models. In turn, the specificity of the model, which is defined as the true negatives as a percentage of the total non-crises periods, decreases slightly in the dynamic models, though remaining very high.

All in all, a large battery of metrics confirms that adding a dynamic component to early warning crises models substantially improves the quality of the results, most notably in reducing the percentage of missed crises and in increasing the percentage of those that are correctly predicted. As discussed in Section 2.1, this methodology was part of a horse race between different methodologies presented in an ECB workshop. As mentioned in Alessi *et al*. (2014), dynamic probits were amongst the best performing methodologies.

3.3 Robustness

The results presented so far assess the in-sample performance of the model. However, the quality of the model hinges on its forecasting accuracy. It is thus essential to test the model's out-of-sample performance. To do that, two different exercises were considered. First, an out-of-period estimation was implemented, excluding the global financial crisis period from the sample for all countries (we excluded all quarters from 2007Q1 onwards). The second exercise was an out-of-sample estimation, by excluding Denmark, Finland and Sweden, where there was a systemic banking crisis in the late 1980s/early 1990s, from the estimation and testing the accuracy of the model for these countries *ex-post*.

The results of the simple and dynamic models' performance in these two exercises are presented in table 5. The table shows several evaluation metrics for the simple and dynamic probits, in the three estimation windows considered (total, early and late periods). The in-sample results are compared to the out-of-period and out-of-sample estimations. In these two cases, the models are estimated excluding, respectively, the period and countries mentioned above. The metrics refer to the performance of the prediction of the model for these excluded observations.

We find that the AUROC for the out-of-sample and out-of-period estimations does not decrease significantly in most of the specifications. On the contrary, it actually increases in the simple probit estimations for the total period, as well as in all the out-of-sample dynamic estimations. In turn, the AUROC for the out-of-period estimations decreases only slightly, thus confirming that the performance of the model does not critically depend on the global financial crisis. This could be a concern, as a significant part of the crisis observations in different countries is recorded after 2007.

Nevertheless, the percentage of false alarms increases somewhat, most notably in the out-of-sample estimations. Moreover, the percentage of missed crises increases more significantly in the out-of-period estimation, thus suggesting that the model would not be able to predict the global financial crisis in all the countries in the sample. The percentage of correctly predicted crises also decreases more in this estimation. These latter results are not unexpected, as this crisis was driven in many countries by exogenous shocks rather than by underlying vulnerabilities.

4. Concluding remarks

Systemic banking crises are rare, yet extremely costly, events. Accurately predicting them is still very challenging, despite the large body of literature in this domain. In this paper, we provide a methodological contribution to this literature, by exploring the role of dynamic probits in predicting these events.

Using a comprehensive dataset of systemic banking crisis in Europe, we find that equity prices, house prices growth, credit-to-GDP gaps and the growth of debt to service ratios are among the most useful indicators in signalling emerging crises. The last two indicators provide the strongest and most consistent signals in a multivariate setting.

We show that adding a dynamic component to the multivariate modelling of systemic banking crises substantially improves the models' accuracy. This result holds both in and out of sample.

Table 5 • Out-of-sample and out-of-period estimation

	Simple probit			Simple probit -out-of-period			Simple probit - out-of-sample			Dynamic probit			Dynamic probit -out-of-period			Dynamic probit -out-of-sample		
	Total	Early	Late	Total Period	Early Period	Late Period	Total Period	Early Period	Late Period	Total	Early	Late	Total Period	Early Period	Late Period	Total Period	Early Period	Late Period
AUROC	0.898	0.792	0.819	0.915	0.743	0.790	0.906	0.792	0.806	0.959	0.834	0.952	0.947	0.788	0.943	0.966	0.842	0.953
Confusion matrix - full sample																		
True positives	149	79	96	72	12	37	28	8	19	190	106	204	106	16	106	42	20	42
False positives	46	34	42	19	0	14	27	15	14	29	41	37	9	6	4	17	22	11
False negatives	113	207	200	82	142	119	30	50	48	63	185	78	42	140	47	16	40	18
True negatives	1008	1151	1183	155	174	166	154	197	239	992	1148	1098	153	169	176	156	191	190
TOTAL	1316	1471	1521	328	328	336	239	270	320	1274	1480	1417	310	331	333	231	273	261
% false alarms	3.5	2.3	2.8	5.8	0.0	4.2	11.3	5.6	4.4	2.3	2.8	2.6	2.9	1.8	1.2	7.4	8.1	4.2
% missed crises	8.6	14.1	13.1	25.0	43.3	35.4	12.6	18.5	15.0	4.9	12.5	5.5	13.5	42.3	14.1	6.9	14.7	6.9
% correctly predicted	87.9	83.6	84.1	69.2	56.7	60.4	76.2	75.9	80.6	92.8	84.7	91.9	83.5	55.9	84.7	85.7	77.3	88.9
Sensitivity (TP/(TP+FN))	56.9	27.6	32.4	46.8	7.8	23.7	48.3	13.8	28.4	75.1	36.4	72.3	71.6	10.3	69.3	72.4	33.3	70.0
Specificity (TN/(FP+TN))	95.6	97.1	96.6	89.1	100.0	92.2	85.1	92.9	94.5	97.2	96.6	96.7	94.4	96.6	97.8	90.2	89.7	94.5

Sources: Babecky *et al.* (2012), BIS, Detken *et al.* (2014), ECB, Eurostat, IMF, OECD, Thomson Reuters, and authors' calculations.
Notes: the results for the out-of-sample exercise exclude Denmark, Finland and Sweden, where there was a systemic banking crisis in the late 1980s/early 1990s, and the results for the out-of-period exclude the global financial crisis that started in 2007. The total period refers to lags [4;20], the early period [12;20] and the late period [4;12].

Notes

1. We are thankful to participants in the ECB/MaRs Workshop on Early Warning Tools and Tools for Supporting Macroprudential Policies and in a seminar at Banco de Portugal for insightful comments and suggestions. The analyses, opinions and findings of this article represent the views of the authors, which are not necessarily those of Banco de Portugal.

2. Banco de Portugal, Economics and Research Department and Nova School of Business and Economics.

3. Banco de Portugal, Economics and Research Department.

4. Banco de Portugal, Economics and Research Department.

5. Banco de Portugal, Economics and Research Department and Nova School of Business and Economics.

6. Despite these efforts, the information is not exactly the same as that that would be available to policymakers, as many macroeconomic variables are subject to ex-post revisions. Edge and Meisenzahl (2011) show that these differences can be sizeable when computing the credit-to-GDP ratio, thereby leading to potential differences when setting macroprudential instruments such as the countercyclical capital buffer ratio.

7. For instance, for Portugal, one additional stress episode that was not effectively a crisis, but in which sizeable vulnerabilities were building up was included. In this period, the occurrence of an endogenous or exogenous shock could have originated an abrupt adjustment of underlying vulnerabilities. Based on this, the quarters 1999Q1 – 2000Q1 were classified as a stress period. See Bonfim and Monteiro (2013) for further details.

8. See definitions of these concepts in Section 3.2 Model assessment.

9. The only series that was not possible to update was the debt-to-service ratio.

10. For an illustration of the impacts of using different smoothing parameters in a similar setting, please see Bonfim and Monteiro (2013).

11. According to the Basel Committee (2010) and Drehmann *et al.* (2010), the deviation of the ratio between credit and GDP from its long term trend is the indicator that better performs in signaling the need to build up capital before a crisis, when examining several indicators for different countries. Given this evidence, the Basel Committee (2010) proposes that buffer decisions are anchored on the magnitude of these deviations (though recognizing the need to complement the decisions with other indicators, as well as with judgment).

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