A LOGISTIC MODEL ON PANEL DATA FOR SYSTEMIC RISK ASSESSMENT – EVIDENCE FROM ADVANCED AND DEVELOPING ECONOMIES[1]

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Abstract

The present paper proposes a framework for developing a new early warning system (EWS) for identifying systemic banking risk and finding the macroeconomic indicators which turn to be the best indicators in predicting stressful situation in the economic environment. The research problem is very much debated in the specialty literature, as the exposure of the financial system is generally derived from deteriorating systemic conditions. We propose a logistic model applied on two panel data sets – advanced and emerging economies. Results are satisfactory, as apart from the GDP Growth or Debt level, as main triggers for financial stress situation, we also find the Output Gap as a significant early warning signal for predicting financial and economic crisis.

Keywords: *systemic risk, early warning systems, financial crisis, binary variables panel data*

1. Introduction

A well-functioning financial system is mandatory for an efficient economy. However, the fragility of financial systems can cause financial crisis and have significant impact in the real economy. The topic of financial crisis is highly relevant in terms of policy, as outlined by Kauko (2014). Crises trigger output losses and social costs, with an average production loss of 20% of annual Gross Domestic Product (GDP). It is very important to have a good understanding of the past crisis events, of the mistakes made and to learn the lessons from the crisis that happened over time because, as time showed us, history could repeat itself.

In the last twenty years, the world economy has been faced with a significant number of financial crises, from Latin America, to Asia, from Nordic Countries to East and Central European countries, it all culminated with the financial tsunami which burst in 2007. A new and critical need for the Early Warning Systems has appeared since 2008: an updated EWS that would correctly include in the model the way financial markets are affected by changes in risk factors and risk transmission. Since the Great Financial Crisis, it has come as an evidence the exposure to systemic risk is affected by propagation effects and links among financial institutions which are strongly determined by the structure of the financial system.

Considering the increased complexity of the financial systems and risk associated within, attention is drawn by the specialists that a new EWS tool should be used an orientation rather than a signaling technique. The main role and value of the EWS is providing a systemic overview and functioning as a monitor for the systemic risk. As mentioned in Gramlich et al (2010), the results of an EWS should not be overestimated. However, once critical signals are emitted, the supervisory authorities would need support "on the basis of an expected, but not yet realized, deterioration".

In the present paper we propose a logistic macroeconomic model for panel data with the aim of finding the macroeconomic leading indicators of distress. We carry out two models – for advanced and emerging economies and find which are the macroeconomic variables having the highest weight in the probability of a crisis. The rest of the paper is organized as follows. In section 2 we review literature in what concerns the construction of early warning systems for banking crisis – the role of the EWS, the main concepts and techniques used to model the systems, with reference to the latest findings in the literature; section 3 – gives an overview on the particularities of modeling binary outcomes for panel data – which is the methodology employed in the case study. In section four, we propose two models – one for advanced, one for emerging economies and find which are the macroeconomic indicators of systemic risk. The study is innovative as it includes data for both types of economies and also the whole period of the last 5 years since the burst of the Global Financial Crisis. Including the output gap variable in the list of signals is a new concept in the literature and proves to be a significant early trigger for systemic risk. Section five presents the conclusions.

2. Literature review – early warning systems for systemic banking crisis

As the cost of the most recent financial crisis was estimated at app. USD 12 trillion (reaching 20% of the GDP in most affected countries), the forward-looking instruments of supervisory banks gain more and more importance as the amplitude of financial crisis increases. With the crisis becoming more prominent, the literature on EWS models has grown significantly. However, the existing EWS models failed to predict the recent global crisis and this is mainly due to the fact that they do not fully reflect the way that financial markets are affected by changes in risk factors and risk transmission.

Basically, an early warning system (EWS) has the role of anticipating whether an economy will be affected by a financial crisis by developing a framework which would allow for predicting financial stressful situations. In the literature there are three approaches for constructing an Early Warning System for predicting banking crisis: the bottom-up approach, the aggregate approach and the macroeconomic approach. In the first approach mentioned, the probability of insolvency is estimated for each bank and the signal for systemic instability is triggered when the probability of insolvency becomes significant for a high proportion of the banking assets in the respective economy. For the second approach, the same model is applied to aggregate bank data instead of individual bank data. In what concerns the third approach, the attention is focused on establishing a relationship between economy wide variables, based on the fact that a number of macroeconomic variables are expected to affect the financial system and reflect its condition. The third approach will also be used in the case study that we are proposing in the paper.

Gramlich et al. (2010) make a critical review of earlier EWS literature and highlight the main components of a EWS risk model:

- Risk measures – stress assessment; in the literature this can take the form of a binary index (Kaminsky, Reinhart – 1999; Edison – 2003), three-state index (Bussiere; Fratzscher – 2002) or continous index (Illing Liu – 2003, Hanschel, Monnin – 2005);
- Risk factors – risk indicators – usually chosen between micro risks, macro risks (most cited being the work of Reinhart, Rogoff – 2009) and structural risks;
- The risk model – a theory on how to combine the risk measures and the risk factors. Basically there are two approaches for this: the leading indicator (or signal theory) and data-focused regression models.

The approaches of the EWS models are mainly statistical driven. First models are proposed by Diebold and Rudebusch (1989) for constructing economic indexes. The technique was adapted by Kaminsky and Reinhart (1999) who propose the signal approach: a potential crisis is signaled when a risk factor exceeds a predefined threshold. The threshold is adjusted to balance type I errors (model failed to predict crises when they actually take place) and type II errors (models wrongly predicts crises that do not occur). This technique has also been approached by Borio (2002, 2009). Demirguc-Kunt and Detragiache (1998) are the first to use regression analysis for evaluating the predictive power of risk factors. In their later study (2005), the compare both techniques and conclude that the logit model is the most suitable in assessing financial risk. We also note, the neuro-fuzzy approach of Lin et al (2006) for identifying the drivers of currency crisis and find that this artificial intelligence tool improves the prediction of crisis. Still, the black-box pattern of these methods remains a disadvantage for understanding the big picture of the crisis mechanisms.

Other approaches from the specialty literature include : a non-parametric method based upon K-means clustering to predicting crisis events (Fuertes, Kalotychou, 2004) - in their study they find that the optimal model can be constructed based on the decision-makers preferences regarding the desired trade-off between missed defaults and false alarms; Kalman filter estimation of state space models (Mody, Taylor, 2003) – with the aim of extracting a measure of regional vulnerability for emerging economies; factor model with Markov regime switching dynamics (Chauvet, Dong, 2004) for the prediction of nominal exchange rates in the East Asian countries.

3. Binary outcome models – particularities for panel data

Considering that in our case, the dependent variable takes the form of a binary variable (presence or absence of the crisis event), we will turn our attention to the binary choice models. In this case, the model will have the following form :

$$Prob\ (Y = 1|x) = F\ (x, \beta)$$
$$Prob\ (Y = 0|x) = 1 - F\ (x, \beta)$$

where x is the vector of explanatory factors and β is the vector of parameters that reflect the changes in x on the probability. The problem that arises is to find a suitable model for the function F. If we would use the familiar liner regression model, we would encounter a series of problems. First of all, the disturbances in the model would be heteroscedastic due to the restriction imposed to have the dependent variable 0 or 1. Assuming that this problem can be solved by a GLS estimation, a more serious problem is that we cannot be assured that the predictions in the model will look like probabilities. That is the main reason for which we have to use another type of function, that would have the following properties:

$$\lim_{x'\beta \to +\infty} Prob\ (Y = 1|x) = 1$$

$$\lim_{x'\beta \to -\infty} Prob\ (Y = 1|x) = 0$$

As stated in Greene, in principle, any "proper, continuous probability distribution defined over the real line will suffice". If the normal distribution is being used, the probit model is obtained:

$$Prob\ (Y = 1|x) = \int_{-\infty}^{x'\beta} \Phi(t)\, dt = \Phi\ (x'\beta)$$

Due to its mathematical advantages, the logistic distribution is also often used, determining the logit model:

$$Prob\ (Y = 1|x) = \frac{e^{x'\beta}}{1 + e^{x'\beta}} = \Lambda\ (x'\beta)$$

where $\Lambda\ (\cdot)$ indicates the logistic cumulative distribution function. The question arises on which one of the two models to use. The two distributions have similar bell shaped distributions, with the difference that the tails are heavier in the logistic one. The logistic distribution tends to give larger probabilities to $Y = 1$ for extremely small values of $x'\beta$ than the normal distribution would. Or otherwise said, the conditional probability approaches 0 or 1 at a slower rate in logit than in probit. One would expect to obtain different predictions from the two models if the sample contains very few favorable cases (Y's equal to 1) or very few un-favorable cases (Y's equal to 0). "There are practical reasons for favoring one the other in some cases for mathematical convenience, but it is difficult to justify the choice of one distribution or another on theoretical grounds" (Greene). Most applications would state the models generally give similar results, with the limitations expressed before.

An important thing to note for logit and probit models is that the parameters in the model are not necessarily the marginal effects like in the classical regression models. This happens because the marginal effect of a regressor in the logit model depends not only on the coefficient of that regressor, but also on the value of all regressors in the model. For computing marginal effects, we can evaluate the expression for the samples means of the data or evaluate the marginal effects at every observation and use the sample average of the individual marginal effects.

The literature dedicated to the binary choice models for panel data is rapidly growing. An overview is given in Greene (2011). We distinguish between random and fixed effects models by the relationship existing between the unobserved, individual specific hetereogeneity and the vector of regressors. The effect model has the following form:

$$y_{it}^* = x_{it}'\beta + v_{it} + u_i, i = 1, \dots, n; t = 1, \dots, T_i$$

$$y_{it} = 1\ if\ y_{it}^* > 0, and\ 0\ otherwise.$$

As per Greene (2011), the assumption that u_i is unrelated to x_{it} produces the random effects model. However, this places a restriction on the distribution of the heterogeneity. If the model permits correlation between u_i and x_{it} , then we have a fixed effects model. The disadvantage of the fixed effect model is that the maximum likelihood estimator becomes inconsistent, while in the random effects model strong assumptions regarding heterogeneity should be made.

4. Case study

In this part of the paper, we propose a framework that could be used a starting point for developing an early warning signals system comprising macroeconomic indicators for monitoring and maintaining financial stability in an economy.

In the first part we describe the data used. As data sources we relied on macroeconomic data publicly available at World Bank and International Monetary Fund. Due to significant discrepancy regarding data availability across countries, but also based on particularities of emergent versus advanced economies, we decided to split the initial sample into two data sets. That is, one data set contains the information for the advanced economies: Austria, Germany, Denmark, Spain, Finland, France, United Kingdom, Greece, Ireland, Italy, Netherlands, Norway, Portugal, Sweden and Belgium. The variables included for this sample are: Cash deficit, GDP growth, Exports, Stocks, Inflation, Output Gap and Debt. The observation period is 1990 – 2012, that is the entire panel for advanced economies contains 315 observations in 15 groups. The second sample will include data on emerging economies: Bulgaria, Czech Republic, Croatia, Hungary, Iceland, Israel, Lithuania, Poland, Romania, Slovak Republic, Slovenia, Latvia. The variables included for the emergent countries sample are: M2 growth, GDP growth, Exports, Stocks, Inflation. Fewer variables are included due to issues regarding data availability. That is also one of the reasons the observation period is reduced to 1995 – 2012. Another reason for reducing the observation period is the particularities of the emergent economies included in the sample, economies which are mainly from the ex-communist bloc and in the first years of the 1990s developed abnormal values of the macroeconomic indicators. Total panel for the emergent economies contains 216 observations in 12 groups. In the next table we present a detailed description of the indicators included, as they are given on the official sites cited.

The dependent variable used in the model is a binary variable and takes the value 1 if the country has been reported as experiencing a banking crisis in the respective year. Data for the banking crises has been taken from official sources in IMF (Leaven, 2008 and further extended).

Table 1. Indicators description

Indicator	Indicator Description	Observations
GDP growth (annual %)	Annual percentage growth rate of GDP at market prices based on constant local currency. Aggregates are based on constant 2005 U.S. dollars. GDP is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products. It is calculated without making deductions for depreciation of fabricated assets or for depletion and degradation of natural resources.	Observation period for advanced economies 1990 – 2012; for emergent economies 1995 – 2012.
Cash surplus/deficit (% of GDP)	Cash surplus or deficit is revenue (including grants) minus expense, minus net acquisition of nonfinancial assets. This cash surplus or deficit is closest to the earlier overall budget balance (still missing is lending minus repayments, which are now a financing item under net acquisition of financial assets).	Observation period for advanced economies 1990 – 2012.
Inflation, consumer prices (annual %)	Inflation as measured by the consumer price index reflects the annual percentage change in the cost to the average consumer of acquiring a basket of goods and services that may be fixed or changed at	Observation period for advanced economies 1990 – 2012; for emergent economies

Indicator	Indicator Description	Observations
	specified intervals, such as yearly. The Laspeyres formula is generally used.	1995 – 2012.
Money and quasi money growth (annual %)	Average annual growth rate in money and quasi money. Money and quasi money comprise the sum of currency outside banks, demand deposits other than those of the central government, and the time, savings, and foreign currency deposits of resident sectors other than the central government. This definition is frequently called M2. The change in the money supply is measured as the difference in end-of-year totals relative to the level of M2 in the preceding year.	Observation period for emergent economies 1995 – 2012.
Exports of goods and services (% of GDP)	Exports of goods and services represent the value of all goods and other market services provided to the rest of the world. They include the value of merchandise, freight, insurance, transport, travel, royalties, license fees, and other services, such as communication, construction, financial, information, business, personal, and government services. They exclude compensation of employees and investment income (formerly called factor services) and transfer payments.	Observation period for advanced economies 1990 – 2012; for emergent economies 1995 – 2012.
Stocks traded, total value (% of GDP)	Stocks traded refers to the total value of shares traded during the period. This indicator complements the market capitalization ratio by showing whether market size is matched by trading.	Observation period for advanced economies 1990 – 2012; for emergent economies 1995 – 2012.
Output gap (% of potential GDP)	Output gaps for advanced economies are calculated as actual GDP less potential GDP as a percent of potential GDP.	Observation period for advanced economies 1990 – 2012.
General government net debt (% of GDP)	Net debt is calculated as gross debt minus financial assets corresponding to debt instruments. These financial assets are: monetary gold and SDRs, currency and deposits, debt securities, loans, insurance, pension, and standardized guarantee schemes, and other accounts receivable.	Observation period for advanced economies 1990 – 2012.

Source: World Bank Data, International Monetary Fund

4.1. Estimation results for the advanced economies

Before estimating the model, we analyze a graphic representation of the variables included. Although all variables experienced a drop in the 2007 – 2008 period, the most representative evolution is the one of the GDP growth. The graphs for the first panels are reproduced in Figure 1. We notice the evolution of the GDP growth for Greece which remains on a descendent path, although the rest of the economies experience a drop in the GDP growth in 2008 followed by a modest recovery in the next years.

Next step is to test the stationarity of the time series included. For this, we apply specific unit – root tests for panel data. For consistency of results we use four tests: Levin – Lin – Chen , Breitung, Im – Pesaran – Shin, Hedri LM Test. In the first two tests the null hypothesis is that the panels contain unit roots with the alternative hypothesis that panels are stationary, while in the last two tests the null hypothesis is that all panels contain unit roots with the alternative hypothesis that some panels are stationary.

Results are presented in Figure 2 (example for a unit root estimation output – results for the test Levin – Lin – Chen applied to GDP growth) and in tables 2, 3 and 4 which summarize the statistics and p-values for the four tests, for all variables included in the analyze.

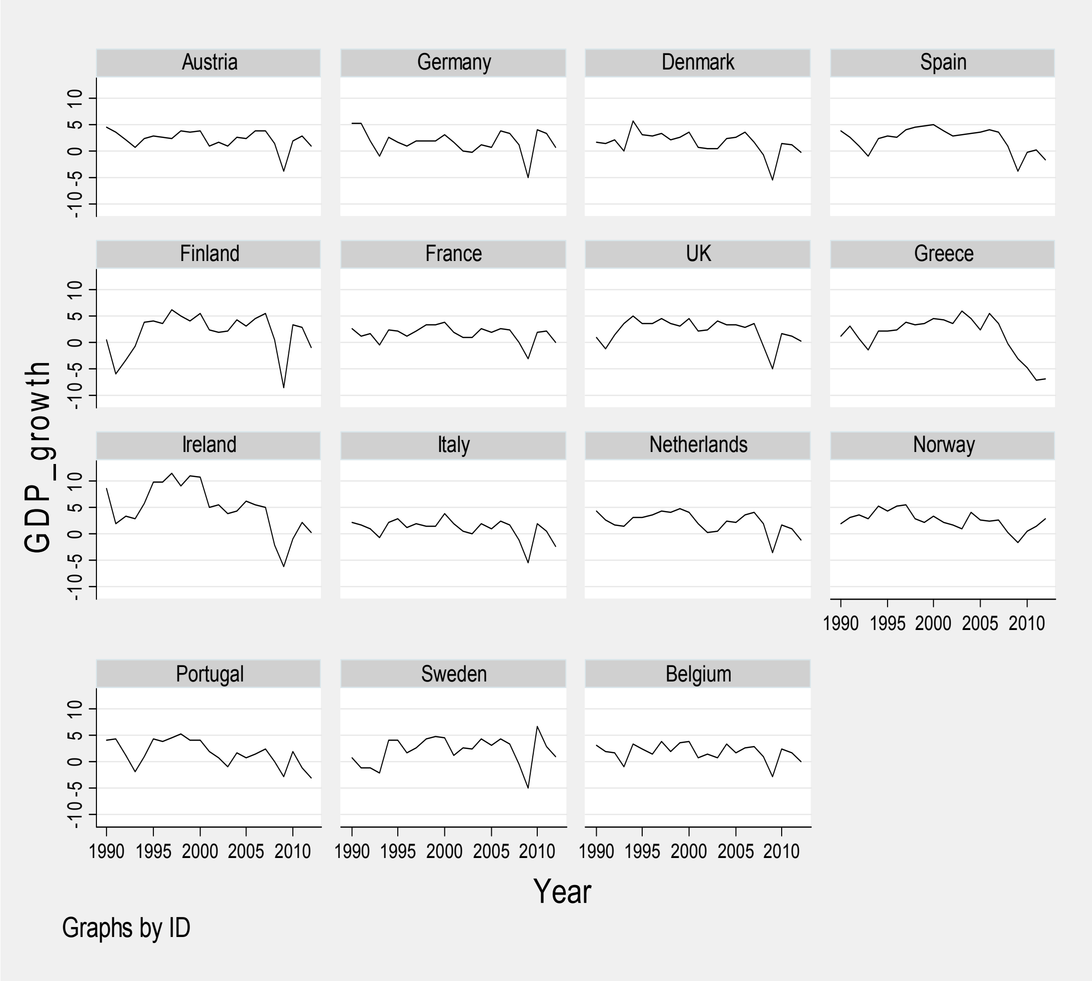

Figure 1. GDP growth evolution in the period 1990 – 2012 for advanced economies

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Levin-Lin-Chu unit-root test for gdp_growth
-------------------------------------------
Ho: Panels contain unit roots              Number of panels  =     15
Ha: Panels are stationary                  Number of periods =     23

AR parameter: Common                       Asymptotics: N/T -> 0
Panel means:  Included
Time trend:   Not included

ADF regressions: 1 lag
LR variance:     Bartlett kernel, 9.00 lags average (chosen by LLC)
------------------------------------------------------------------------------
                    Statistic      p-value
------------------------------------------------------------------------------
 Unadjusted t        -9.5966
 Adjusted t*         -4.6545        0.0000
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Figure 2. Results of test Levin – Lin – Chu for the GDP growth

Table 2. Results of Unit Root Tests for Cash – Deficit and GDP Growth

Unit Root Test	Statistic	P-Value	Unit Root Test	Statistic	P-Value
Levin-Lin-Chu*	-4,6678	0,0000	Levin-Lin-Chu*	-4,6545	0,0000
Breitung*	-7,5674	0,0000	Breitung*	-5,8305	0,0000
Im-Pesaran-Shin **	-3,2867	0,0005	Im-Pesaran-Shin **	-4,6086	0,0000
Hadri LM test **	7,8664	0,0000	Hadri LM test **	9,6757	0,0000

*null hypothesis panels contain unit roots / alternative hypothesis that panels are stationary
**null hypothesis that all panels contain unit roots / alternative hypothesis that some panels are stationary

Table 3. Results of Unit Root Tests for Exports and Stocks

Unit Root Test	Statistic	P-Value	Unit Root Test	Statistic	P-Value
Levin-Lin-Chu*	-1,6862	0,0459	Levin-Lin-Chu*	-3,9922	0,0000
Breitung*	-0,4516***	**0,3258*****	Breitung*	-3,2177	0,0006
Im-Pesaran-Shin **	-2,8915***	0,0019***	Im-Pesaran-Shin **	-1,6853	0,0460
Hadri LM test **	16,5181 ***	0,0000 ***	Hadri LM test **	23,9276	0,0000

*null hypothesis panels contain unit roots / alternative hypothesis that panels are stationary
**null hypothesis that all panels contain unit roots / alternative hypothesis that some panels are stationary
*** including time trend; if the time trend component were not included, the series would contain unit roots

Table 4. Results of Unit Root Tests for Inflation and Output Gap

Unit Root Test	Statistic	P-Value	Unit Root Test	Statistic	P-Value
Levin-Lin-Chu*	-8,7241	0,0000	Levin-Lin-Chu*	-4,3547	0,0000
Breitung*	-1,3878***	**0,0826*****	Breitung*	-2,9368	0,0017
Im-Pesaran-Shin **	-6,8070	0,0000	Im-Pesaran-Shin **	-2,4560	0,0070
Hadri LM test **	24,7587	0,0000	Hadri LM test **	6,1074	0,0000

*null hypothesis panels contain unit roots / alternative hypothesis that panels are stationary
**null hypothesis that all panels contain unit roots / alternative hypothesis that some panels are stationary
*** including time trend; if the time trend component were not included, the series would contain unit roots

Considering the results above, we can conclude, based on all four tests applied that the variables: Cash Deficit, GDP growth, Stocks, Inflation and Output Gap are stationary (for a significance level of maximum 5%). However, for variable exports, the results of the test show the presence of the unit root if trend component is not included (null hypothesis cannot be rejected – Table 4) and for variable Debt all tests have associated p-values larger than 0.1 concluding that the series is not stationary. For these two variables we take the first difference of the variables and obtain that the resulted series are stationary. Results are summarized in table 5.

Table 5. Results of Unit Root Tests for D(Exports) and D(Debt)

Unit Root Test	Statistic	P-Value	Unit Root Test	Statistic	P-Value
Levin-Lin-Chu*	-8,5419	0,0000	Levin-Lin-Chu*	-2,1655	0,0152
Breitung*	-9,3639	0,0000	Breitung*	-5,3703	0,0000
Im-Pesaran-Shin **	-8,5182	0,0000	Im-Pesaran-Shin **	-4,8709	0,0000
Hadri LM test **	-1,2660***	0,1027***	Hadri LM test **	6,3528	0,0000

*null hypothesis panels contain unit roots / alternative hypothesis that panels are stationary
**null hypothesis that all panels contain unit roots / alternative hypothesis that some panels are stationary
*** including time trend

Next, we begin estimating the models. As stated before, we have the option of estimating logit or probit models with the random or fixed effects (random effects possible only for logistic models). Considering the nature of the “early warning signals” model we are proposing, we include in our list of variables all the variables with lagged for two periods.

However, we obtain that only three of them are significant, that is : the GDP growth with lag one, the Output gap with lag two and the first difference of variable Debt with lag one.

Table 6. Results for the estimation of the logistic model for advanced economies (random effects)

```
Random-effects logistic regression              Number of obs      =       315
Group variable: id                              Number of groups   =        15

Random effects u_i ~ Gaussian                   Obs per group: min =        21
                                                               avg =      21.0
                                                               max =        21

Integration method: mvaghermite                 Integration points =        12

                                                Wald chi2(10)      =     49.11
Log likelihood  = -82.941931                    Prob > chi2        =    0.0000
```

bc	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
cash_deficit	-.0684804	.0846879	-0.81	0.419	-.2344657	.0975049
gdp_growth	-1.630855	.2672036	-6.10	0.000	-2.154564	-1.107146
stocks	.0132952	.0060939	2.18	0.029	.0013514	.025239
inflation	.0941213	.1648881	0.57	0.568	-.2290534	.417296
outputgap	1.320462	.3052972	4.33	0.000	.7220906	1.918834
d_exports	.0791391	.114939	0.69	0.491	-.1461373	.3044155
d_debt	.1446802	.0426859	3.39	0.001	.0610174	.228343
gdp_growth						
L1.	-1.321017	.2696935	-4.90	0.000	-1.849607	-.7924275
outputgap						
L2.	-1.227266	.2600205	-4.72	0.000	-1.736897	-.7176349
d_debt						
L1.	.0907671	.0441878	2.05	0.040	.0041606	.1773736
_cons	1.843755	.9490806	1.94	0.052	-.016409	3.703918
/lnsig2u	1.019219	.6333285			-.2220818	2.26052
sigma_u	1.664641	.5271323			.8949022	3.096462
rho	.457198	.1571719			.1957724	.7445347

Likelihood-ratio test of rho=0: chibar2(01) = 18.28 Prob >= chibar2 = 0.000

Results for the logit model with random effects are presented in table 6. The model is valid, considering the likelihood-ratio test for rho (p-value = 0.0000). Considering the p-values of the variables included in the sample, at a 0.05 significance level, the following variables are significant: GDP growth and GDP growth lagged one period (both coefficients with negative signs, as expected): Stocks (positive sign), Output Gap and Output Gap lagged two periods (first with a positive sign and second with a negative sign); first difference of the governmental debt and first difference of the governmental debt lagged with one period (both coefficients positive).

The results show that cash deficit, inflation level and variation in exports are not significant early warning signs for predicting crisis. The signs of the significant variables are related to economic theory. A decrease in the GDP growth and the increase in the output gap are the most significant early warning signs for the advanced economies. Also, an increase in the variation of governmental debt (one year prior to crisis) and the increase in volumes of stocks traded can be viewed as early warning indicators, but with smaller contributions to the probability of a crisis appearance.

Apart for this model, we also estimate (using same variables) a logit model with fixed effects. The results of the estimation are presented in a comparative manner in Table 7 below.

Table 7. Comparative results of Logit models (fixed / random effects)

Variable	Coefficient	Std. Error	Model
GDP Growth	-1.6308	0.2672	Logit Random Effects
	-1.6779	0.2690	Logit Fixed Effects
Stocks	0.0132	0.0060	Logit Random Effects
	0.0078	0.0071	Logit Fixed Effects
Output Gap	1.3204	0.3052	Logit Random Effects
	1.6748	0.3572	Logit Fixed Effects
D(Debt)	0.1446	0.0426	Logit Random Effects
	0.1459	0.0396	Logit Fixed Effects
GDP Growth (L1)	-1.3210	0.2696	Logit Random Effects
	-1.4626	0.2862	Logit Fixed Effects
Output Gap (L2)	-1.2272	0.2600	Logit Random Effects
	-1.3160	0.2732	Logit Fixed Effects
D (Debt) (L1)	0.0907	0.0441	Logit Random Effects
	0.1310	0.0463	Logit Fixed Effects

The results are similar for the two types of models. However, considering the estimated probabilities of the model (probability that the outcome is positive), we conclude that the random effects model is much more suitable for the underlying data. The post estimation results are in Table 8. As per IMF statistics used, the only countries that did not experience crisis in 2009 from the advanced economies selected are Finland and Norway. That is, the probability estimated for Norway is very good, but the one estimated for Finland is associated to a crisis situation, although the country has not been reported as so. We also note, the low probability reported for Sweden, although the country has been reported as affected by the crisis. Greece, Italy and Ireland, as well as Portugal have estimated probabilities very close to one – these being the countries the most affected by the crisis, thus with the level of the macroeconomic variables most eroded.

Table 8. Post estimation results for the logistic model – advanced economies (random effects)

Country	**Year**	**Exp Prob**
Austria	2009	0.5582764
Germany	2009	0.8579196
Denmark	2009	0.9491678
Spain	2009	0.7292508
Finland	2009	0.8606029
France	2009	0.9507059
UK	2009	0.9999521
Greece	2009	0.9997895

Country	Year	Exp Prob
Ireland	2009	0.9878655
Italy	2009	0.9950404
Netherlands	2009	0.6415532
Norway	2009	0.0431651
Portugal	2009	0.9893235
Sweden	2009	0.2477488
Belgium	2009	0.5460162

4.2. Estimation results for the emergent economies

The graphic representation of the GDP growth's evolution for the emergent economies in the panel is found in Figure 3 below. The graph analyze is similar with the one that we had for the advanced economies. However, we note some particularities – the countries from the former communist block experienced a drop GDP also in the period 1995 – 1996, due to transition period. Also, Baltic Countries (Latvia and Lithuania) experienced the most severe drops in GDP in the crisis years, as can be easily observed from Figure 3.

In Table 9 and 10 we have the results for the unit root tests applied to the variables M2 growth, GDP growth, Exports, Stocks and Inflation. We find that M2 growth, GDP growth and Stocks are all stationary. For Inflation, all tests (except the Breitung test) confirm the that the variable is stationary. However, considering that for Exports, the null hypothesis that panels contain unit roots cannot be rejected for three of the four tests, we decide to use the first difference of exports in the model – where we accept the stationarity of the variable in three out of four tests (results of unit root tests before and after differentiation are presented in Table 11).

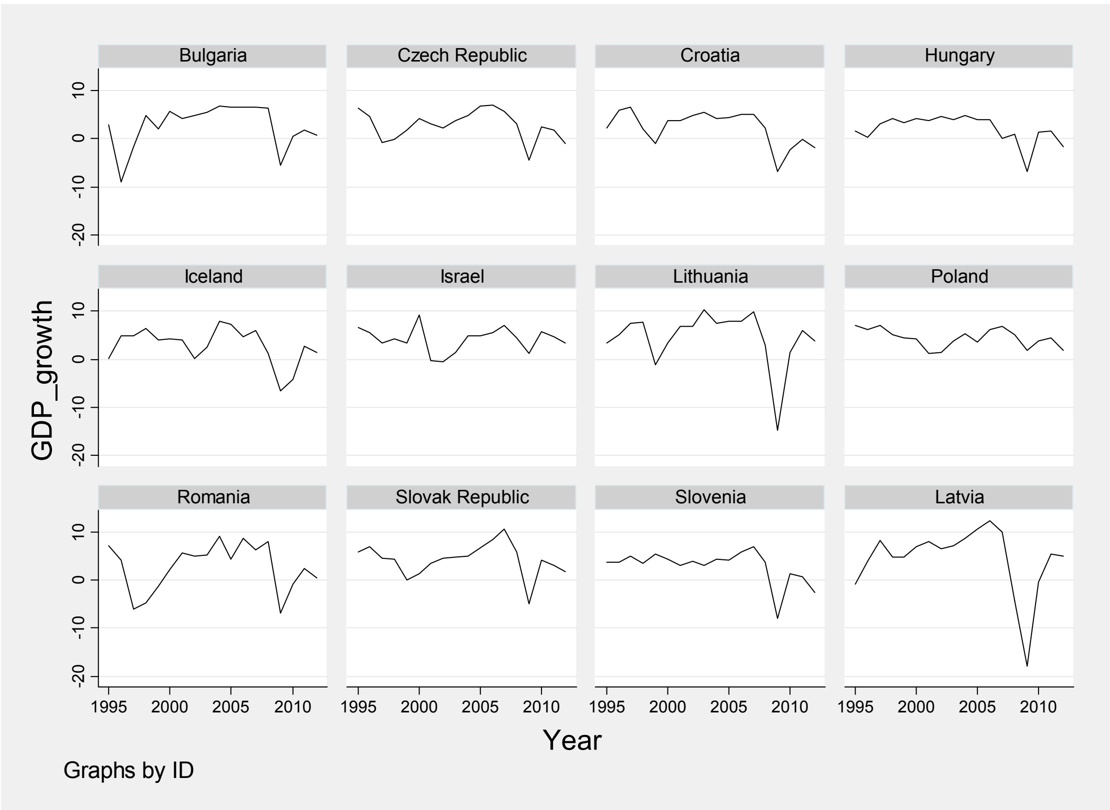

Figure 3. GDP growth evolution in the period 1995 – 2012 for advanced economies

Table 9. Results of Unit Root Tests for M2 Growth and GDP Growth

Unit Root Test	Statistic	P-Value	Unit Root Test	Statistic	P-Value
Levin-Lin-Chu	-3.4923	0.0002	Levin-Lin-Chu	-4.8273	0.0000
Breitung	-2.3557	0.0092	Breitung	-5.5205	0.0000
Im-Pesaran-Shin	-4.1504	0.0000	Im-Pesaran-Shin	-3.7274	0.0001
Hadri LM test	7.7165	0.0000	Hadri LM test	2.0937	0.0181

Table 10. Results of Unit Root Tests for Stocks and Inflation

Unit Root Test	Statistic	P-Value	Unit Root Test	Statistic	P-Value
Levin-Lin-Chu	-4.9641	0.0000	Levin-Lin-Chu	-5.5655	0.0000
Breitung	-3.4122	0.0003	Breitung	0.1903	0.5754
Im-Pesaran-Shin	-1.7552	0.0396	Im-Pesaran-Shin	-4.6811	0.0000
Hadri LM test	6.3827	0.0000	Hadri LM test	3.3155	0.0005

Table 11. Results of Unit Root Tests for Exports and Variation in exports (first difference)

Unit Root Test	Statistic	P-Value	Unit Root Test	Statistic	P-Value
Levin-Lin-Chu	-1.6202	0.0526	Levin-Lin-Chu	-5.0471	0.0000
Breitung	0.5703	0.7158	Breitung	-6.9226	0.0000
Im-Pesaran-Shin	0.3539	0.6383	Im-Pesaran-Shin	-5.5524	0.0000
Hadri LM test	20.7622	0.0000	Hadri LM test	-0.7522	0.7740

In what follows, we proceed to the same steps as for the sample of advanced economies. We estimate the logistic model – with random and fixed effects. As we did previously, we include in the list of variables all the variables lagged for two periods. This time, we obtain that only the GDP growth with lag one, the variation of exports with lag two are significant in the model. The results of the estimation with random effects are presented in Table 12.

The model is valid, considering the likelihood-ratio test for rho (p-value = 0.001). Considering the p-values of the variables included in the sample, at a 0.05 significance level, the following variables remain significant: M2, GDP growth, Variation in Exports and GDP growth lagged one period (both coefficients with negative signs, as expected). Inflation level and stocks, as well as the variation in exports lagged with two periods are not significant early warning signs for predicting crisis in the case of emerging economies. The signs of the significant variables are related to economic theory. A decrease in the GDP growth or a decrease in the money supply can be considered the most significant early warning signals for the emergent economies. In Table 13 we present the post-estimation results for the random effects logistic model. We notice that the model give weaker results than the one for the advanced economies. This could be mainly due to the lower number of variables included in the model. The expected probabilities for the Baltic Countries (Lithuania, Latvia) are, as expected, the most close to one, as these are countries which experienced the most dramatic fall in the economy (as also shown from the graph).

Table 12. Results for the estimation of the logistic model for emerging economies (random effects)

```
Random-effects logistic regression              Number of obs      =       180
Group variable: id                              Number of groups   =        12

Random effects u_i ~ Gaussian                   Obs per group: min =        15
                                                               avg =      15.0
                                                               max =        15

Integration method: mvaghermite                 Integration points =        12

                                                Wald chi2(7)       =     27.20
Log likelihood  = -56.892479                    Prob > chi2        =    0.0003
```

bc	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
m2_growth	-.1219335	.0436757	-2.79	0.005	-.2075362	-.0363308
gdp_growth	-.3857805	.104889	-3.68	0.000	-.5913591	-.1802019
d_exports	.1089936	.0505533	2.16	0.031	.0099109	.2080763
stocks	-.0069754	.0180328	-0.39	0.699	-.0423191	.0283683
inflation	-.0020855	.0561766	-0.04	0.970	-.1121897	.1080186
gdp_growth						
L1.	-.1313661	.0790617	-1.66	0.097	-.2863241	.0235919
d_exports						
L2.	.0880516	.0593502	1.48	0.138	-.0282727	.2043759
_cons	.4819724	.7813385	0.62	0.537	-1.049423	2.013368
/lnsig2u	1.478609	.832565			-.1531886	3.110406
sigma_u	2.094478	.8718945			.9262655	4.736048
rho	.571448	.2038912			.2068471	.8720892

Likelihood-ratio test of rho=0: chibar2(01) = 10.26 Prob >= chibar2 = 0.001

Table 13. Post estimation results for the logistic model – emerging economies (random effects)

Country	Year	Exp Prob
Bulgaria	2009	0.5983654
Czech	2009	0.7480773
Croatia	2009	0.9052944
Hungary	2009	0.8786198
Iceland	2009	0.9756301
Israel	2009	0.1613406
Lithuania	2009	0.9918979
Poland	2009	0.1706047
Romania	2009	0.7642968
Slovak Republic	2009	0.3201566
Slovenia	2009	0.5925208
Latvia	2009	0.9994201

5. Conclusions

In the present paper, we propose a framework to be used for developing an Early Warning System for assessing systemic risk. We find important insight regarding the macroeconomic variables that could be considered early triggers of banking distress. On one hand, for advanced economies, the cash deficit, the variation in exports and inflation are not significant signals for situation of crisis, while for emerging economies, inflation and value of stocks traded turn out to have no prediction power for predicting crisis (a note should be made here that the indicator value of stocks traded is significant for the advanced economies – this could be explained by the still immature stock market in emerging economies). On the other hand, the evolution on GDP growth is the most important signal for a crisis situation, that is one year prior to crisis eruption. Moreover, the paper ads important contribution to the specialty literature by considering the Output Gap in the model – which is find to be a significant trigger for the inefficiency of the economy and a good predictor of crises. The model has very good estimates of the probability of default, confirming the set of most affected economies by the Financial Crisis (Greece, Italy, Ireland, Portugal, Baltic Countries) and stable economies – the Nordic Countries.

Paper is subject to further development – quarterly data could be used instead on annually for a more dynamic picture of the crisis development; also, instead of the binary variable, a continuous index for banking or financial stability would offer much more information for the economy's evolution.

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