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Banking crises in Europe:

The importance of region - specific early warning models

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Abstract

Banking crises, albeit rare, can have nefarious consequences. As such, it is relevant to understand not only what factors cause these crises, but what variables can be used in their early detection. Economic integration still requires country specificities to be considered in macro-prudential monitoring. This project explores the dynamics of banking crises, the role of economic and stock market growth as warning variables for several European regions. Dynamic probit models are used in a panel dataset. Results show that real GDP, stock market growth and house price growth are good indicators of crisis, and separate models for regions within the Eurozone predict crisis more accurately.

Keywords: Banking crises; dynamic probit models; binary data; panel data.

Acknowledgments: I would like to thank Professor Paulo Rodrigues for his unwavering dedication to this project, which benefited greatly from his extensive knowledge. To my amazing mother, grandparents and fantastic boyfriend, for all the love and support throughout this process. To all my friends, for their patience and kindness. All of you were instrumental to the materialization of this work project.

1 Introduction

The occurrence of banking crises imposes severe consequences and costs to the economy. Distress situations in the banking sector may compromise the financing of economic activities, both to consumers and firms. Furthermore, whenever a bank faces difficulties, it is possible that it triggers panic and mistrust in other banks as well, leading to bank runs and bankruptcy of initially sound and viable banks, in a self-fulfilling cycle[1].

When banking crises materialize, governments will usually intervene, to prevent further losses to the economy and avoid, if possible, the reduction of financing to the economy. However, a bailout may open a precedent that induces excessive risk-taking behaviour in the banking sector, since the government is ready to step in to avoid massive losses. Hence, from a policy point of view, it would be desirable to fully avoid the fruition of these type of crises. This poses a modelling problem, from an econometric perspective: if a crisis is indeed avoided, then the causal relationship between variables (and their behaviour) may be altered by the intervention, which may cause difficulties in understanding the underlying dynamics.

Economic integration in Europe has increased in the last decades, being its current stage of development the monetary union. It has been widely discussed, especially since the onset of the 2008 crisis that European countries have fundamental differences among them and, if this is the case, then it is crucial to account for them in a successful early warning system.

From a macro-prudential perspective, if the countries comprising the Euro-Area or, in a broader approach, the European Union have fundamental differences among them, then these are crucial in preventing the onset of a crisis: if a country-specific characteristic causes a

[1] See, for example, Diamond and Dybvig (1983) for a detailed theoretical model on bank runs.

banking crisis in the home economy, contagion may extend to the entire monetary union. This thesis focuses on the role of real GDP growth, equity returns and house price growth as Early Warning variables of an impending crisis, and whether these indicators differ among economic regions in Europe. The aim is to assess if recessions and financial distress can be helpful indicators in detecting banking crisis with sufficient time for policy action and if monitoring is more efficient for models specific to a given set of countries, as opposed to the entire Eurozone.

Also, as is commonly found in the literature, dynamic models tend to outperform static models in this type of framework[2] since they allow for inter-temporal connections. Hence, both static and dynamic models are estimated and their performance compared.

This project is organized as follows: in section 2, an overview of the existing literature is presented. Section 3 presents the methodology, dataset and estimation procedure, Section 4 presents the main results, weaknesses of the models and possible steps for future research. Section 5 concludes.

2 Literary Review

Banking crisis are rare events but impose severe costs when occurring and output can take several years to recover from these events, as is described by Cecceti et al.(2009). Several types of Early Warning Systems have been developed, using different variables and methodologies. Gramlich et al.(2010) provide a comprehensive survey on the existing research on early warning systems for banking risk. The literature on crises has focused on developing

[2] See the Literary Review section for more details.

economies, and different types of crises are usually analysed together, namely banking, debt and currency crises. Wong et al. (2010) estimate a panel probit model to forecast banking crises in the EMEAP economies, using as leading variables GDP growth, inflation, measures of currency vulnerability, credit risks and vulnerability to shocks in other economies. Candelon et al. (2012) extend the simple probit model to a multivariate one to predict these three types of crises in a non-linear probit VAR framework, to emerging economies. Hagen et al.(2007) applies an index of money market pressure to identify banking crises, to a set of emerging and developed economies. The application of binary models to study crises in developed economies is somewhat sparser. Kauppi and Saikonnen (2008) apply binary probit models to forecast recessions in the US economy, using the interest rate spread as a leading indicator of crises. Antunes et al. (2016) also use probit models to forecast banking crises for the countries comprising the European Union, using private credit gap, house prices growth and other variables as early warning. Babecky et al. (2012) use a VAR model to predict banking, debt and currency crises for a set of developed economies, comprising European Union and OECD economies. This project is methodologically closer to Kauppi and Saikonnen (2008) and Antunes et al.(2016), where dynamic panel probit models are used to account for time dependence among crisis episodes, with better results than those obtained in a static framework. Similar results are obtained by Candelon et al. (2010) for currency crises to a set of emerging economies. Other than dependence among different types of crises, contagion effects between economies are likely to occur, increasingly so in more integrated economic systems. As such, exploiting these spillover effects is helpful in understanding the scope and effects of crises. The use of panel data models allows to somewhat consider these effects and has become more common in the literature, also due to the fact that it allows for a significant enlargement of the dataset (Wong et al. (2010), Antunes et al. (2016)). As pointed out in Candelon et al. (2010) and Babecky et al. (2012), the use of heterogeneous countries in a single panel may distort the results and the quality of the Early Warning Variables. This project considers this possibility by dividing the countries comprising the European Union into three separate samples: the Eurozone that, due to its single currency, is of special interest to monitor and two sub-regions within the Eurozone: the periphery countries and the remaining ones. This is done to assert if the variables chosen retain significance as early warning and if model accuracy changes.

3 Methodology

All models estimated in this work use as dependent variable a binary variable, the banking crises occurence. As is standard in the literature, we consider the dependent variable, y_{it}, to take the value of 1 if a crises occurs in a given quarter and zero otherwise, with probabilities p_i and $(1 - p_i)$, respectively.

$$y_{it} = \begin{cases} 1, & \text{with probability } p_i \\ 0, & \text{with probability } 1 - p_i \end{cases}$$

The probability mass function of the Bernoulli distribution is given by $(p_i)^{y_{it}}(1 - p_i)^{1-y_{it}}$ where $E(y_{it}) = p_i$ and $Var(y_{it}) = p_i(1 - p_i)$. The regression model is built by making the probability p_i depend on an index $\boldsymbol{x_{it}}'\beta$, where $\boldsymbol{x_{it}}$ is a Kx1 vector of explanatory variables and β a Kx1 vector of coefficients. Hence, the conditional probability is the following:

$$p_i = Pr(y_{it} = 1|\boldsymbol{x_{it}}) = F(\boldsymbol{x_{it}}'\beta)$$

where F (.) is usually chosen as a cumulative distribution function on $(-\infty; +\infty)$, since it ensures that the values of the probability are contained in the interval between zero and one. It is in the choice of F (.) that the difference materializes between the logit and the probit models: in the logit model, it corresponds to the cumulative distribution function of the logistic distribution, while in the probit model it is the cumulative distribution function of the normal distribution.

A common interpretation of this class of models is the existence of a latent (thus unobserved) variable y^*_{it}, given by $y^*_{it} = \boldsymbol{x_{it}}'\beta + u_{it}$. The unobservable variable,y^*_{it}, signals the behaviour of y_{it}:

$$y_{it} = \begin{cases} 1, & \text{if } y^*_{it} > 0 \\ 0, & \text{if } y^*_{it} < 0 \end{cases}$$

Hence, we obtain:

$$Pr(y_{it} = 1) = Pr(y^*_{it} > 0) = Pr(\boldsymbol{x_{it}}'\beta + u_{it} > 0) = Pr(\boldsymbol{x_{it}}'\beta > -u_{it}) = F(\boldsymbol{x_{it}}'\beta)$$

This yields a probit model if u_{it} is assumed to be normally distributed or a logit model if it is assumed to be logistically distributed.

3.1 Data

The dataset is the one used in Antunes et al.(2016), which is composed of quarterly time series, for every member-state of the European Union, from the first quarter of 1970 until the fourth quarter of 2012. The binary crises indicator equals one if a country is in a crises in a given quarter and zero otherwise, and corresponds to the systemic banking crises database of the Czech National Bank, which was built with the contributions of the Heads of Research

Table 1: Summary Statistics of Data

Variable	Nr. Observations	Mean	Standard Deviation	Min.	Max.
Real GDP Growth	1859	.01	.01	-.13	.13
Equity Returns	2293	.02	.1	-.68	.70
House Prices Growth	1394	.02	.09	-.22	2.37

of the Eurosystem[3].

The independent variables used are real GDP, equity prices and house prices.[4]. Variables are not included in levels, but in quarter-on-quarter growth rates. This serves two purposes: the first is to correct for non-stationarity[5], which is a typical feature of these variables, and the second is to remove the scale effect since, for the same variables, scale may differ among countries, which is undesirable in panel data.

Due to small data availability Belgium, Cyprus, Luxembourg, Malta, Poland and Romania are removed from the dataset and estimation is carried out for the remaining 22 member-states of the European Union. Table 1 presents some summary statistics of the dataset used in this project.

The variable that shows the largest amplitude in values is the growth of house prices, the maximum being for Bulgaria, in the first quarter of 1997[6]. Equity returns is the variable with the highest volatility, as expected.

[3]See Babecky et al (2012) for a full description on constructing this database.

[4]Other variables were available but, for consistency of estimation when the sample is restricted, only these three variables are included, to preserve degrees of freedom.

[5]Unit root test results can be found in Appendix 1

[6]This period was one of strong political instability in the country, leading to inflation rates as high as 300%.

3.2 Baseline Specification

The baseline model follows the estimation procedure developed in Antunes et al. (2016), where two types of models are estimated, marginal and transitional models, for different time-windows. Since the purpose is to contribute to the early warning of banking crises, all variables are included with a lag of four to twenty quarters. Each model is estimated for three time-windows: the full-period, where lags four to twenty of the variables are included; the late period, which considers only lags four to twelve, and the early period for lags twelve to twenty. The baseline specification is estimated for the countries of the European Union, and model performance of the remaining models is compared to this one.

3.2.1 Marginal Models

Marginal models consider that the probability of banking crises can be captured by the covariates alone, not accounting for the role of time dependence in the variable of interest. Particularly, a static probit model assumes that observations are independent among each other. Thus,

$$y^*_{it} = \alpha + \textstyle\sum_{k=1}^{3} \sum_{j=4}^{20} \beta_{kj} \boldsymbol{x_{ik,t-j}} + \epsilon_{it}.$$

It has been shown in the literature that estimators of marginal models are consistent and asymptotically normal. However, standard-errors may be biased and inference thusly inaccurate. This can be of course mitigated by the use of robust standard errors but the dynamic behaviour of the variable may be of interest in itself, which is the reason for the estimation of transitional models.

3.2.2 Transitional Models

Transitional models specifically account for the inter-temporal dependence of the dependent variable, associated with the change in covariates. This can be represented as a dynamic probit model, where the effect of the binary variable is to shift the probability by θ, if there was a crisis in period $t-j$, i.e.,

$$y_{it}^{*} = \alpha + \sum_{k=1}^{3} \sum_{j=4}^{20} \beta_{kj} \boldsymbol{x_{ik,t-j}} + \sum_{j=4}^{20} \theta_j y_{i,t-j} + \epsilon_{it}$$

This specification implicitly assumes that the unconditional probability of a crisis is dependent on its previous occurrences.[7]

3.2.3 Coefficient Interpretation

The models estimated in this project are non-linear and, as such, coefficients do not have a direct interpretation over their effect in the probability of a crisis. The marginal effect of a given variable in the overall probability of a crisis is given by:

$$dP(y_{it} = 1)/dx = f(x_{it}'\beta)\beta_{i,j}$$

where $f(\boldsymbol{x_{it}}'\beta)$ is the density function of the normal distribution. This function only takes on positive values and one can thusly infer the direction of the marginal effect by looking at the sign of the coefficients. The models estimated use several coefficients for the same variable, at different time lags. Hence, one can infer on a dominant marginal effect, if signs differ across lags, or the direction of the effect, if it is the same sign across all lags. Also, for similar signs one can compare the overall magnitude of the effects among models.

[7] There is also the possibility of conditioning the probability on the previous occurrences of the latent variable, but that is beyond the scope of this project.

3.2.4 Model Assessment

The quality of the estimated models is evaluated in two different areas: overall model fit, evaluated by McFadden R^2 and the Area Under the ROC Curve (AUROC), and event classification, measured by sensitivity and specificity. Sensitivity measures the percentage of crises observations correctly classified as such, and specificity the number of non-crises observations correctly classified. The model classifies an observation as crises whenever the predicted probability is above 50%. This threshold was chosen so as to be not strict and risk missing crises events.The working assumption here is that, from a regulatory perspective, the cost of receiving a warning that does not come to fruition is smaller than the cost of missing a crises. Hence, a model that has a high percentage of sensitivity is a model that correctly classifies more crises correctly, and is thusly preferred.

3.3 Estimation Procedure

The likelihood function of the probabilistic model is given by:

$$L = \prod_{t=1}^{T} \prod_{i=1}^{N} p_i^{y_{it}} (1 - p_i)^{1-y_{it}}$$

Since we are dealing with probit models, p_i is specified as the cumulative function of the normal distribution, evaluated at $\boldsymbol{x_{it}}'\beta$. Then, the likelihood function becomes:

$$L = \prod_{t=1}^{T} \prod_{i=1}^{N} F(\boldsymbol{x_{it}}'\beta)^{y_{it}} (1 - F(\boldsymbol{x_{it}}'\beta))^{1-y_{it}}$$

The log-likelihood function is described by:

$$L = \sum_{t=1}^{T} \sum_{i=1}^{N} y_{it} ln(F(\boldsymbol{x_{it}}'\beta)) + (1 - y_{it}) ln(1 - F(\boldsymbol{x_{it}}'\beta))$$

This is a highly non-linear problem and the estimation is carried out by numeric optimization methods. As is common in panel data, the standard errors are robust to correlation, heteroskedasticity and adjusted for clustering in countries.

3.4 Region Specific Effects

As pointed out in Candelon et al. (2010) and Babecky et al. (2012), the use of heterogeneous countries in a single panel may distort the results and the quality of the early warning variables. The methodology chosen to account for these possible region-specificities is to divide the sample of countries into four subsamples: European Union, Euro-Area countries, periphery countries [8], and Euro-Area without the periphery countries. This approach is chosen because, although random effects[9] or a contagion variable could account for such differences, in a successful early-warning system one should take into account the possibility that different magnitudes and effect time-frames may occur for the same signalling variables, which is, in itself, information worth exploring.

4 Results and Discussion

4.1 Baseline Model

The baseline model is estimated using the set of countries comprising the European Union and as explanatory variables the growth of real GDP, the return of equity prices and the

[8] Periphery countries include Portugal, Spain, Ireland, Italy and Greece.

[9] The use of fixed effects in probit models has been contested in the literature. See, for instance, Greene (2003)

growth of house prices. The results are presented in Table 2. In both the static and dynamic specifications, the full and late period estimations are the ones with the highest predictive power, signalling that the indicator variables tend to show effects within three years of the onset of the crisis. Regarding the static specification, real GDP growth is a significant indicator at nearly all time lags for the late period model, having a negative impact, which points towards an increase in the probability of a crises for negative real growth rates, such as one finds in a recession. The growth of stock market indices warns significantly only in the 4th lag, signalling the crisis later than real GDP. As for the growth of house prices, it warns between lags 8 and 11, indicating that growth in house prices increases the probability of a banking crises, *ceteris paribus*.

The dynamic specification of the model, where lags of the binary variable are included in the estimation, increases the extension of stock returns as a warning variable, both in the full period estimation and in the late period. The coefficient of the 4th lag is negative for both estimation periods, being positive in the remaining ones. This points towards an overall positive effect of stock market growth in the probability of a crises. Also, this behavioural change may be indicative that crashes in stock markets gain significance closer to crisis, while exuberant periods of growth are more meaningful in earlier periods. Real GDP growth remains as a highly significant indicator of impending crises, being the dominant effect a negative one, i.e., periods of recessions will increase the probability of a crisis. The positive coefficients in lags further away from the crises may point towards an effect of booms, while recessions gain significance closer to the crises, with larger magnitude. As for house price growth, there is an increased probability of crisis if in lags 4 and 17 there is a fall in house prices, and an increase in prices for other lags. Overall, for the full period of estimation,

Table 2: Baseline Model - Results

European Union												
	Static Probit						Dynamic Probit					
	Full Period		Late Period		Early Period		Full Period		Late Period		Early Period	
	L.	Cf.	L.	Cf.	L.	Cf.	L.	Cf.	L.	Cf.	L.	Cf.
Constant	—	-0.54***	—	-0.54***	—	-0.64***	—	-1.51***	–	-1.55***	–	-1.23***
Equity Returns	4	-1.92***	4	-1.95***	–	—	4 7 8	-2.07*** 2.24** 2.54***	4 7 8 9	-2.09*** 1.74** 2.12*** 1.02*	–	–
Real GDP Growth	4 5 6 7 11 12	-8.48** -12.45*** -13.76*** -10.15*** -7.87*** -10.74***	4 5 6 7 8 9 11 12	-9.06*** -12.05*** -13.34*** -10.03*** -5.88*** -3.97* -8.21*** -10.91***	12 13 14	-5.39** -4.80** -3.75*	5 6 7 9 10 11	-12.59** -13.94*** -18.40*** 8.74** 10.62** 6.23***	6 7 8 10 11	-13.41** -19.61*** -11.96** 12.26*** 7.69**	–	—
House Prices Growth	9 11	3.33*** 3.56***	8 9 10 11	2.46* 2.95*** 2.07*** 2.93**	13	3.26***	4 8 9 17	-4.49* 4.51*** 5.13*** -5.09**	4 8 9	-4.28** 5.35*** 5.90***	–	—
Crisis Dummy	—	—	—	—	—	—	4 5 11 12 18	7.38*** -4.48*** -0.58* 0.43** -1.45***	4 5 8	7.27*** -4.03*** -0.81*	12 18	1.30*** -0.90***

Note: *, **, *** indicates statistical significance at 10%, 5% and 1% significance levels, respectively. All coefficients are rounded to two decimal places.

the effect of House Price growth seems to cancel out, while it remains positive for the late period. As for the lagged dependent variable, it increases the probability of a crises if there was one in the 4th and 12th lags and decreases the probability if there was a crisis in lags 5, 11 and 18. The change in sign between lags 4 and 5 seems to be indicative of an intervention between those periods that is captured by the model. Overall, the effect of a previous crisis is positive on the occurence of a new one.

4.1.1 Model Assessment

Table 3: Baseline Model - Assessment

	Static Model		Dynamic Model	
	R^2	AUROC	R^2	AUROC
Full Period	11.64%	0.7538	52.20%	0.9286
Late Period	12.21%	0.7612	49.08%	0.9219
Early Period	0.9%	0.5735	7.33%	0.6186

Overall, the model seems to be robust to changes for the period specification, with coefficients maintaining the sign and similar magnitudes. The bulk of explanatory power is concentrated in the late period estimation (see Table 3). Introducing dynamics in the model allows for significant improvements both in the explanatory power of the variables, captured by McFaddens R^2, and in the models ability to accurately predict crisis, measured by AUROC. Sensitivity measures the percentage of crises correctly classified as such, and specificity the number of non-crises correctly classified. Non-crises events, being the most common, are easier to classify in the models, and the percentage of correct classification is always above 95%

Table 4: Event Classification - Baseline Model

Event Classification						
Measures of Event Classification	Static Models			Dynamic Models		
	Full Period	Late Period	Early Period	Full Period	Late Period	Early Period
Sensitivity	16.52%	16.07%	0.83%	72.49%	70.51%	20.27%
Specificity	95.09%	95.09%	99.86%	96.58%	94.84%	97.06%
Crisis classified as non-crisis	83.48%	83.93%	99.17%	27.51%	29.49%	79.73%
Correctly Classified	75.87%	75.76%	74.66%	91.12%	88.72%	86.94%

for all model specifications. Dynamic models clearly outperform static models in correctly predicting the occurrence of banking crises. As for miss-classification of crises observations, it is greatly mitigated by the use of dynamic models. The bulk of explanatory power and correct prediction of crises is concentrated in the late period of estimation, as one can observe by the similarity of predictive power of the late and full period estimations.

4.2 Region Estimation

The estimation procedure in Section 4.1 is repeated for the countries comprising the Euro zone, the periphery countries and for the Euro zone excluding the periphery countries. Since the sample size decreases when dealing with these sub-samples, only the late and early period estimations are presented, since these are the most robust ones. These are the ones used for comparison purposes with the results obtained for the European Union. Concerning the static models, equity returns are a strong indicator of distress for the Euro zone without

Table 5: Estimation Results - Region Estimation, Static Models

<table>
<tr><th rowspan="3"></th><th colspan="8">Late Period</th><th colspan="8">Early Period</th></tr>
<tr><th colspan="2">EU</th><th colspan="2">EA</th><th colspan="2">Periphery</th><th colspan="2">EA w/o periphery</th><th colspan="2">EU</th><th colspan="2">EA</th><th colspan="2">Periphery</th><th colspan="2">EA w/o periphery</th></tr>
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<tr><td>Constant</td><td>–</td><td>-0.54***</td><td>–</td><td>-0.70***</td><td>–</td><td>-0.27</td><td>–</td><td>-0.81**</td><td>–</td><td>-0.64***</td><td>–</td><td>-0.98***</td><td>–</td><td>-0.87</td><td>–</td><td>-1.11***</td></tr>
<tr><td rowspan="8">Equity Returns</td><td rowspan="8">4</td><td rowspan="8">-1.95***</td><td rowspan="8">4</td><td rowspan="8">-1.70**</td><td rowspan="8">4</td><td rowspan="8">-2.04*</td><td>4</td><td>-3.06***</td><td rowspan="8">–</td><td rowspan="8">—</td><td>12</td><td>-0.98***</td><td>13</td><td>1.63***</td><td>12</td><td>-0.88*</td></tr>
<tr><td>5</td><td>-1.37***</td><td>14</td><td>-0.85***</td><td>18</td><td>1.89***</td><td rowspan="7">20</td><td rowspan="7">1.45*</td></tr>
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<tr><td>11</td><td>2.93***</td><td>19</td><td>7.69*</td></tr>
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Note: see note under Table 2

the periphery, warning significantly for the entire length of the late period that losses in the stock market contribute to an increase in the probability of banking crisis. As for real GDP growth, there is no significant warning at a 10% level for the late period estimation for the periphery countries. For the Euro zone as a whole, the impacts of a fall in GDP have similar magnitudes to the ones found for the European Union. Housing prices have a stronger impact in the probability of crises for the periphery countries, closer to the occurrence. For the Early period estimation, equity returns are indicators of crises for all regions specified, which is not the case for the European Union. Real GDP growth has an impact in the periphery, but stronger than the one found for the European Union. Overall, the cumulative effect for the periphery seems to cancel out. House price growth is significant in two different periods for the periphery: for lags 12 and 13, with a negative sign, while for lags 17 and 19 it presents a positive sign. Overall, the dominant effect is negative, meaning that a decrease in house price growth will increase the probability of a banking crisis.

Table 6: Estimation Results - Region Estimation, Dynamic Models

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<tr><th colspan="2">EU</th><th colspan="2">EA</th><th colspan="2">Periphery</th><th colspan="2">EA w/o periphery</th><th colspan="2">EU</th><th colspan="2">EA</th><th colspan="2">Periphery</th><th colspan="2">EA w/o periphery</th></tr>
<tr><th>L.</th><th>Cf.</th><th>L.</th><th>Cf.</th><th>L.</th><th>Cf.</th><th>L.</th><th>Cf.</th><th>L.</th><th>Cf.</th><th>L.</th><th>Cf.</th><th>L.</th><th>Cf.</th><th>L.</th><th>Cf.</th></tr>
<tr><td>Constant</td><td>–</td><td>-1.55***</td><td>–</td><td>-1.50***</td><td>–</td><td>-1.26**</td><td>–</td><td>-1.73***</td><td>–</td><td>-1.23***</td><td>–</td><td>-1.01***</td><td>–</td><td>-0.66</td><td>–</td><td>-1.31***</td></tr>
<tr><td rowspan="4">Equity Returns</td><td>4</td><td>-2.09***</td><td>4</td><td>-2.12***</td><td>4</td><td>-2.15*</td><td>4</td><td>-3.11***</td><td rowspan="4">–</td><td rowspan="4">—</td><td rowspan="4">20</td><td rowspan="4">1.05*</td><td>19</td><td>1.75**</td><td rowspan="4">20</td><td rowspan="4">1.78***</td></tr>
<tr><td>7</td><td>1.74**</td><td rowspan="3">7</td><td rowspan="3">1.43*</td><td rowspan="3">6</td><td rowspan="3">2.06**</td><td rowspan="3">5</td><td rowspan="3">-1.25***</td><td rowspan="3">20</td><td rowspan="3">2.37***</td></tr>
<tr><td>8</td><td>2.12***</td></tr>
<tr><td>9</td><td>1.02*</td></tr>
<tr><td rowspan="5">Real GDP Growth</td><td>6</td><td>-13.41**</td><td>7</td><td>-11.46***</td><td>5</td><td>-21.42**</td><td rowspan="5">7</td><td rowspan="5">-8.58***</td><td rowspan="5">–</td><td rowspan="5">—</td><td rowspan="5">–</td><td rowspan="5">–</td><td>13</td><td>-19.87*</td><td rowspan="5">–</td><td rowspan="5">—</td></tr>
<tr><td>7</td><td>-19.61***</td><td>10</td><td>8.88*</td><td rowspan="4">10</td><td rowspan="4">18.13*</td><td rowspan="4">20</td><td rowspan="4">40.87*</td></tr>
<tr><td>8</td><td>-11.96**</td><td>11</td><td>7.70***</td></tr>
<tr><td>10</td><td>12.26***</td><td rowspan="2">12</td><td rowspan="2">6.41***</td></tr>
<tr><td>11</td><td>7.69*</td></tr>
<tr><td rowspan="5">House Price Growth</td><td>4</td><td>-4.28**</td><td>4</td><td>-5.77*</td><td>5</td><td>-47.06***</td><td>8</td><td>4.29***</td><td rowspan="5">–</td><td rowspan="5">—</td><td rowspan="5">17</td><td rowspan="5">3.70*</td><td>12</td><td>-20.86**</td><td>12</td><td>3.96**</td></tr>
<tr><td>8</td><td>5.35***</td><td>5</td><td>-6.42**</td><td>6</td><td>-26.48**</td><td rowspan="4">9</td><td rowspan="4">4.81***</td><td>13</td><td>-13.14**</td><td rowspan="4">13</td><td rowspan="4">3.79***</td></tr>
<tr><td>9</td><td>5.90***</td><td>8</td><td>5.19**</td><td>9</td><td>27.67*</td><td>15</td><td>-10.65***</td></tr>
<tr><td></td><td></td><td rowspan="2">9</td><td rowspan="2">6.41***</td><td rowspan="2">10</td><td rowspan="2">23.20*</td><td>16</td><td>14.95***</td></tr>
<tr><td></td><td></td><td>17</td><td>10.23**</td></tr>
<tr><td rowspan="3">Crisis Dummy</td><td>4</td><td>7.27***</td><td>4</td><td>6.69***</td><td>4</td><td>7.39***</td><td>4</td><td>6.94***</td><td>12</td><td>1.30***</td><td>12</td><td>1.25***</td><td rowspan="3">19</td><td rowspan="3">-1.12*</td><td>12</td><td>1.64***</td></tr>
<tr><td>5</td><td>-4.03***</td><td rowspan="2">5</td><td rowspan="2">-4.28***</td><td rowspan="2">5</td><td rowspan="2">-5.33***</td><td>7</td><td>1.58**</td><td rowspan="2">18</td><td rowspan="2">-0.90***</td><td rowspan="2">18</td><td rowspan="2">-1.14**</td><td rowspan="2">18</td><td rowspan="2">-1.43**</td></tr>
<tr><td>8</td><td>-0.81*</td><td>8</td><td>-6.07***</td></tr>
</table>

Note: see note under Table 2.

For the dynamic specification of the model, the impacts of being in a crisis in previous periods are similar across all regions, for both late and early period estimations. Equity returns are significant closer to the onset of the crisis, with similar impacts across regions. For real GDP growth, the euro zone presents similar results to the ones found for the European Union. The periphery seems to be more sensitive to recessions and booms, presenting larger coefficients. The growth of housing prices is significant for similar lags across countries, but the periphery shows a stronger fragility to fluctuations in this variable than all other regions analyzed. Overall, the impact on the periphery is negative and stronger in absolute terms, whereas it tends to be overall positive for other regions, or very close to zero. In the early period estimation, house price growth is significant at most lags for the periphery, with a higher magnitude than the comparable lags for the other regions. Real GDP growth has an impact in the periphery for the early period, not present elsewhere.

4.2.1 Model Assessment

Table 7: Model Assessment - Region Estimation, Static Models

Static Models	European Union		Eurozone		Periphery		Eurozone w/o Periphery	
	R^2	AUROC	R^2	AUROC	R^2	AUROC	R^2	AUROC
Late Period	12.21%	0.7612	10.69%	0.7628	32.98%	0.8538	18.72%	0.7962
Early Period	0.9%	0.5735	1.59%	0.5705	21.70%	0.7855	1.22%	0.5992

Table 8: Model Assessment - Region Estimation, Dynamic Models

Dynamic Models	European Union		Eurozone		Periphery		Euro zone w/o Periphery	
	R^2	AUROC	R^2	AUROC	R^2	AUROC	R^2	AUROC
Late Period	49.08%	0.9219	46.19%	0.9147	52.70%	0.9138	54.87%	0.9429
Early Period	7.33%	0.6186	10.72%	0.7089	20.04%	0.7786	17.37%	0.7617

Regarding model performance, there is a clear outperformance of dynamic models over static specifications, in all sub-samples estimated. Since dynamic models consistently outperform static models, they are thusly preferred in building a successful early warning model.

Table 9: Event Classification - Region Estimation, Static Models

Static Models								
Measures of Event Classification	Late Period				Early Period			
	EU	EA	Periphery	EA w/o Periphery	EU	EA	Periphery	EA w/o Periphery
Sensitivity	16.07%	6.90%	40.32%	27.87%	0.83%	0%	42.19%	0%
Specificity	95.09%	98.14%	98.42%	93.46%	99.86%	100%	91.22%	100%
Crisis classified as non-crisis	83.93%	93.10%	59.68%	72.13%	99.17%	100%	57.81%	100%
Correctly Classified	75.76%	81.98%	86.98%	78.91%	74.66%	84.58%	76.42%	86.05%

For the static specifications of the model, it is evident that events are predicted much more accurately for the periphery than for other regions. Also, the rate of miss-classification of crises observations is significantly lower. Dynamic specifications allow for a more accurate

Table 10: Event Classification - Region Estimation, Dynamic Models

Dynamic Models								
Measures of Event Classification	Late Period				Early Period			
	EU	EA	Periphery	EA w/o Periphery	EU	EA	Periphery	EA w/o Periphery
Sensitivity	70.51%	69.60%	72.58%	76.56%	20.27%	29.37%	36.36%	38.33%
Specificity	94.84%	94.42%	96.63%	96.51%	97.06%	95.13%	93.24%	96.06%
Crisis classified as non-crisis	29.49%	30.40%	27.42%	23.44%	79.73%	70.63%	63.64%	61.67%
Correctly Classified	88.72%	88.44%	90.42%	92.15%	86.94%	80.25%	75.70%	85.03%

classification of crises episodes. One striking feature is that crises are predicted with greater accuracy when the periphery and the remaining members of the Euro Area are included in separate models, and the miss-classification of crises observations also decreases, despite the reduction in the number of observations.

4.3 Robustness and Weaknesses of the model

One of the main weaknesses of the models presented is the fact that the limited number of observations prevents adding more variables, that could in principle contribute to improve upon the forecasting accuracy of the model. The models for the European Union are reestimated using the sample only until the last quarter of 2006, to remove the systemic banking crisis that followed. Due to the smaller dataset, only late and early period estimation is possible and, altough the results are qualitatively similar[10], model performance decreases substantially in what regards crises classification.[11] This type of analysis is not possible to conduct for the other regions estimated, since the already small sample does not allow further decreases in sample size.

5 Conclusions

The main conclusions are that, as established in the literature, dynamic models outperform static models in accurately predicting crises and in model fit. Also, it is substantialy more difficult to forecast accurately in the early period, that is, three to five years prior to the occurence of banking crises.

Real GDP growth, stock market returns and house price growth are good Early Warning

[10]Dynamic models still outperform static models in crises detection and the bulk of explanatory power is concentrated in the late period estimation. Static models improve performance for the restricted sample. For dynamic models, the percentage of crisis being miss-classified suffers a significant increase when sample size decreases.

[11]The results of this estimation are available in the extra appendix that was delivered along with this dissertation.

variables, presenting signs that are consistent with economic theory, and their monitoring can be key in preventing the onset of crises.

This study suggests that altough the same variables can be used for early warning purposes, their impact may differ among regions, either in magnitude or in timeliness. Hence, region estimation allows to account for different fragilities that are somewhat downplayed in models that encompass a larger number of countries. Particularly, housing price growth has a stronger impact in the periphery, and should be monitored more closely for this set of countries. These countries seem to be more sensitive to recessions for longer periods of time, which is also valuable information for efficient macro-prudential monitoring.

As such, separate models for the periphery and remaining countries of the Eurozone outperform a single model in crisis detection for the entire monetary union and should therefore be preferred for efficient monitoring of economic conditions.

This should be considered by authorities in macro-prudencial monitoring and separate models should be developed within the monetary union, since they are more efficient and can thus increase the probability of crises detection, even with a decrease in the number of observations. Accounting for these types of diferences among countries increases the scope for intervention and policy action, since it allows policymakers to design region specific policies, with the aim of preventing contagion within the monetary union.

Further research should focus on the relationship between stock market crashes and banking crises, using a Panel Probit VAR model to account for possible endogeneity. This would require a binary variable of stock market crises, unavailable for the sample used in this project. Also, the estimation of Early Warning Models with sub samples of countries within the Euro Area should be further explored, for other possible variables and model specifications.

6 Appendix 1

H_0: All panels contain unit roots

H_1: Some panels are stationary

Table 11: Im-Pesaran-Shin Test for unit root

	No Trend		Trend Included	
	Z_t	P>$\|z\|$	Z_t	P>$\|z\|$
Equity Prices	1.9089	0.9719	0.1054	0.5420
Real GDP	-0.3913	0.3478	6.5570	1.000
House Prices	2.4441	0.9927	3.4834	0.9998
Equity Returns	-23.5789	0.0000	-23.8552	0.0000
Real GDP Growth	-19.8914	0.0000	-21.7334	0.0000
House Prices Growth	-15.7253	0.0000	-16.7004	0.0000

For equity prices, real GDP and house prices it is not possible to reject the null hypothesis of all panels containing unit roots. For equity returns, real GDP growth and house price growth there is enough evidence to reject the null hypothesis for a significance level of 5%.

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