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The analyses, opinions and findings of these papers represent the views of the authors, they are not necessarily those of the Banco de Portugal or the Eurosystem

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Forecasting banking crises with dynamic panel probit models

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Abstract

Banking crises are rare events, but when they occur their consequences are often dramatic. The aim of this paper is to contribute to the toolkit of early warning models available to policy makers by exploring the dynamics and non-linearities embedded in a panel dataset covering several countries over four decades (from 1970Q1 to 2010Q4). The in-sample and out-of-sample forecast performance of several dynamic probit models is evaluated, with the objective of developing a common vulnerability indicator with early warning properties. The results obtained show that adding dynamic components and exuberance indicators to the models substantially improves the ability to forecast banking crises.

JEL: C12, C22

Keywords: Banking crisis, binary data, dynamic probit models, early warning indicators.

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1. Introduction

Predicting banking crises is certainly a difficult endeavour. On the one hand, it is econometrically very challenging to predict these rare events, which in many cases have different causes and consequences. On the other, even 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 help identify the main drivers of financial crises and 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; Chang and Velasco 2001; Burnside *et al.* 2004). Often currency crises 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.* 2011, 2013).

Although every crisis is different and unique (Reinhart and Rogoff 2011), we explore the commonalities of these rare events in a dataset of European systemic banking crises. Our main contribution relies on exploring the dynamics and exuberant behaviour in the time series of the dependent and independent variables, respectively. A wide range of methodologies has been used in the literature to forecast banking crises¹. Demirgüç-Kunt and Detragiache (2005) and Davis and Woutersen (2008) have used a signal approach and a multivariate binary model, building upon the important contribution of Estrella and Hardouvelis (1991), who were among the first to show that binary models could be used successfully for forecasting purposes. Bussière and Fratzscher (2006) and Caggiano *et al.* (2014) used a multinomial logit approach, which allows for the distinction between more than two states (for instance, tranquil, crisis and post-crisis periods). To explore the contribution of a joint deterioration in

1. For a recent and comprehensive review of this literature see, for instance, Frankel and Saravelos (2012) and Kauko (2014).

several variables, Duttagupta and Cashin (2011) use binary classification trees. More recently, Alessi and Detken (2011) use a related methodology to predict banking crises. These authors use a random forest method, which bootstraps and aggregates a multitude of decision trees.

We find that using a dynamic probit specification significantly contributes to enhance the forecast accuracy of early warning models. Exploring the dynamics intrinsic to the panel dataset allows us to substantially improve the forecasting power of the models, when compared to static binary models. This is true for both the in- and the out-of-sample exercises, when looking at a wide array of metrics to assess the performance of the model.

Despite the ever-growing literature on early warning tools and the variety of methodologies used, the dynamics embedded in the dependent variable have not been greatly explored. Falcetti and Tudela (2006) were perhaps the first authors to study the determinants of currency crises in emerging markets using maximum smoothly simulated likelihood on a lagged dependent variable model, thereby allowing them to explicitly model the existence of inter temporal links between crises episodes. Methodologically, our paper is closer to the estimation technique used by Kauppi and Saikkonen (2008). These authors estimate a dynamic binary probit model to predict US recessions, using the interest rate spread as the leading variable. They observe that dynamic probit models outperform static probit models both in- and out-of-sample. Bismans and Majetti (2013) use a similar methodology to forecast recessions. Candelon *et al.* (2012, 2014) generalize the univariate dynamic probit model developed by Kauppi and Saikkonen (2008) to a multivariate setting and also apply it to forecast crises.

To further explore the information content of the time series available, we extend the previous literature and explore the signalling power of exuberance indicators. Our approach is simple and intuitive. Given that systemic banking crises are rare events of large magnitude, we try to explore the signalling properties embedded in the distribution of the explanatory variables used in our early warning models. To the best of our knowledge, this is the first paper using this approach. Our results show that giving more strength to specific values of the distribution of the variables may allow us to improve even further the performance of dynamic models as early warning tools.

Finally, we deal with the difficulties associated with predicting crises that never happened, due to the successful intervention of policymakers or to favorable external developments. We are able to do so by using a database constructed by central bankers that includes both observed banking crises and also episodes of heightened vulnerability, in which the likelihood of occurrence of a crisis was perceived as very high.

This paper is organized as follows. In Section 2 we describe in detail the estimation methodology (models and parameter estimation) used and its relation to existing literature. In Section 3 we present the empirical analysis, 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. 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, for instance, Wright 2006; Kauppi and Saikkonen 2008; Nyberg 2010).

To introduce the models that we will use in the empirical application, consider y_{it} as the banking crisis indicator in country i in period t , which only takes the values of one and zero (binary) and \mathbf{x}_{it} as the $(k \times 1)$ vector of exogenous variables. Let $\mathcal{F}_t := \sigma\{(y_{is}, \mathbf{x}_{is}), s \leq t\}$ be the information set available at time t and assume that, conditional on \mathcal{F}_{t-1} , y_{it} has a Bernoulli distribution with probability p_{it} , *i.e.*, $y_{it}|\mathcal{F}_{t-1} \sim B(p_{it})$. Our objective is to model the conditional probability p_{it} as a function of the variables in \mathcal{F}_{t-1} . Hence, we assume, as in *e.g.* Kauppi and Saikkonen (2008), that the generation mechanism of y_{it} is

$$y_{it} = I(y_{it}^* \geq u_{it}) \quad (1)$$

where $I(\cdot)$ is an indicator function, u_{it} is an *i.i.d.* process and y_{it}^* is a latent variable related to the conditional probability p_{it} through the common cumulative distribution function of the random variables u_{it} . Specifically, assume that $y_{it}^* := F^{-1}(p_{it})$ where $F(\cdot)$ is a cumulative distribution function which is assumed to be monotonically increasing and twice continuously

differentiable. Thus, considering the conditional expectation and conditional probability given \mathcal{F}_{t-1} , it follows that

$$E(y_{it}|\mathcal{F}_{t-1}) = P(y_{it}^* \geq u_{it}|\mathcal{F}_{t-1}) = F(y_{it}^*) = p_{it}.$$

In the literature, it is typically assumed that u_{it} has either a normal or a logistic distribution such that the resulting model is either a probit or a logit model, respectively. Furthermore, as suggested by Jackman (1998) one can classify models of discrete data into two general classes: i) as marginal models or ii) as transitional models.

2.1. Marginal models

Marginal models are only concerned with explaining the effects of covariates on the probability outcomes and treat serial dependence as a nuisance which is captured through association parameters. In these models there is no explicit conditioning on the history of the discrete response.

For the purpose of the empirical analysis below, the marginal model we consider is

$$y_{it}^* = \alpha + \sum_{k=1}^p \sum_{j=1}^d \beta_{jk} x_{ij,t-k} + u_{it}. \quad (2)$$

Note that ordinary probit models make the restrictive assumption that all observations are independent, and hence no dynamics of the dependent variable is considered. However, given that when observations over time (time series) are available, time dependence may exist and explicitly accounting for this dynamics may be of interest.

It is known in the literature that estimates from conventional probit models, *i.e.* estimates obtained under the assumption of independence, are consistent and asymptotically normal under serial correlation (Poirier and Ruud 1988). However, probit standard errors will be incorrect, originating wrong inference. To detect this potential problem, tests for serial correlation and robust estimation procedures of standard errors are available in the literature; see, for instance, Gouriéroux *et al.* (1982) and Liang and Zeger (1986). However, these procedures do not explicitly model the dynamics; they are only aimed at correcting the standard errors to improve inference.

An alternative approach, which is the one we prefer and also follow in this paper, is to explicitly account for the dynamics parametrically through

augmentation of the model with lags of either the latent variable or the binary crisis indicator.

2.2. Transitional models

As highlighted by Jackman (1998) “*as the length of the series becomes longer, the serial component of the data is less a ‘nuisance’ and perhaps more a ‘feature’ of the data, and so in these circumstances a transitional model might be preferred to a marginal model.*”

Transitional models explicitly incorporate the history of the response in the computation of the latent variable y_{it}^* . Hence, in this way, each unit specific history can be used to generate forecasts for that specific unit, as opposed to marginal models which make forecasts solely on the basis of information on the exogenous variables. Furthermore, within this class Cox *et al.* (1981) distinguishes two types of transitional models: a) observation driven models, where the transitions are with respect to observed data, and b) parameter driven models, where the transitions are with respect to a latent process and a threshold parameter.

2.2.1. Observation-driven transitional models. The observation-driven transitional models assume that past realizations of the discrete response are informative about the current response, and are therefore introduced in the model as additional predictors. A two-state Markov chain is a straightforward way to model a binary time series, and forms the basis of the transitional model. Since with binary data there are only two unique elements of the 2-by-2 transition matrix of a first order Markov chain, a simple way to relate covariates to the transitional probabilities is via a link function and a regression model for each of the two transition probabilities (Jackman 1998).

Hence, for the purpose of our analysis, a simple specification is the dynamic probit model,

$$y_{it}^* = \alpha + \sum_{k=1}^p \sum_{j=1}^d \beta_{jk} x_{ij,t-k} + \sum_{k=1}^p \gamma_k y_{i,t-k} + v_{it} \quad (3)$$

where $y_{i,t-k}$, $k = 1, \dots, p$, corresponds to the binary crisis indicator variable for country i at time $t - k$.

Beck *et al.* (2001) define a model such as (3) as a “restricted transition” model. Essentially, in this model the latent variable, y_{it}^* , is simply shifted up/down by γ_k , $k = 1, \dots, p$, when $y_{i,t-k}$ is equal to one. However, as Beck *et al.* (2001) also indicate, the probabilities do not shift as a simple function of γ_k , $k = 1, \dots, p$, due to the nonlinear nature of the probit. The main argument for the use of this type of models is the belief that past realized values of y_{it} can be informative about its current value.

2.2.2. Exuberance Indicator. A further extension considered in our empirical application aimed at capturing periods in which explanatory variables display exuberant behaviour are considered as

$$y_{it}^* = \alpha + \sum_{k=1}^p \sum_{j=1}^d \beta_{jk} x_{ij,t-k} + \sum_{k=1}^p \gamma_k y_{i,t-k} + \sum_{k=1}^p \sum_{j=1}^d \delta_{jk} D_{ij,t-k}^\kappa + v_{it} \quad (4)$$

where $D_{ij,t-k}^\kappa$ is a dummy variable which is equal to one when variable i in country j exceeds its κ percentile ($\kappa \in (0,1)$) and is zero otherwise. Note that the κ threshold is not necessarily the same for all variables considered. In particular, in our empirical analysis, the choice consists in choosing the percentile for each of the variables considered which provides the largest AUROC.

This allows to embed into the analysis non-linearities of the independent variables. Given the rare frequency of crises and the non-linearities in the data usually observed around these events, this extension of the model may help in improving the forecasting accuracy of our estimates.

2.2.3. Parameter-driven transitional models. In contrast to the observation driven transitional models described above, in the parameter-driven transitional models the transitions are determined by the latent variable y_{it}^* instead of y_{it} . This approach combines familiar time series methods for continuous variables with standard response models. In particular, in our analysis we consider that

$$y_{it}^* = \alpha + \sum_{k=1}^p \sum_{j=1}^d \beta_{jk} x_{ij,t-k} + \sum_{k=1}^p \varphi_k y_{i,t-k}^* + a_{it}. \quad (5)$$

The difference between model (3) and model (5) resides in that the former uses realized values of $\{y_{it}\}$, whereas in the latter the underlying latent variable is used (Beck *et al.*, 2002).

Although model (5) looks more like a conventional time series model, it is harder to estimate. The resulting likelihood function for the binary response model with autoregressive errors is considerably more complex than the likelihood in the serially independent case.

2.3. Parameter Estimation

In a recent paper, de Jong and Woutersen (2011) provide conditions under which a dynamic process is stationary and strong mixing. However, to the best of our knowledge for a general model such as (5) no results are available yet in the literature. Nevertheless, as argued in Kauppi and Saikkonen (2008), it seems reasonable to expect that a necessary condition for such a result is that the parameters $\varphi_1, \dots, \varphi_p$ in (5) satisfy the usual stationarity condition, i.e., that the roots of the polynomial $(1 - \varphi_1 z - \dots - \varphi_p z^p)$ lie outside the unit circle.

Regarding parameter estimation of the models introduced, consider the general representation

$$y_{it}^* = \mathbf{Z}_{it}'\theta + u_{it} \quad (6)$$

where \mathbf{Z}_{it} is a $(d \times 1)$ vector of explanatory variables which differs according to the model considered in (2), (3), (4) and (5), θ is the corresponding vector of parameters and u_{it} is an *n.i.i.d.* $(0, \sigma^2)$.

Considering that we have observed data on y_{it} and \mathbf{Z}_{it} for $t = 1, \dots, T$ and that p initial values $y_{i,-p+1}, \dots, y_{i,0}$ are available. Then, the (conditional) log-likelihood function in a Probit type framework has the form,

$$\ell(\theta) = \sum_{i=1}^N \sum_{t=1}^T [y_{it} \log \Phi(y_{it}^*(\theta)) + (1 - y_{it}) \log(1 - \Phi(y_{it}^*(\theta)))] \quad (7)$$

where $\Phi(\cdot)$ corresponds to the Normal cumulative distribution function. Note that when specification (5) is used, also the initial values $y_{i,-p+1}^*, \dots, y_{i,0}^*$ are needed.

The maximization of the log-likelihood function in (7) is a highly nonlinear problem, but it can be straightforwardly carried out by standard numerical methods. In the case of a specification as in (5) in a time series context, de Jong

and Woutersen (2011) showed that, under appropriate regularity conditions, the conventional large sample theory applies to the ML estimator of the parameter vector θ , denoted by $\hat{\theta}$. The assumed regularity conditions include stationarity of the explanatory variables and normality of the random variable u_{it} , and the obtained result are

$$T^{1/2} \left(\hat{\theta} - \theta \right) \xrightarrow{d} N \left(0, \mathcal{I}(\theta)^{-1} \right) \quad (8)$$

where $\mathcal{I}(\theta) = \text{plim} \sum_{i=1}^N \sum_{t=1}^T \left[\left(\frac{\partial l_{it}(\theta)}{\partial \theta} \right) \left(\frac{\partial l_{it}(\theta)}{\partial \theta} \right)' \right]$ and \xrightarrow{d} denotes convergence in distribution.

de Jong and Woutersen (2011) also note that their results on ML estimation are valid when the normality assumption does not hold. A misspecification may result when the model is used for forecasting. Specifically, if at time t the purpose is to forecast the value $y_{i,t+h}$ ($h \geq 1$) this will require forecasts of the explanatory variables. However, if one is unwilling to build a forecasting model for the explanatory variables, one can modify the model specifications by replacing \mathbf{Z}_{it} by $\mathbf{Z}_{i,t-h}$ (see e.g. Estrella and Mishkin 1998). Thus, if the data generation process is any of the models previously discussed, such a modification results in misspecified models when $h > 0$.

For inference purposes (following Chortareas *et al.* 2010) we use a Newey-West [NW] type estimator of the parameters' variance/covariance matrix, adapted to a pooled panel data model, which is robust to the presence of heteroscedasticity and autocorrelation in the residuals. The Newey-West procedure has been used by Estrella and Rodrigues (1998) and Kauppi and Saikkonen (2008) when working with probit models using only time series data.

Berg and Coke (2004) also introduced a robust covariance matrix estimator for pooled static panel probit models. However, this estimator does not account for the presence of different clusters (*e.g.* countries). Therefore, following the suggestion of Chortareas *et al.* (2010), Berg and Coke's (2004) estimator for the covariance matrix of the parameters is modified as recommended by Petersen (2009). This author focused on the estimation of the standard errors of linear panel data models, by applying a NW estimator to each cluster (*e.g.* country) in the pooled panel.

Remark: *An alternative approach for the estimation of the variance/covariance matrix is through bootstrap methods. The basic idea is simple:*

- i) draw, with replacement, from the set of actual data used to estimate the model. In other words, start with an empty data set and pick a country at random and include the actual data from that country in the data set. This is repeated, with replacement, as many times as there are countries in the sample.*
- ii) Estimate θ as described above and define the resulting estimate as $\hat{\theta}^B(j)$.*
- iii) Repeat j times and then estimate the bootstrap variance of $\hat{\theta}$, Ω_{θ}^B , as the variance of $\hat{\theta}^B(j)$ across the j samples; see Berg and Coke (2004) for more details.*

In the next section we will estimate and evaluate the forecast performance of the models introduced in (2)–(5) in order to empirically analyze the different specifications and dynamic components considered for the development of early warning tools.

3. Empirical Analysis

3.1. Data

The most critical variable for our analysis is y_{it} , the binary crisis indicator. Several authors have constructed extensive databases of financial crises (Reinhart and Rogoff 2011; Laeven and Valencia 2012). However, 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 the distress in itself. To ensure the best quality possible for this critical variable, we use the systemic banking crises database collected by the Czech National Bank (Babecký *et al.* 2012). This database benefited from the inputs of the Heads of Research of the Eurosystem. The database was recently updated with contributions from the European Systemic Risk Board (ESRB) Expert Group on establishing guidance for setting countercyclical buffer rates (see Detken *et al.* 2014, for further details). 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 has effectively

occurred. Our analysis focuses on the broader crisis definition, but the results are broadly robust for the stricter crisis definition as well as with other publicly available crisis databases.

To identify the variables with stronger signaling properties ahead of crisis, we used several macroeconomic and financial variables from various data sources: private credit (from the BIS and the IMF); house prices (EU, BIS and OECD data); equity prices (EU and IMF); nominal and real GDP (EU, IMF); and debt service ratio (BIS, ECB and EUROSTAT; calculations were performed by the ECB based on the methodology by Drehmann and Juselius, 2012). In addition, also several bank variables were considered: net interest income (OECD), net pre-tax income (OECD), capital and reserves (OECD, EU), leverage ratio (EU), and total assets (EU).²

The longest series in the dataset span from 1970Q1 to 2010Q4. The results presented in our paper rely on an updated version of the dataset initially provided by the ECB, using Thomson Reuters. To maximize the information set available, in some cases we extended the series from a given source with data from other sources available in the dataset. When the data sources were not the same, the series were extended using chain growth rates with data up to 2013Q2.³ In some cases, the series were also extended back to previous periods. Most variables are provided on a quarterly basis.

In order to ensure that the data used in the estimations replicates as closely as possible the data available to policy makers in each moment of time, we used lagged variables to consider lags in data releases and we computed only one-sided or recursive filters. Despite these efforts, the information is not exactly the same as that that would be available to policy makers, 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 macro-prudential instruments such as the countercyclical capital buffer ratio. Nevertheless, this is the best approximation possible for researchers.

We implemented a few transformations of the original variables. First, we computed several ratios, such as the credit-to-GDP and the total assets of

2. See Alessi *et al.* (2014) for more details.

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

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.⁴

After performing these transformations, we obtain 35 possible explanatory variables. In order to select the potentially more relevant ones, we performed an univariate analysis, examining the AUROC of each series. In addition, the availability of information was also considered as important and the shorter series were not included in this analysis. Hence, from this analysis, we determined that the best performing variables are the credit-to-GDP gap with a smoothing parameter of 400 000⁵, the debt service ratio, the year-on-year growth rate of house prices, and the equity price index.⁶

Table 1 presents some descriptive statistics on these variables for the whole sample, while Table 2 displays country specific 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 (namely, Belgium, Cyprus, Luxembourg, Malta, Poland, and Romania). The final sample thus consists of 22 European countries.

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

5. According to the Basel Committee on Banking Supervision (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 on Banking Supervision (2010) proposes that countercyclical capital buffer decisions be anchored on the magnitude of these deviations (though recognizing the need to complement the decisions with other indicators, as well as with judgment).

6. These results are consistent with those of Drehmann and Juselius (2014), who show that the best performing indicators to forecast banking crises are the credit-to-GDP gap and the debt service ratio. They find that the former performs better at longer forecasting horizons, while the latter performs better closer to the emergence of a crisis.

	Total sample					
	N	Mean	St. dev.	min	Median	max
Crisis dummy	4816	0.10	0.29	0	0	1
Equity price index	2516	57.0	43.9	1	46.2	265.1
Debt service ratio	2380	0.19	0.17	0.01	0.15	1.08
Credit-to-GDP gap	2522	4.8	11.6	-47.2	2.4	62.5
House price index (yoy)	2252	9.4	46.2	-42.2	5.4	1442.4

TABLE 1. Summary statistics

Note: yoy - year on year growth rate (%). The crisis dummy takes the value 1 during banking crises or during periods of heightened 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 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, with a smoothing parameter of 400.000. The house price index combines data from the BIS and OECD.

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

	Equity price index		Debt service ratio		Credit-to-GDP gap		House price index (yoy)		Crisis dummy	
	N	median	N	median	N	median	N	median	N	mean
Austria	172	32.7	171	0.15	167	0.5	127	2.83	172	0.00
Belgium									172	0.00
Bulgaria	54	48.0	64	0.06	57	13.4	127	3.00	172	0.13
Cyprus									172	0.02
Czech Republic	79	50.3	70	0.10	78	3.9	75	4.62	172	0.10
Germany	172	53.8	170	0.15	167	-1.4	127	2.82	172	0.09
Denmark	93	65.7	39	0.25	139	2.9	127	5.11	172	0.27
Estonia	66	54.6	65	0.13	67	1.9	28	7.02	172	0.02
Spain	172	26.1	171	0.15	167	1.5	127	6.95	172	0.27
Finland	172	21.4	171	0.14	167	2.4	127	6.65	172	0.10
France	100	77.7	171	0.13	167	1.9	127	3.61	172	0.16
Greece	80	67.9	45	0.14	127	1.9	127	11.50	172	0.12
Croatia	61	89.1	7	0.17	45	3.4	60	3.50	172	0.06
Hungary	88	42.4	71	0.08	83	4.3	83	9.13	172	0.10
Ireland	172	30.1	131	0.21	127	9.2	127	6.66	172	0.10
Italy	172	38.5	171	0.13	167	6.1	127	5.44	172	0.05
Lithuania	48	77.4	72	0.05	61	3.5	53	9.75	172	0.10
Luxembourg									172	0.00
Latvia	67	65.9	72	0.05	62	7.2	24	1.11	172	0.05
Malta									172	0.00
Netherlands	172	33.9	170	0.17	139	1.3	144	4.51	172	0.15
Poland									172	0.00
Portugal	100	81.9	143	0.25	139	13.7	125	4.20	172	0.13
Romania									172	0.05
Sweden	172	24.0	171	0.75	127	1.0	127	6.13	172	0.14
Slovenia	62	55.2	36	0.13	43	1.2	20	-0.16	172	0.19
Slovakia	70	44.4	28	0.10	59	0.3	75	6.82	172	0.00
United Kingdom	172	46.1	171	0.21	167	3.5	168	8.84	172	0.27
Total	2516	46.2	2380	0.15	2522	2.4	2252	5.37	4816	0.10

TABLE 2. Summary statistics by country

Note: all variables are defined in Table 1.

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

Equity prices reached higher median values in Croatia, Portugal, France and Lithuania and were more subdued in Finland, Sweden and Spain. The highest debt service ratio was observed in Sweden, while in Latvia, Lithuania, Hungary and Bulgaria this ratio stood closer to zero. The credit-to-GDP gap, which has been found to be one of the best predictors of banking crises (Drehmann *et al.* 2010), displays a negative median value for Germany and relatively low median values in Slovakia and Austria. The highest median values for this gap are observed in Bulgaria, Portugal, Ireland, Italy and Latvia. Finally, house prices have increased more significantly in Greece, the UK, Hungary and Lithuania, and displayed a smaller magnitude in Germany, Austria, Slovenia and Latvia.

3.2. Main results

The first step in the analysis consisted of the estimation of the models described in Section 2 and variants of these. For reference purposes, we will refer to the models in (2) as simple probit models, to the models in (3) as dynamic probit models, to the models in (4) as exuberance probit models and finally to the models in (5) as latent probit models. Thus, considering y_{it} , the endogenous binary response indicator of banking crisis, the multistep ahead projections were obtained through pooled panel probit specifications, where the conditional probability forecast of observing a crisis at time t , $P(y_{it} = 1)$, is given by $\Phi(y_{it}^*)$. In particular, $\Phi(\cdot)$ is the Gaussian cumulative distribution function and y_{it}^* is a latent variable. Defining h as the forecast horizon, we adjust (6) to produce the necessary forecasts from,

$$y_{it}^* = \mathbf{Z}'_{i,t-h}\theta + v_{it}.$$

The model was estimated with three different lag structures. First we considered 4 to 20 lags of all explanatory variables ($\mathbf{Z}_{i,t-4}, \dots, \mathbf{Z}_{i,t-20}$), which allowed 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 12 and 20 quarters. This allowed us to identify the variables with stronger early warning signals, thus giving enough time for policymakers to act. Finally, we also estimated the model in the “late period”, using information lagged between 4 and 12 quarters, to understand which variables may be more relevant to signal a crisis in the near future. In

this period, signals may be stronger and policy action may need to be prompter. A similar reasoning is presented by Oet *et al.* (2013).

Simple Probit										Dynamic probit									
Total Period			Early Period - 20-12 lags			Late Period - 12-4 lags				Total Period			Early Period - 20-12 lags			Late Period - 12-4 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.	6.73	0.00	L12.	1.204	0	L4.	7.26	0.00	
										L5.	-3.75	0.00	L15.	-0.04	0.618	L5.	-4.15	0.00	
										L8.	-0.35	0.44	L17.	-0.63	0.01	L7.	-0.33	0.44	
										L9.	0.15	0.57				L11.	-0.44	0.15	
										L10.	-0.30	0.44							
										L17.	-1.05	0.00							
Equity price index	L12.	0.00	0.24	L12.	0.01	0.01	L6.	0.00	0.84	L9.	0.01	0.06	L12.	0.013	0.005	L6.	0.01	0.05	
	L15.	0.00	0.80	L15.	0.00	0.02	L12.	0.00	0.16	L11.	0.00	0.82	L13.	-0	0.176				
	L17.	0.00	0.68	L17.	0.00	0.77				L18.	0.00	0.94	L17.	1E-04	0.952				
				L18.	0.01	0.00							L19.	-0.01	0.153				
				L19.	-0.01	0.02													
Debt service ratio	L7.	8.08	0.01	L12.	11.01	0.003	L4.	0.45	0.17	L4.	27.26	0.00	L12.	14.2	0	L4.	17.52	0.00	
	L12.	3.05	0.17	L15.	-4.24	0.397				L6.	-7.16	0.06	L14.	-7.94	0.027	L7.	-17.56	0.00	
	L14.	-3.89	0.14	L20.	-6.93	0.031				L7.	-5.71	0.20	L20.	-6.59	0.02				
	L15.	0.93	0.63							L10.	-8.03	0.06							
	L16.	2.55	0.48							L14.	-0.39	0.95							
	L17.	-5.37	0.08							L18.	-7.68	0.10							
	L20.	-5.94	0.17																
Credit-to-GDP gap	L6.	-0.05	0.01	L14.	0.024	0.059	L4.	-0.05	0.03	L4.	-0.05	0.02	L14.	0.024	0.05	L6.	0.00	0.89	
	L9.	0.04	0.00				L5.	0.01	0.44	L6.	0.01	0.61				L11.	0.09	0.00	
	L14.	0.02	0.15				L6.	0.01	0.27	L9.	0.03	0.12				L12.	-0.07	0.00	
							L9.	0.05	0.00	L10.	0.01	0.65							
										L11.	0.05	0.04							
										L13.	-0.03	0.07							
										L16.	0.00	0.92							
House price index (yoy)							L5.	-0.05	0.04	L12.	-0.01	0.61				L5.	-0.01	0.32	
							L6.	0.03	0.03	L20.	0.00	0.62				L9.	0.01	0.21	
							L10.	0.01	0.25										
Constant	-1.40	0.00		-1.45	0.00		-1.49	0.00		-1.95	0.00		-1.55	0.00		-2.28	0.00		
R^2		0.18			0.15			0.18			0.57			0.20			0.5417		
N		1721			1749			1585			1395			1749			1604		

TABLE 3. Regression results: simple and dynamic probits

Note: all variables are defined in Table 1. The total period refers to lags [20;4], the early period [20; 12] and the late period [12;4]. Standard errors clustered by country.

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

For all models, we began by estimating the regressions with all the lags of the four selected explanatory variables (equity price index, debt service ratio, 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% nominal level, thereby allowing us to re-estimate a more parsimonious model. The results of this second round of estimates are presented in Table 3. The first three columns show the results for the marginal model defined in (2) (simple probit) and the last three show the results for the transition model defined in (3).

In the full period estimation, the equity price index is never statistically significant in this specification. In contrast, the public debt service ratio is statistically significant (at a 10% nominal level) at several quarters ($t - k$, for $k = 7$ and 17). The credit-to-GDP gap displays several statistically significant coefficients ($t - 6$ and $t - 9$). 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 is absent from this specification, as this variable was never significant in the first step of the estimation.

In the early period ($t - 12$ to $t - 20$), the results are somewhat different. The debt service ratio appears significant at $t - 12$ and $t - 20$, albeit with different coefficient signs. Equity price indices display significant coefficients with a lag of 12, 15, 18 and 19 quarters, suggesting that this variable may provide useful indications well ahead of crisis. The credit-to-GDP gap is only relevant at $t - 14$.

In the period closer to the crisis, the so called late period ($t - 4$ to $t - 12$), the results are also different. Both the debt to service ratio and the equity price index are not statistically significant at any lag, while the credit-to-GDP gap is significant at $t - 4$ and $t - 9$. House price index growth turns out to be significant at $t - 5$ and $t - 6$, showing that the variables have different signaling powers in different horizons.

In the second part of Table 3 we present the results for the dynamic models (model (3)). 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 difference is perhaps that the debt service ratio is now more significant in several specifications.

In the Appendix, we provide the estimation results for the models (4) and (5).

All in all, the equity price index and the debt to service ratio seem to provide useful early guidance for policymakers while the credit-to-GDP gap has better signaling properties closer to the emergence of a crisis.

3.3. 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; and as "non-crisis" otherwise. 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. Naturally, a perfect model would classify correctly all observations. This does not happen in practice. As a matter of fact, a very low 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, and we can think of it 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.

[Please insert Figure 1 about here]

We define specificity as the fraction of non-crisis observations that are classified as non-crisis by the model, and as sensitivity the fraction of crisis

observations that are classified as crisis 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 (ROC) curve (Figure 1). In the horizontal axis we represent 1 minus specificity, that is, the percentage of non-crisis observations classified as crisis by the model. In the vertical axis we represent sensitivity, that is, the fraction of crisis observations classified as crisis by the model. A given point (x,y) on 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?

As previously indicated, in a perfect model we would have to incorrectly classify 0 percent of the non-crisis observations in order to correctly classify 100 percent of crisis observations. 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 45° 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, and so forth. This fact suggests that an adequate measure for the performance of the model is the area under the ROC curve, commonly known as AUROC. Figure 1 illustrates two hypothetical ROC curves, with different sensitivity and specificity values.

	Simple Probit			Dynamic probit			Exuberance probit			Latent Variable		
	Total	Early	Late	Total	Early	Late	Total	Early	Late	Total	Early	Late
N	1721	1749	1585	1395	1749	1604	-	1417	1558	1102	1414	1388
R2	0.179	0.152	0.183	0.569	0.205	0.542	-	0.306	0.605	0.626	0.226	0.553
AUROC	0.790	0.774	0.809	0.949	0.824	0.941	-	0.864	0.955	0.962	0.831	0.943
Confusion matrix - full sample												
True positives (TP)	89	64	79	212	91	237	-	144	237	195	82	218
False positives (FP)	46	47	58	32	54	44	-	66	37	22	48	35
False negatives (FN)	253	284	244	84	251	89	-	155	82	48	195	80
True negatives (TN)	1333	1354	1204	1067	1347	1234	-	1052	1202	837	1089	1055
TOTAL	1721	1749	1585	1395	1743	1604	-	1417	1558	1102	1414	1388
% false alarms	3.3	3.4	4.6	2.9	3.9	3.4	-	5.9	3.0	2.6	4.2	3.2
% missed crises	74.0	81.6	75.5	28.4	73.4	27.3	-	51.8	25.7	19.8	70.4	26.8
% correctly predicted	82.6	81.1	80.9	91.7	82.5	91.7	-	84.4	92.4	93.6	82.8	91.7
Sensitivity (TP/(TP+FN))	26.0	18.4	24.5	71.6	26.6	72.7	-	48.2	74.3	80.2	29.6	73.2
Specificity (TN/(FP+TN))	96.7	96.6	95.4	97.1	96.1	96.6	-	94.1	97.0	97.4	95.8	96.8

TABLE 4. Model Evaluation

Note: the results refer to the regressions presented in Table 3 and in the Appendix. The total period refers to lags [20;4], the early period [20;12] and the late period [12;4]. The model with exuberance indicators does not converge when the entire period is considered.

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

Figure 2 plots the ROC curves for the specifications presented in Table 3 (simple and dynamic probits), while Figure 3 plots similar curves for probits with exuberance indicators and latent variables. Table 4 presents several indicators to assess the quality of these models: the number of true positives (TP - number of correctly predicted crisis periods), the number of true negatives (TN), the number of false positives (FP) and the number of false negatives (FN). These elements can be used to compute two performance measures for binary classification tests: the sensitivity, defined as the true positives rate ($TP/(TP+FN)$), and the specificity, defined as 1 minus the false positive rate. We also present results for the percentage of false alarms, the percentage of missed crises and the percentage of correctly predicted crises.

[Please insert Figures 2 and 3 about here]

Examining the model's goodness of fit (McFadden's R^2) and the AUROC provides indication on the quality of the model. The early period estimations provide the weakest results. This is not surprising, as it would be expected that signals are stronger immediately before the crisis than 3 years before.

Regarding the methodology, the model's performance, assessed by McFadden's R^2 and the AUROC, is substantially better when we include dynamic components, i.e., the lagged dependent (both the observed or latent) 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. Further, the addition of exuberance indicators improves the model even more, although only for early and late period configurations (for the total period, convergence was not achieved for this model).

Although the model's goodness of fit and the AUROC are useful summary measures to assess the performance of each model, it is also relevant to consider how many crises the models correctly predict, how many they fail to predict and how many false alarms exist. This is relevant especially in a setting such as ours, with potentially relevant implications for decision-making. Indeed, as noted by Alessi and Detken (2011), Betz *et al.* (2014), Bussière and Fratzscher (2006) or Davis and Woutersen (2008), 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 probit models are able to reduce the percentage of false alarms for the total and late periods estimation. Nevertheless, this percentage is very small in all models (at most 5.9 per cent). In contrast, dynamic probit models significantly reduce the percentage of missed crises (from 74 to 28.4 per cent, in the total period estimation). Given that missing a crisis may be costlier than issuing a false alarm (Borio and Lowe 2002; Demirgüç-Kunt and Detragiache 2005; Borio and Drehmann 2009), this result suggests that dynamic models may be very 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 considered.

It is also interesting to see that dynamic probit models show significantly increased 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, also increases slightly in the dynamic models, except in the early period.

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.

Adding exuberance terms to the estimation improves these results even further. The evaluation metrics improve in all the estimation horizons. The only exception is the percentage of false alarms in the early period. The dynamic model with exuberance indicators misses 51.8% of the crises in the sample of the early period setup, while in the late period configuration it misses only 25%. The performance of the model is substantially better when we consider the percentage of correctly predicted crises.

Regarding the estimation with lags of the latent variable, the results provide a slight improvement over the dynamic model introduced before. In turn, this model slightly underperforms the one including exuberance indicators.

In sum, our results show that accounting for the dynamics in the dependent variable and the exuberance indicators for the independent variables allows to substantially improve the performance of early warning models for banking crises.

3.4. *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 exercise in which Denmark, Finland and Sweden were excluded given the systemic banking crisis in the late 1980s/early 1990s. Afterwards we test the accuracy of the model for these countries *ex post*.

The results of the performance of the simple, dynamic and exuberance models in these two exercises are presented in Table 5 and Figures 4 to 7. The table shows several evaluation metrics for 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.

[Please insert Figures 4 to 7 about here]

We find that the performance for the out-of-period estimations generally decreases in the simple probits. This is indeed a reason for concern, as a significant part of crises observations in different countries are recorded after 2007. The percentage of missed crises increases significantly in the out-of-period estimation, showing that the model would not be able to predict the global financial crisis in all the countries considered. The percentage of correct predictions of crises also decreases more in this estimation. These latter results are not unexpected, as this crisis was driven in many countries mainly by exogenous shocks rather than by underlying vulnerabilities.

	Simple Probit			Out-of-period			Out-of-sample		
	Total	Early	Late	Total	Early	Late	Total	Early	Late
AUROC	0.790	0.774	0.809	0.588	0.582	0.601	0.877	0.860	0.846
Confusion matrix - full sample									
True positives	89	64	79	13	8	27	36	20	27
False positives	46	47	58	11	12	14	14	15	20
False negatives	253	284	244	180	191	157	24	40	33
True negatives	1333	1354	1204	222	253	217	211	210	190
TOTAL	1721	1749	1585	426	464	415	285	285	270
% false alarms	3.3	3.4	4.6	4.7	4.5	6.1	6.2	6.7	9.5
% missed crises	74.0	81.6	75.5	93.3	96.0	85.3	40.0	66.7	55.0
% correctly predicted	82.6	81.1	80.9	55.2	56.3	58.8	86.7	80.7	80.4
Sensitivity (TP/(TP+FN))	26.0	18.4	24.5	6.7	4.0	14.7	60.0	33.3	45.0
Specificity (TN/(FP+TN))	96.7	96.6	95.4	95.3	95.5	93.9	93.8	93.3	90.5
	Dynamic probit			Out-of-period			Out-of-sample		
	Total	Early	Late	Total	Early	Late	Total	Early	Late
AUROC	0.949	0.824	0.941	0.898	0.664	0.906	0.959	0.864	0.956
Confusion matrix - full sample									
True positives	212	91	237	110	22	128	47	25	45
False positives	32	54	44	9	29	5	6	14	5
False negatives	84	251	89	70	177	60	13	35	15
True negatives	1067	1347	1234	198	236	231	170	211	201
TOTAL	1395	1743	1604	387	464	424	236	285	266
% false alarms	2.9	3.9	3.4	4.3	10.9	2.1	3.4	6.2	2.4
% missed crises	28.4	73.4	27.3	38.9	88.9	31.9	21.7	58.3	25.0
% correctly predicted	91.7	82.5	91.7	79.6	55.6	84.7	91.9	82.8	92.5
Sensitivity (TP/(TP+FN))	71.6	26.6	72.7	61.1	11.1	68.1	78.3	41.7	75.0
Specificity (TN/(FP+TN))	97.1	96.1	96.6	95.7	89.1	97.9	96.6	93.8	97.6
	Exuberance probit			Out-of-period			Out-of-sample		
	Total	Early	Late	Total	Early	Late	Total	Early	Late
AUROC	-	0.864	0.955	-	0.552	0.725	-	0.834	0.960
Confusion matrix - full sample									
True positives	-	144	237	-	39	37	-	26	46
False positives	-	66	37	-	27	19	-	12	3
False negatives	-	155	82	-	146	146	-	34	14
True negatives	-	1052	1202	-	206	206	-	164	199
TOTAL	-	1417	1558	-	418	408	-	236	262
% false alarms	-	5.9	3.0	-	11.6	8.4	-	6.8	1.5
% missed crises	-	51.8	25.7	-	78.9	79.8	-	56.7	23.3
% correctly predicted	-	84.4	92.4	-	58.6	59.6	-	80.5	93.5
Sensitivity (TP/(TP+FN))	-	48.2	74.3	-	21.1	20.2	-	43.3	76.7
Specificity (TN/(FP+TN))	-	94.1	97.0	-	88.4	91.6	-	93.2	98.5
	Latent Variable			Out-of-period			Out-of-sample		
	Total	Early	Late	Total	Early	Late	Total	Early	Late
AUROC	0.962	0.831	0.943	0.830	0.626	0.911	0.812	0.721	0.871
Confusion matrix - full sample									
True positives	195	82	218	78	30	112	42	33	52
False positives	22	48	35	10	35	8	20	71	38
False negatives	48	195	80	80	136	70	5	12	8
True negatives	837	1089	1055	175	207	203	60	118	135
TOTAL	1102	1414	1388	343	408	393	127	234	233
% false alarms	2.6	4.2216	3.211	5.4	14.5	3.8	25.0	37.6	22.0
% missed crises	19.8	70.397	26.846	50.6	81.9	38.5	10.6	26.7	13.3
% correctly predicted	93.6	82.815	91.715	73.8	58.1	80.2	80.3	64.5	80.3
Sensitivity (TP/(TP+FN))	80.2	29.603	73.154	49.4	18.1	61.5	89.4	73.3	86.7
Specificity (TN/(FP+TN))	97.4	95.778	96.789	94.6	85.5	96.2	75.0	62.4	78.0

TABLE 5. Out-of-sample and out-of-period estimation

Note: 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 [20;4], the early period [20;12] and the late period [12;4]. The model with exuberance indicators does not converge when the entire period is considered.

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

However, when we consider dynamic models, the decrease in performance is milder. This is a relevant result, showing that even though it would be quite challenging to predict the global financial crises, adding a dynamic component to the model would help policymakers to be more successful in detecting heightened vulnerabilities at an early stage.

In turn, the performance of the models in the out-of-sample exercises is actually better than that of the baseline estimations in some cases. This means that the models are able to perform well when we exclude the Nordic crisis from the sample. However, this improved performance might be driven by the fact that most crisis events left in the database now refer to the global financial crisis.

Looking at the different models, the results show that the dynamic component is the main source of improvement from the simple probit regression. Despite being slightly outclassed by the exuberance and latent variable approach (through the in-sample AUROC), its results' consistency over all periods and its performance in the out-of-sample and out-of-time exercises show that this may be the most reliable model.

4. Concluding Remarks

Systemic banking crises are rare, yet extremely costly, events. Despite the large body of existing literature, accurately predicting crises is still a very challenging exercise. 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 crises in Europe, we find that equity prices, house prices growth, credit-to-GDP gaps and debt to service ratios are among the most useful indicators in signalling emerging crises.

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. Furthermore, taking into account nonlinearities in the dependent variables around crisis events also improves the quality of early warning tools. These small changes in model estimation may significantly improve policymakers' ability to better meet the challenge of being able to identify an emerging crises, thus allowing them to act in advance.

References

- Alessi, L., A. Antunes, J. Babecký, S. Baltussen, M. Behn, D. Bonfim, O. Bush, C. Detken, J. Frost, R. Guimarães, T. Havránek, M. Joy, K. Kauko, J. Matějů, N. Monteiro, B. Neudorfer, T. Peltonen, P. M. M. Rodrigues, M. Rusnák, W. Schudel, M. Sigmund, H. Stremmel, K. Šmídková, R. van Tilburg, B. Vašíček, and D. Žigraiová (2014). “A Horse Race of Early Warning Systems Developed by the Macroprudential Research Network.” Mimeo, European Central Bank.
- Alessi, Lucia and Carsten Detken (2011). “Quasi real time early warning indicators for costly asset price boom/bust cycles: A role for global liquidity.” *European Journal of Political Economy*, 27(3), 520–533.
- Babecký, Jan, Tomas Havranek, Jakub Mateju, Marek Rusnák, Katerina Smidkova, and Borek Vasicek (2012). “Banking, debt and currency crises: early warning indicators for developed countries.” Working Paper 1485, European Central Bank.
- Basel Committee on Banking Supervision (2010). “Guidance for national authorities operating the countercyclical capital buffer.”
- Beck, Nathaniel, David L. Epstein, Simon Jackman, and Sharyn L. O’Halloran (2001). “Alternative models of dynamics in binary time-series-cross-section models: The example of state failure.” URL <http://www.nyu.edu/gsas/dept/politics/faculty/beck/emory.pdf>.
- Berg, Andrew and Rebecca N. Coke (2004). “Autocorrelation-corrected standard errors in panel probits: an application to currency crisis prediction.” Working Paper 04/39, International Monetary Fund.
- Betz, Frank, Silviu Oprică, Tuomas A. Peltonen, and Peter Sarlin (2014). “Predicting distress in European banks.” *Journal of Banking and Finance*, 45, 225–241.
- Bismans, Francis and Reynald Majetti (2013). “Forecasting recessions using financial variables: the French case.” *Empirical Economics*, 44(2), 419–433.
- Bonfim, Diana and Nuno Monteiro (2013). “The implementation of the countercyclical capital buffer: rules versus discretion.” *Banco de Portugal Financial Stability Report*, November.
- Borio, Claudio and Mathias Drehmann (2009). “Assessing the risk of banking crises—revisited.” *BIS Quarterly Review*, March.

- Borio, Claudio and Philip William Lowe (2002). "Asset prices, financial and monetary stability: exploring the nexus." Working Paper 114, BIS.
- Boyd, John H., Gianni De Nicolò, and Elena Loukoianova (2009). "Banking crises and crisis dating: theory and evidence." Working Paper 09/141, IMF.
- Burnside, Craig, Martin Eichenbaum, and Sergio Rebelo (2004). "Government guarantees and self-fulfilling speculative attacks." *Journal of Economic Theory*, 119(1), 31–63.
- Bussière, Matthieu and Marcel Fratzscher (2006). "Towards a new early warning system of financial crises." *Journal of International Money and Finance*, 25(6), 953–973.
- Caggiano, Giovanni, Pietro Calice, and Leone Leonida (2014). "Early warning systems and systemic banking crises in low income countries: A multinomial logit approach." *Journal of Banking and Finance*, 47, 258–269.
- Candelon, Bertrand, Elena-Ivona Dumitrescu, and Christophe Hurlin (2012). "How to evaluate an early-warning system: Toward a unified statistical framework for assessing financial crises forecasting methods." *IMF Economic Review*, 60(1), 75–113.
- Candelon, Bertrand, Elena-Ivona Dumitrescu, and Christophe Hurlin (2014). "Currency crisis early warning systems: Why they should be dynamic." *International Journal of Forecasting*, 30(4), 1016–1029.
- Cecchetti, Stephen G., Marion Kohler, and Christian Upper (2009). "Financial crises and economic activity." Working Paper 15379, National Bureau of Economic Research.
- Chang, Roberto and Andrés Velasco (2001). "A model of financial crises in emerging markets." *Quarterly Journal of Economics*, 116(2), 489–517.
- Chaudron, Raymond and Jakob De Haan (2014). "Identifying and dating systemic banking crises using incidence and size of bank failures." Working Paper 406, De Nederlandsche Bank.
- Chortareas, G., A. Cipollini, and G. Kapetanios (2010). "Forecasting financial distress in emerging markets: a dynamic probit analysis." Mimeo.
- Cox, David R., Gudmundur Gudmundsson, Georg Lindgren, Lennart Bondesson, Erik Harsaae, Petter Laake, Katarina Juselius, and Steffen L. Lauritzen (1981). "Statistical analysis of time series: some recent developments." *Scandinavian Journal of Statistics*, 8(2), 93–115.

- Davis, R. and Tiemen M. Woutersen (2008). “Comparing Early Warning System for Banking Crises.” *Journal of Financial Stability*, 2(4), 89–120.
- de Jong, Robert M. and Tiemen Woutersen (2011). “Dynamic time series binary choice.” *Econometric Theory*, 27(4), 673–702.
- Demirgüç-Kunt, Asli and Enrica Detragiache (2005). “Cross-country empirical studies of systemic bank distress: a survey.” Working Paper 05/96, IMF.
- Detken, Carsten, Olaf Weeken, Lucia Alessi, Diana Bonfim, Miguel M. Boucinha, Christian Castro, Sebastian Frontczak, Gaston Giordana, Julia Giese, Nadya Jahn, J. Kakes, B. Klaus, J. H. Lang, N. Puzanova, and P. Welz (2014). “Operationalising the countercyclical capital buffer: indicator selection, threshold identification and calibration options.” Occasional paper, European Systemic Risk Board.
- Drehmann, Mathias, Claudio Borio, Leonardo Gambacorta, Gabriel Jimenez, and Carlos Trucharte (2010). “Countercyclical capital buffers: exploring options.” Working Paper 317, BIS.
- Drehmann, Mathias and Mikael Juselius (2014). “Evaluating early warning indicators of banking crises: Satisfying policy requirements.” *International Journal of Forecasting*, 30, 759–780.
- Duttagupta, Rupa and Paul Cashin (2011). “Anatomy of banking crises in developing and emerging market economies.” *Journal of International Money and Finance*, 30, 354–376.
- Edge, Rochelle M. and Ralf R. Meisenzahl (2011). “The unreliability of credit-to-GDP ratio gaps in real-time: Implications for countercyclical capital buffers.” *International Journal of Central Banking*, 7(4), 261–298.
- Estrella, Arturo and Gikas A. Hardouvelis (1991). “The term structure as a predictor of real economic activity.” *Journal of Finance*, 46(2), 555–576.
- Estrella, Arturo and Frederic S. Mishkin (1998). “Predicting US recessions: Financial variables as leading indicators.” *Review of Economics and Statistics*, 80(1), 45–61.
- Estrella, Arturo and Anthony P. Rodrigues (1998). “Consistent covariance matrix estimation in probit models with autocorrelated errors.” Staff Report 39, Federal Reserve Bank of New York.
- Falcetti, Elisabetta and Merxe Tudela (2006). “Modelling Currency Crises in Emerging Markets: A Dynamic Probit Model with Unobserved Heterogeneity and Autocorrelated Errors.” *Oxford Bulletin of Economics and Statistics*,

- 68(4), 445–471.
- Frankel, Jeffrey and George Saravelos (2012). “Can leading indicators assess country vulnerability? Evidence from the 2008–09 global financial crisis.” *Journal of International Economics*, 87(2), 216–231.
- Gourieroux, Christian S., Alain Monfort, and Alain Trognon (1982). “Estimation and test in probit models with serial correlation.” Working Paper Couverture Orange 8220, CEPREMAP.
- Jackman, Simon (1998). “Time Series Models for Discrete Data: solutions to a problem with quantitative studies of international conflict.” In *Annual Meeting of the Society for Political Methodology*, San Diego.
- Jordà, Òscar, Moritz Schularick, and Alan M. Taylor (2011). “Financial crises, credit booms, and external imbalances: 140 years of lessons.” *IMF Economic Review*, 59(2), 340–378.
- Jordà, Òscar, Moritz Schularick, and Alan M. Taylor (2013). “When credit bites back.” *Journal of Money, Credit and Banking*, 45(2), 3–28.
- Kaminsky, Graciela L. and Carmen M. Reinhart (1999). “The twin crises: the causes of banking and balance-of-payments problems.” *American Economic Review*, 89(3), 473–500.
- Kauko, Karlo (2014). “How to foresee banking crises? A survey of the empirical literature.” *Economic Systems*, 38(3), 289–308.
- Kauppi, Heikki and Pentti Saikkonen (2008). “Predicting US recessions with dynamic binary response models.” *Review of Economics and Statistics*, 90(4), 777–791.
- Krugman, Paul (1979). “A model of balance-of-payments crises.” *Journal of Money, Credit and Banking*, 11(3), 311–325.
- Laeven, Luc and Fabian Valencia (2012). “Systemic banking crises database: An update.” Working Paper 12/163, IMF.
- Liang, Kung-Yee and Scott L. Zeger (1986). “Longitudinal data analysis using generalized linear models.” *Biometrika*, 73(1), 13–22.
- Nyberg, Henri (2010). “Dynamic probit models and financial variables in recession forecasting.” *Journal of Forecasting*, 29(1-2), 215–230.
- Obstfeld, Maurice (1986). “Rational and Self-fulfilling Balance-of-Payments Crises.” *American Economic Review*, 76(1), 72–81.
- Oet, Mikhail V., Timothy Bianco, Dieter Gramlich, and Stephen J. Ong (2013). “SAFE: An early warning system for systemic banking risk.” *Journal of*

Banking and Finance, 37(11), 4510–4533.

Petersen, Mitchell A. (2009). “Estimating standard errors in finance panel data sets: Comparing approaches.” *Review of Financial Studies*, 22(1), 435–480.

Poirier, Dale J. and Paul A. Ruud (1988). “Probit with dependent observations.” *Review of Economic Studies*, 55(4), 593–614.

Reinhart, Carmen M and Kenneth Rogoff (2011). *This Time Is Different: Eight Centuries of Financial Folly*. Princeton University Press.

Wright, Jonathan H. (2006). “The yield curve and predicting recessions.” Finance and Economics Discussion Series 2006-07, Federal Reserve Board.

FIGURES

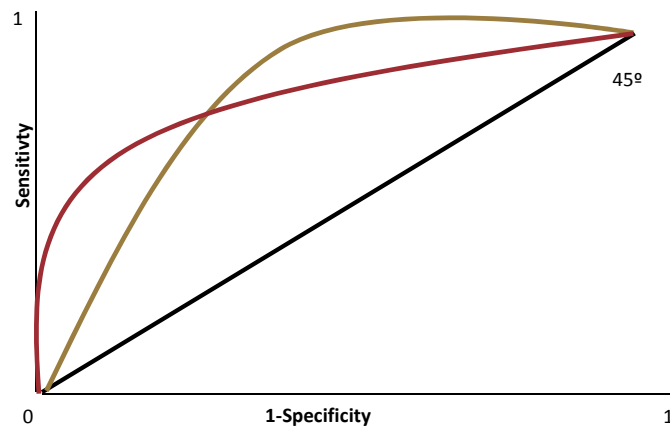
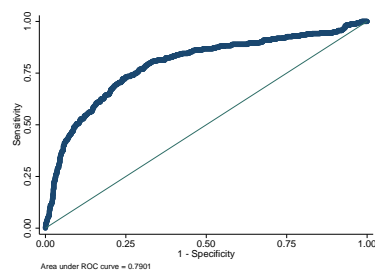
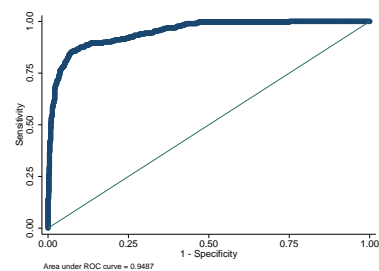


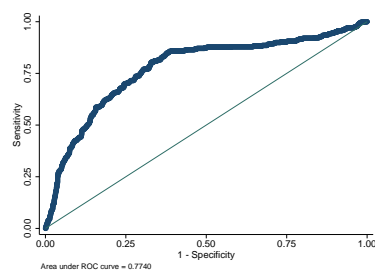
FIGURE 1: Examples of ROC Curves



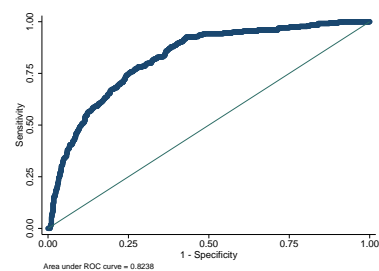
(A) Simple - Total Period



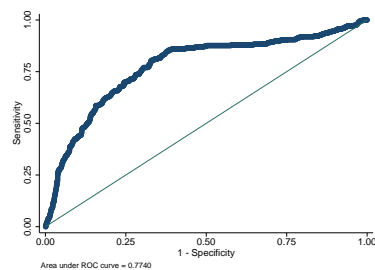
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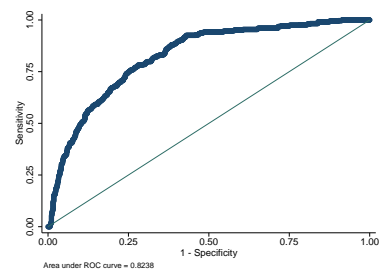
(C) Simple - Early Period



(D) Dynamic - Early Period



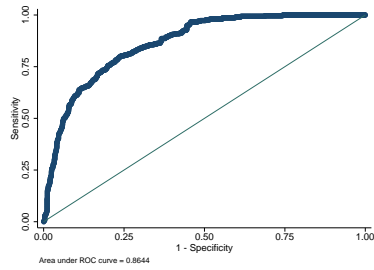
(E) Simple - Late Period



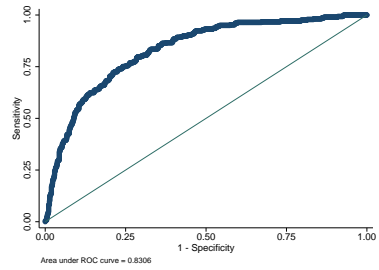
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FIGURE 2: Simple and Dynamic Models

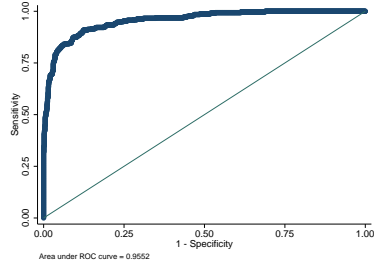
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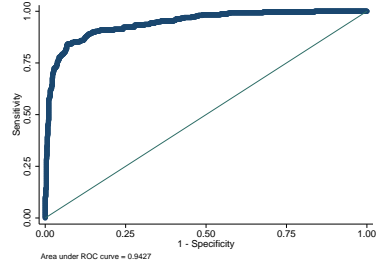
(A) Exuberance - Early Period



(B) Latent - Early Period



(C) Exuberance - LatePeriod

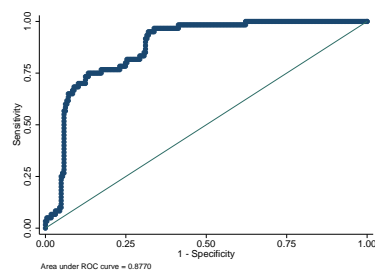


(D) Latent - Late Period

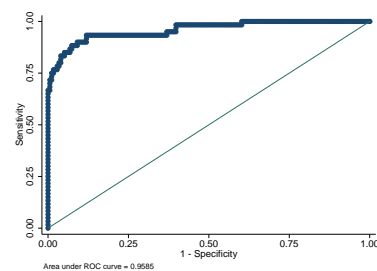
FIGURE 3: Exuberance and Latent Variable Models

Note: The model with exuberance indicators does not converge when the entire period is considered.

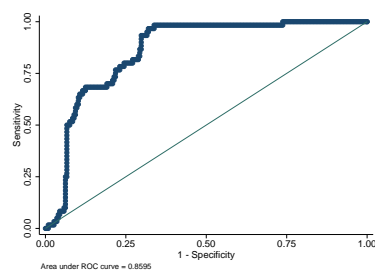
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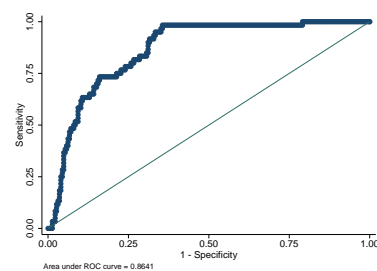
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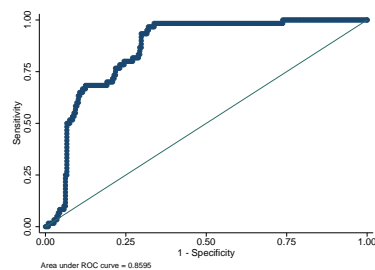
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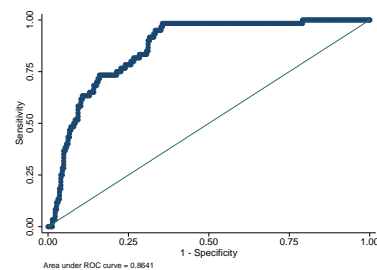
(C) Simple - Early Period



(D) Dynamic - Early Period



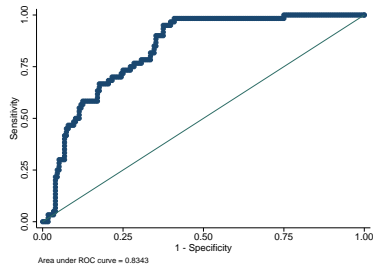
(E) Simple - Late Period



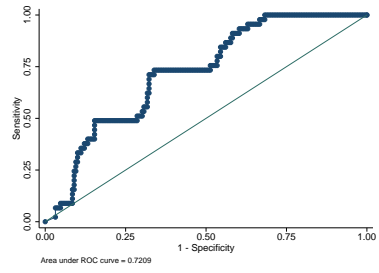
(F) Dynamic - Late Period

FIGURE 4: Out-of-Sample exercise (Simple and Dynamic Models)

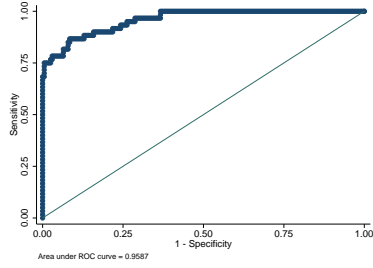
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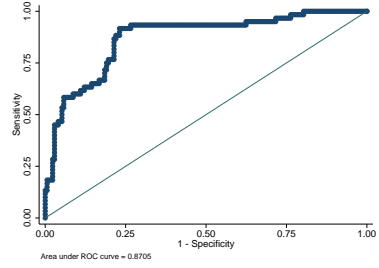
(A) Exuberance - Early Period



(B) Latent - Early Period



(C) Exuberance - LatePeriod

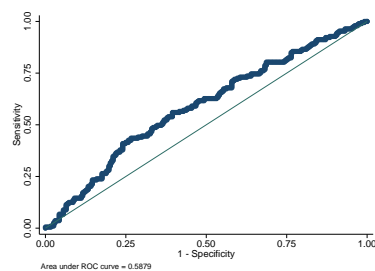


(D) Latent - Late Period

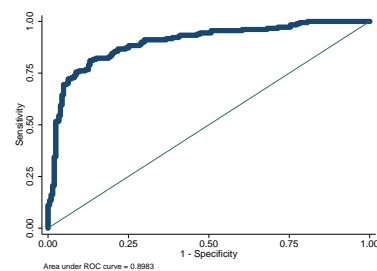
FIGURE 5: Out-of-Sample exercise (Exuberance and Latent Variable Models)

Note: The model with exuberance indicators does not converge when the entire period is considered.

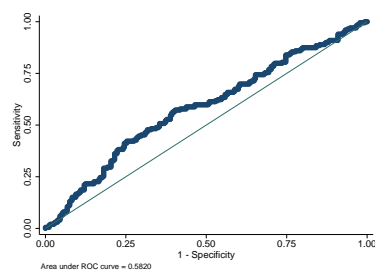
Sources: Babecky et al (2012), BIS, ECB, Detken et al. (2014), Eurostat, IMF, OECD, Thomson Reuters, and authors' calculations.



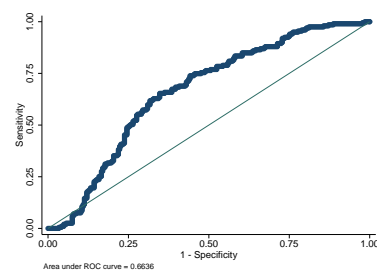
(A) Simple - Total Period



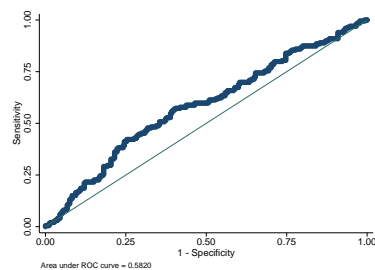
(B) Dynamic - Total Period



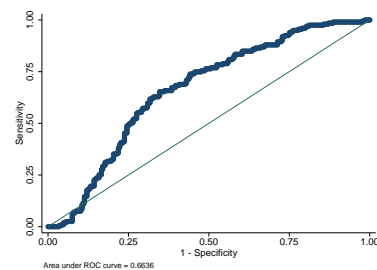
(C) Simple - Early Period



(D) Dynamic - Early Period



(E) Simple - Late Period



(F) Dynamic - Late Period

FIGURE 6: Out-of-Time exercise (Simple and Dynamic Models)

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

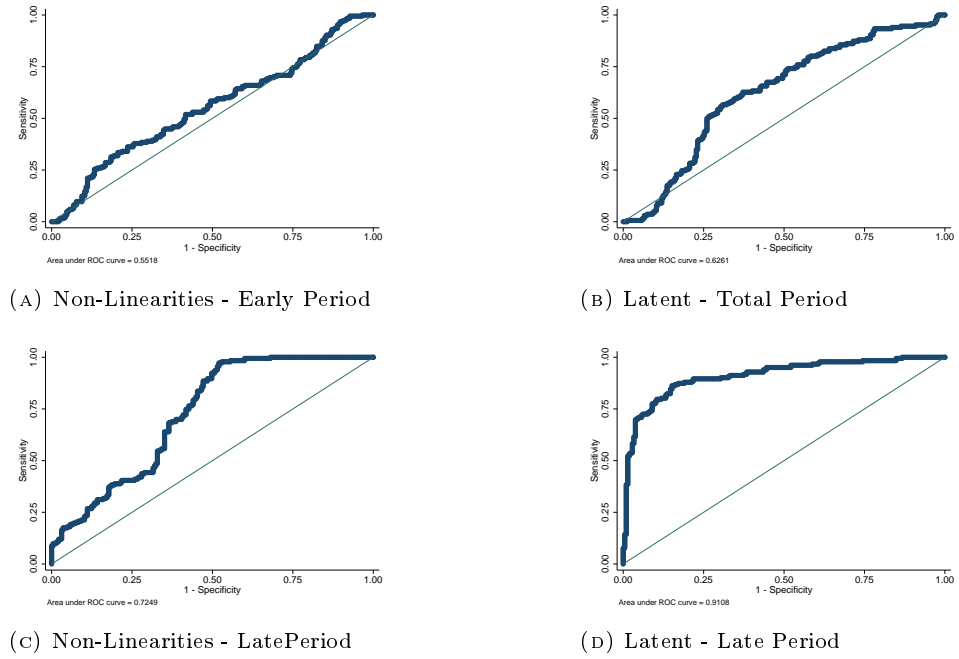


FIGURE 7: Out-of-Time exercise (Exuberance and Latent Variable Models)

Note: The model with exuberance indicators does not converge when the entire period is considered.

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

	Early Period - 20-12 lags			Late Period - 12-4 lags		
	Lags	Coef.	P> z	Lags	Coef.	P> z
Crisis dummy	L12.	0.79	0.00	L4.	7.44	0.00
	L15.	0.04	0.81	L5.	-4.05	0.00
	L17.	-1.19	0.00	L8.	-0.68	0.23
				L10.	-0.42	0.25
				L11.	-0.13	0.59
				L12.	0.06	0.75
Equity price index	L12.	0.01	0.00	L6.	0.01	0.01
	L19.	-0.01	0.02			
Debt service ratio	L12.	12.52	0.00	L4.	25.30	0.00
	L14.	-7.24	0.07	L6.	-9.31	0.04
	L20.	-5.21	0.02	L7.	-15.92	0.00
Credit-to-GDP gap	L14.	0.01	0.24	L4.	-0.04	0.05
				L5.	0.01	0.50
				L6.	0.03	0.11
				L11.	0.07	0.00
				L12.	-0.07	0.00
House price index (yoy)				L4.	-0.03	0.26
				L5.	0.02	0.12
				L6.	0.02	0.02
				L7.	-0.01	0.64
Equity price index (P90)	L12.	-0.20	0.32	L7.	0.18	0.27
	L15.	-0.19	0.18	L8.	0.20	0.16
	L20.	0.01	0.95	L9.	-0.34	0.03
Debt service ratio (P90)	L15.	0.40	0.06	L5.	-0.13	0.68
	L20.	0.42	0.08	L7.	0.37	0.13
				L9.	0.52	0.00
Credit-to-GDP gap (P50)	L12.	0.20	0.57	L4.	-0.13	0.55
	L16.	0.26	0.15	L5.	-0.08	0.65
	L18.	0.09	0.53	L7.	0.20	0.33
	L20.	0.24	0.21	L9.	0.19	0.26
				L10.	0.22	0.29
				L12.	0.16	0.51
House price index (yoy, P30)	L15.	-0.12	0.43	L4.	-0.32	0.07
	L17.	-0.02	0.74	L5.	-0.32	0.01
	L18.	-0.02	0.87	L6.	-0.18	0.36
				L9.	-0.09	0.59
				L10.	0.03	0.87
				L11.	0.23	0.16
Constant		-2.39	0.00		-2.86	0.00
R^2		0.3060			0.6045	
N		1417			1558	

TABLE A1. Table - Regression results: probits with exuberance indicators

Note: all variables defined in Table 1. The total period refers to lags [20;4], the early period [20;12] and the late period [12;4]. Standard errors clustered by country.

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

	Total Period			Early Period - 20-12 lags			Late Period - 12-4 lags		
	Lags	Coef.	P> z	Lags	Coef.	P> z	Lags	Coef.	P> z
Latent Variable (latent1)									
	L4.	-0.0907	0.162	L12.	-0.16	0.00	L4.	-0.05	0.31
	L5.	0.11299	0.008	L15.	0.07	0.05	L5.	-0.03	0.42
	L8.	0.01482	0.708	L17.	0.18	0.03	L7.	0.10	0.02
	L9.	-0.0601	0.023				L11.	0.05	0.25
	L10.	0.02908	0.503						
	L17.	0.09501	0.025						
Crisis dummy									
	L4.	7.13029	0	L12.	1.47	0.00	L4.	7.20	0.00
	L5.	-4.1274	0	L15.	-0.23	0.15	L5.	-4.12	0.00
	L8.	0.21887	0.656	L17.	-0.62	0.01	L7.	-0.03	0.94
	L9.	-0.8222	0.125				L11.	-1.19	0.03
	L10.	0.47344	0.071						
	L17.	-1.4402	0						
Equity price index									
	L9.	0.00446	0.327	L12.	0.01	0.03	L6.	0.01	0.04
	L11.	0.00014	0.966	L13.	0.00	0.50			
	L18.	-0.0007	0.836	L17.	0.00	0.90			
				L19.	0.00	0.35			
Debt service ratio									
	L4.	42.2889	0	L12.	14.09	0.00	L4.	17.62	0.00
	L6.	-13.825	0.008	L14.	-4.78	0.08	L7.	-17.72	0.00
	L7.	-5.6671	0.27	L20.	-9.22	0.00			
	L10.	-6.9766	0.212						
	L14.	-10.246	0.19						
	L18.	-7.5366	0.169						
Credit-to-GDP gap									
	L4.	-0.0675	0.02	L14.	0.02	0.18	L6.	0.00	0.78
	L6.	0.01286	0.65				L11.	0.09	0.00
	L9.	0.01922	0.2				L12.	-0.07	0.00
	L10.	0.01338	0.533						
	L11.	0.05665	0.071						
	L13.	-0.0375	0.064						
	L16.	-0.0103	0.509						
House price index (yoy)									
	L12.	-0.0062	0.754				L5.	-0.02	0.21
	L20.	0.00735	0.656				L9.	0.02	0.42
Constant		-1.5709	0		-1.59	0.00		-2.08	0.00
R^2		0.6264			0.23			0.5533	
N		1102			1414			1388	

TABLE A2. Regression results: Latent variable

Note: all variables defined in Table 1. The total period refers to lags [20;4], the early period [20;12] and the late period [12;4]. Standard errors clustered by country.

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



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