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In search of insolvency among European countries

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ABSTRACT
The global financial crisis has proven to be one of the worst and most-demanding events ever. According to common understanding, it is highly unlikely for a country to go bankrupt. However, we have seen a number of countries on the verge of bankruptcy, as well as many which have officially gone bankrupt. It is probable that many more will do so in the future. This knowledge has led us to the question: how probable is it that a sovereign might suffer serious solvency problems? The purpose of this study was to apply a multivariate discriminant analysis (MDA) as an effective tool for a recognition and differentiation among defaulted and non-defaulted nations. The performed analysis was based on data up to 2012 for 26 emerging and 20 developed European countries. The results indicated a high predictive power for 'non-liquid' macroeconomic variables like import, export, investment, population and GDP ratios, underlining MDA as the most suitable model for insolvency prediction, compared to other popular methods like probit and logit model. But unlike in other studies the debt/lending/revenue ratios were characterised by weak predictive power.

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1. Introduction

According to common understanding, it is highly unlikely for a country to go bankrupt. However, the events of recent years have shown how erroneous this belief is.

Iceland officially announced bankruptcy in 2008, a highly unexpected development for the international society, especially because it was one of the richest and most financially stable countries in Europe. From that moment, it was only a matter of time before similar declarations followed. This was also a moment when issues concerning sovereign liquidity cropped up in public discussion (e.g., Rose & Spiegel, 2009). Researchers have focused on measuring and forecasting financial distress in many industrial sectors in different countries (Mackevicius & Sneidere, 2010; Rashid & Abbas, 2011). The European Union (EU) has started working on a new common insolvency law (Bundesministerium für Wirtschaft und Technologie, 2011) and at the same time has introduced the Macroeconomic Imbalance Procedure (MIP) supported by the MIP scoreboard with 11 early warning indicators, which should act as a security buffer, with the purpose to protect and prevent both the whole European community and the individual countries against the MIPs (European

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Commission, E. a. F. A, 2013) and thus reduces the exposure of individual countries to the potential crisis appearance. Extensive discussion has also been applied to the role and effectiveness of credit rating agencies in assessing the likelihood of the threat of sovereign bankruptcy (Sy, 2003; Bussière & Ristiniemi, 2012; Brauers & Zavadskas, 2013; Rębisz, 2015; Tennant & Tracey, 2015).

Considerable research has been conducted to investigate sovereign default among different countries. Alshubiri (2015) and Hilscher and Nosbusch (2010) analysed 32 emerging countries from five regions: Latin America, Africa, Eastern Europe, Southeast Asia, Middle East and South Asia, (Chakrabarti & Zeaiter, 2014) including 190 countries between 1970–2010 in their analysis, while Georgievska, Georgievska, Stojanovic and Todorovic (2008) investigated 124 emerging countries over 1981–2002. Some researchers have focused their research on European countries solely, for example, Josifidis, Hall, Supic and Beker Pucar (2015), Rady (2012) and Alexander (2009) analysed causes and implications of the Greek debt crisis and default, Bi and Traum (2012) analysed the probability of default of Greece and Italy, Gündüz and Kaya (2013), Lucas, Schwaab and Zhang (2013) and Yıldırım, (2015) considered country risk of default countries from the eurozone area and Daniel and Shiamptanis (2010), Gotz (2015), Kregzde (2015) based their research on the member nations of European Monetary Union. Taking into consideration the literature, there is a visible lack of analysis of the economies of Visegrad countries. The existing literature, such as that by Helisek (2015) and Balcerzak (2015), concern only a part of the subject or only one country.

The evolution of country risk treatment is characterised also by a shift from the application of qualitative to advanced quantitative methods. This has occurred from the need to create an effective and powerful early warning system linked to the signs of a crisis in order to estimate the likelihood of country/sovereign default. The variety of quantitative models is impressive: the binomial multivariate qualitative response approach (Kamin, Schindler, & Samuel, 2001; Bussiere & Fratzscher, 2002; Lestano & Kuper, 2003), the multivariate probit/logit approach (Boonman, Jacobs, & Kuper, 2011; Bucevska, 2011; Jacobs, Kuper, & Lestano, 2007), the mixed logit model (Nakanish, 2012), neural networks (Kang, 2010; Sarlin & Marghescu, 2011), regression models (Succurro, 2012), Multiple Indicator Multiple Cause (MIMIC) model (Rose & Spiegel, 2009), the multivariate Generalized Autoregressive Conditional Heteroskedasticity (GARCH) method (Louzis & Vouldis, 2012) and the non-linear Granger causality (Dajcman, 2015).

The above applied methodology studies relate only to latest scientific achievements. It cannot be forgotten that, in the past decades, scores of papers on Early Warning System (EWS) and sovereign risk of default issues have been published, all with different assumptions and conclusions. Although the literature contains a rich spectrum of papers on sovereign risk of default, this topic remains to be fully explored.

This article contributes to the research on sovereign risk of default through the application of multivariate discriminant analysis (MDA) as an effective tool for a recognition and differentiation among defaulted and non-defaulted nations. It will be shown that it can perform just as well as other popular methods, with which it will be compared. MDA has gained popularity in the study of business and corporate failure because of its many advantages, like the ability to reduce dimensions, simplicity, robustness and efficiency in dealing with a large data sets, but has not been widely applied in studies concerning sovereign risk of default. MDA has been proven to perform better than other methods like probit, logit or regression analysis under the condition, that the underlie assumptions are met. However Chen and Peng (2014) claimed that MDA is robust on violation of normality or equality of variance-covariance matrix assumption, but is highly sensitive to outliers and strong skewness This article demonstrates that used macroeconomic data do not conflict with the assumptions of the model, and the obtained results confirm the utility of this model in the study of sovereign default, what will be supported with the extraction of financial indicators that might have an impact on the prediction of sovereign default.

To avoid any misunderstandings, the words default, bankruptcy, insolvency and distress will be used alternatively, having the same meaning.

The rest of the article is organised as follows: Section 2 presents current achievements on financial disability research – approach development, methodology applied, and variables in use. Section 3 introduces the empirical methodology. Section 4 describes the data used for the analysis as well as insolvency case selection rules. Section 5 discusses the results, and Section 6 brings the discussion to an end with a summary of the findings.

2. Literature overview

The available literature on sovereign risk is extensive and has a wide use with the world becoming increasingly global. Free capital flow, broad knowledge transfer, continuous information exchange, need to search for new investment possibilities and realise that above-average profits forced investors to go abroad and consider country-specific risk. After 2007, the whole situation became even more interesting. The European economic crisis began with Iceland declaring bankruptcy and Greece as well as some other European countries on the verge of default. Recalling the Thai crisis, Krugman (2000) has 'in advance' aptly summed up the inherent crisis we are dealing with: 'The good old days probably weren't better, but they were certainly calmer. … The [Thai] crisis, however, was terrifying while it lasted, and its aftereffects are still being felt.' Recurrence, pace, and uncertainty of appearance exemplify why research on country risk of default is constantly growing and why knowledge of this phenomenon has been and continues to be explored.

The literature on sovereign default is extensive but not homogeneous. This was visible in particular during the global crisis, when sovereign default became of interest for many researchers. Some of them were trying to understand and to analyse sovereign default from the perspective of different types of crises preceding default, for example, Rose and Spiegel (2009), Blundell-Wignall (2012) identified and associated defaults with the financial crisis, Soros (2011) with a banking crisis, others such as Arezki, Candelon and Sy (2011) and Lane (2012) with a debt crisis. The difficulty of precise and unique determination of the nature of the current crisis has resulted in the development of the theory of twin and triplet crises. Reinhart and Rogoff (2010) stressed the connection and interaction between different kinds of crisis among 70 countries experiencing default between 1800 and 2009. Laeven and Valencia (2013) recognised 66 cases of sovereign default and debt restructuring during the investigated period 1970–2011, from which 5% (19 cases) was simultaneous occurrence of debt-currency crisis, 1% (2) debt-banking crisis and 3% (10) of all cases was a debt-banking-currency crisis.

There is a group of researchers who are trying to shed some new light on the issue of sovereign default through the incorporation of new explanation concepts, like the role of politics and governmental decision-making (Enderlein, Trebesch, & von Daniels, 2012; Cuadra & Sapriza, 2008); costs of default (Borensztein & Panizza, 2008; Kolb, De Paoli, Hoggarth, & Saporta, 2011; Yue, 2010),a business cyclical dynamics (Mendoza & Yue, 2012; Bi & Traum, 2012) or through the is discussion rescheduling in the context of sovereign default (Erce, 2012; Das, Papaioannou, & Trebesch, 2012)

The researchers are all trying to select an optimal combination of independent variables for a specific method, to better understand world crises and sovereign default in order to create an efficient EWS. Lestano and Kuper (2003) have categorised sectorial variables of the period 1996–2003, used in some popular works such as Kaminsky et al. (1998), into five groups:

- Current account (real exchange rate, export and import growth, terms of trade, ratio of current account to GDP);
- Capital account (ratio of M2 to foreign exchange reserves, growth of foreign exchange reserves);
- Financial sector (M1 and M2 growth, M2 money multiplier, ratio of domestic credit to GDP, excess real M1 balance, domestic real interest rate, lending and deposit rate spread, commercial bank deposits, ratio of bank reserves to bank assets);
- Domestic real and public sector (ratio of fiscal balance to GDP, ratio of public debt to GDP, growth of industrial production, changes in stock prices, inflation rate, GDP per capita, national savings growth);
- Global economy (growth of world oil prices, US interest rate, OECD GDP growth).

They noticed that, of the above, the variable with the strongest predictive power is the public debt to GDP ratio, which can be applied to explain debt, banking, and currency crises. Other variables considered suitable to describe mainly currency and banking crises are the domestic credit to GDP ratio, domestic real interest rate, ratio of M2 to foreign exchange reserves, inflation rate, and US interest rate. They have also claimed that the terms of trade and the current account to GDP ratio have no explanatory effect. Manasse and Roubini (2009) have identified 10 predictor variables that are sufficient for classification and prediction: total external debt/GDP ratio, short-term debt reserves ratio, real GDP growth, public external debt/fiscal revenue ratio, Consumer Price Index (CPI) inflation, number of years to the next presidential election, US treasury bills rate, external financial requirements (current account balance plus short-term debt as a ratio of foreign reserves), exchange rate overvaluation, and exchange rate volatility. Zymek (2012) has investigated export and yield spreads (Candelon, Dumitrescu, & Hurlin, 2012). Hilscher and Nosbusch (2010) investigated the relation between sovereign default and five dependent variables: volatility of terms of trade, change of terms of trade, years since last default, debt to GDP and reserves to GDP. Chakrabarti and Zeaiter (2014) analysed determinants of sovereign default based on 17 variables: credit worthiness, growth, leverage on export earnings, debt service ratio, reserves, inflation, exchange rate, trade deficit, corruption, democratic accountability, openness, central bank liabilities, interest payments, cost of borrowing, imports, exports per capita GDP, and government stability. The possible explanatory variables and their combinations are almost unlimited because not only are quantitative variable are considered, but so are qualitative variables. Babecký et al. (2012) cites Frankel & Saravelos (2012) and Rose & Spiegel (2011), who respectively used 50 and 60 variables.

III. Methodology

This article focuses on MDA, which allows us to assign an observation into one of several previously set groups (e.g., in a binominal default vs non default case). Additional analysis will also be carried out with the more popular models such as probit and logit to determine the most effective method.

3.1. Multivariate discriminant analysis

This model has its roots in 1930, when the Bureau of Business Research published an analysis of 29 companies based on a comparison of 24 financial ratios with their averages. However, the breakthrough came with Altman's MDA application (Altman, 1968). Altman created the overall index Z with five independent variables. Since then, his idea has been developed and has found application in different fields of science. It must be underlined that MDA is widely used for binary classification of enterprises (bankrupt vs not bankrupt) but is not so popular in research over country/sovereign default. Frank and Cline (1971) adopted this method for the first time in a 26-country study based on a nine-year data set of eight variables, from which three[1] appeared to be significant.

The MDA approach is based on the assumption of existence of a linear discrimination function Z, which enables effective separation between the groups ($\omega_1$and ω_2) and faultless allocation of each observation into one of the previously set classes. Each group is also assumed to be multivariate normally distributed with a common covariance matrix Σ and known means μ1 and μ2. The prediction function (eq. 1) is a combination of explanatory variables $x_1, \ldots, x_n$, weighted with unknown parameters $a_1, \ldots, a_n$., which has a form:

$$Z(x) = a^{'}x = \sum\nolimits_{i=1}^{n} a_i x_i \tag{1}$$

$x_1, \ldots, x_n a_1, \ldots, a_n$The main challenge is the estimation of the weights $a_1, a_2, \ldots ., a_n$,so that the index Z (eq.2) will be able to allocate each observation correctly into one of the a priori set groups with a low misclassification rate. Hence the need to estimate a vector $Z(x)$ (eq.2) so that

$$Z(x) = a^{'}x \begin{cases} > 0, x \in \omega_1 \\ < 0, x \in \omega_2 \end{cases} \tag{2}$$

One of the goodness-of-fit measures for MDA is Wilk's lambda statistic (Λ) ranging from 0 to 1, which indicates the proportion of the total variance not explained by the differences among the groups (Tuffery, 2011). The lower the result, the more probable is the rejection of the null hypothesis. This trend reflects the power of discrimination among the groups or the impact of each explanatory variable on the overall function Z.

The interpretation of Wilk's lambda is however limited, which is why the classification matrix must be considered to prove the efficiency of the model (see Table 1), where p_k is an index (a number and/or percentage) of correct classification and $(1 - p_k)$ an index (a number and/or percentage) of misclassification and $k \in \{1, 2\}$.

The classification matrix reflects also the number of misclassifications related to the appearance of each event and its percentage share of the total observations. With unequal sample sizes and/or violation of model assumptions, leave one out cross-validation should

Table 1. Classification matrix.

Predicted	Event 1	Event 2
Event 1	p_1	$(1 - p_1)$
Event 2	$(1 - p_2)$	p_2

Source: Authors.

be considered as more reliable. It is a measure of a model predictive performance. It is based on an idea of performing an analysis n-1 times, each time omitting one observation from the training set. The obtained result is an average classification rate calculated on the basis of all replicates.

3.2. Logit and probit

Models based on the logit or probit approach assume a binary outcome of an event (e.g., default vs non-default) conditional on a combination of dependent variables. Both models are treated as similar. The material difference relates to an assumed underlying distribution. The logit model is based on a cumulative logistic distribution function (eq. 3) (Gujarati, 2003, p.595),

$$P_k = E\left(Y = 1 \backslash X\right) = \left(1 + e^{-Z_i}\right)^{-1} = e^Z\left(1 + e^Z\right)^{-1} \tag{3}$$

unlike the probit model (eq. 4), which is based on a standard cumulative normal distribution:

$$P_k = E(Y = 1 \backslash X) = \Phi\left(Z_k\right) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{Z_k} e^{-t^2/2} dt; \tag{4}$$

where $Z_k = \alpha_0 + \alpha_1 X_{1i} + \ldots + \alpha_k X_{ik}$ and P_i is the probability of default.

Model effectiveness is verified by the Hosmer-Lemeshow goodness-of-fit test and the Nagelkerke R square coefficient of determination, which is more intuitive than the Cox-Snell R square.

The Hosmer-Lemeshow goodness of-fit test assumes a lack of fit or, conversely, shows how well the model fits the data compared to a zero model, one with no predictors. Rejection of the null hypothesis indicates that the model is well fitted to the data.

The Nagelkerke R square, comparable to an ordinary R^2, complements the Hosmer-Lemeshow goodness-of-fit test. The Nagelkerke R square explains to what extent the data are explained by the model. It ranges between 0 and 1, where 1 indicates the best fit and 0 a lack of fit. As mentioned before, this measure is preferable to the Cox-Snell R^2, as the latter can take on negative values, which are difficult to interpret.

Similar to MDA, both probit and logit models generate a classification matrix.

4. Data and variable selection

The selected sample contains annual data for 26 emerging and 20 developed European countries (see Table 2). The primary sample covers the period 1980–2012. In the past, a lot of data was not available for many countries, hence the need to narrow down the investigated period to one in which all data were attainable. In the primary sample all available macroeconomic data, published by IMF World Economic Outlook were used. The data were adjusted for missing observations, what should ensure the cohesion of the produced results. The final sample, the one actually analysed, contains 1178 full observations and is divided into two country groups: default and non-default

During the last 30 years, there were not many cases of bankruptcy among European sovereigns, so it was not possible to base the analysis on developed or emerging nations

Table 2. Sample countries with periods of analysis.

Developed			Emerging	
1980–2012	1981–2012	1980–2012	1993–2012	1996–2012
Austria	Netherland	Hungary	Latvia	Lithuania
Belgium	Portugal	Poland	Slovakia	Armenia
Cyprus	Spain	Romania	Azerbaijan	1997–2012
Denmark	Switzerland	Bulgaria	Belarus	Albania
Finland	United Kingdom	1981–2012	Slovenia	1998–2012
France	1982–2012	Turkey	Ukraine	Bosnia and Herzegovina
Germany	Sweden	1992–2012	1994–2012	1999–2012
Greece	1987–2012	Croatia	Estonia	Serbia
Iceland	Luxembourg	Kazakhstan	1995–2012	2001–2012
Ireland	1995–2012	Macedonia	Czech	Montenegro
Italy	Malta	Moldova	Georgia	Kosovo
Norway		Russia		

Source: Authors.

Table 3. Default and rescheduling cases.

Country	Default/rescheduling
Azerbaijan	1994
Bulgaria	1990, 1998
Greece	2012
Iceland	2008
Ireland	2010
Latvia	2009
Poland	1982, 1990
Portugal	2011
Romania	1986, 1991
Russia	1993–1996, 1998–1999
Turkey	1982, 1994, 1999
Ukraine	1994, 1995, 1998–2000, 2009

Source: Prepared by the authors based on http://sovins.wordpress.com/, http://www.imf.org/external/index.htm, Nadmitov (2004), Yilanci and Ozcan (2008), and Reinhart and Rogoff (2010)

solely. Therefore, the authors have decided to pool all European countries into a one data sample and to analyse them together, in order to receive the most reliable results and to avoid problems with the model fit.

The division criterion is based on the assumption that default appears when a sovereign suffers a debt crisis, announces bankruptcy, or obtains strategic rescheduling, restructuring, or financial support from a financial institution such as the IMF or the Paris Club (a similar definition was applied by Ciarlone & Trebeschi, 2005). As shown in Table 3, 28 default cases have been identified under these conditions. This number may seem to be small, but it must be emphasised that the countries that faced solvency difficulties during the last three decades were mostly emerging (transformation) economies and that the years 1990–2007 was a period of dynamic development, high investments, and prosperity in Europe (and in South Eastern Europe as well with the support of the European Bank for Reconstruction and Development). Developed countries such as Greece, Iceland, and Spain encountered solvency difficulties relatively recently (during and after the global financial crisis). Sovereign countries, mostly from Western Europe, that have been exposed to financial default but have not officially applied for international financial support have not been classified as insolvent.

Table 4. Primary variables set.

Variable	Group	Variable	Group
Current account balance in US dollars, in billions	D	Inflation: end-of-period consumer prices, percentage change in inflation	I
Gross domestic product corresponding to fiscal year at current prices in the national currency, in billions	D	Inflation: end-of-period consumer prices, index	I
General government structural balance, percentage of potential GDP	D	Inflation: average consumer prices, percentage change	I
General government structural balance in the national currency, in billions	D	Inflation: average consumer prices, index	I
Current account balance, percentage of GDP	D	General government primary net lending/borrowing, percentage of GDP	L
Volume of imports of goods and services, percentage change	D	General government gross debt, percentage of GDP	L
Volume of imports of goods, percentage change	D	General government gross debt in the national currency, in billions	L
Volume of exports of goods, percentage change	D	General government net debt, percentage of GDP	L
Volume of exports of goods and services, percentage change	D	General government net debt in the national currency, in billions	L
Gross domestic product based on purchasing-power-parity (PPP) valuation of country GDP at current international dollars, in billions	D	General government net lending/borrowing, percentage of GDP	L
Output gap, percentage of potential GDP	D	General government primary net lending/borrowing in the national currency, in billions	L
Gross domestic product per capita at current prices, in US dollars	D	General government total expenditure, percentage of GDP	L
Gross domestic product per capita at current prices, in units of the national currency	D	General government total expenditure in the national currency, in billions	L
Gross domestic product per capita at constant prices, in units of the national currency	D	General government revenue, percentage of GDP	L
Gross domestic product deflator, index	D	General government revenue in the national currency, in billions	L
Gross domestic product at current prices in US dollars, in billions	D	General government net lending/borrowing in the national currency, in billions	L
Gross domestic product at current prices in the national currency, in billions	D	Gross national savings, percentage of GDP	L
Gross domestic product at constant prices, percentage change	D	Population, in millions	O
Gross domestic product based on purchasing-power-parity (PPP) per capita GDP at current international dollars	D	Unemployment rate, percentage of total labour force	O
Gross domestic product based on purchasing-power-parity (PPP), percentage share of world total	D	Total investment, percentage of GDP	O
Implied PPP conversion rate of the national currency per current international dollar	D		
Gross domestic product at constant prices in the national currency, in billions	D		

Source: Prepared by the authors based on CIA World Economic Outlook and IMF Economic Review.

In the primary analysis, 42 macroeconomic variables were considered, analysed, and tested for their ability to discriminate among defaulted and non-defaulted nations. The variables were grouped into four categories:

Liquid (L) – country income (revenues), expenditures and demand for money

Domestic (D) – domestic production and trade, reflected by current account and GDP-related factors

Inflation (I)

Other (O) – includes total investments, unemployment rate, and population (see Table 4)

The initial analysis confirmed that 25 variables are normally distributed. The Kolmogorov-Smirnow test did not reject the null hypothesis for all variables included in the final MDA model, except the population variable. This outcome indicates the violation of one of the model assumptions. However, MDA has been found robust to the violation of this assumption but is highly sensitive to outliers. Therefore, MDA was performed twice: once on the original data and again on data adjusted for outliers.

5. Empirical results

5.1. Multivariate discriminant analysis

The stepwise discriminant analysis procedure was performed with SPSS. The goal of the analysis was to set an optimal combination of explanatory variables to differentiate between the two groups, ensuring group separation and prediction accuracy.

The main outcome of the discriminant procedure is a canonical discriminant function coefficient table (see Table 5), which is used to create a prediction equation. It allows us to indicate the impact of each variable on the discrimination score.

The unstandardised coefficients show that 'Gross domestic product at constant prices, percentage change', 'Population in millions', and 'Volume of imports of goods and services, percentage change', are the most important to differentiate among bankrupt and non-bankrupt nations.

The results are in line with the theoretical explanations. Changes in the value of trade increases capital and investment thereby increases income and GDP. Such a relation has an impact on country openness. The more open the nation, the more unskilled workers are required, compared to well skilled workers, thereby their wages rise, followed by a rise in the national income (Anderson, 2005). According to Rodrik and Rosenzweig (2010) countries, which are less open are more likely to default on debt, but at the same time open nations are more exposed to financial disturbances.

Such results are not surprising considering the findings in the relevant literature on sovereign default. The researchers confirm the significant impact of imports and exports to service countries' ability to fulfil their financial obligations (Rawkins, 1992; Calvo, Izquierdo, & Mejía, 2004). This outcome is also in line with the findings presented in the report of SESRIC (2011), which underlined the importance of import, export and emigration in the process of formation of the European debt crisis. The lack of debt variable is explained by Rawkins (1992) and Ciarlone and Trebeschi (2005), who observed that debt ratio is not a predictor of a sovereign default, but rather an indicator of the pace of leaving the country out of a crisis.

Table 5. Unstandardised canonical discriminant function coefficients.

	Function 1
Volume of imports of goods and services, percentage change	.055
Volume of exports of goods and services, percentage change	-.032
Population, in millions	-.052
Gross domestic product based on purchasing-power-parity (PPP) valuation of country GDP at current international dollars, in billions	.002
Gross domestic product at constant prices, percentage change	.102
(Constant)	-.105

Source: Authors' calculations.

Table 6. Functions at group centroids.

Group	Function 1
1	.083
2	-3.544

Source: Authors' calculations.

Table 7. Classification results.

Group			Predicted group membership 1	2	Total
Original	Count	1	1133	18	1151
		2	7	20	27
	%	1	98.4	1.6	100.0
		2	25.9	74.1	100.0
Cross-validated	Count	1	1132	19	1151
		2	8	18	27
	%	1	98.3	1.7	100.0
		2	29.6	70.4	100.0

Note: 1- non-bankrupt, 2-bankrupt.
Source: Authors' calculations.

The efficiency and usefulness of the model applied is reflected in the classification matrix, supported by the functions at group centroids and prior probabilities.

Wilk's lambda coefficient, by this combination of variables, is equal to 0.772. However, in the presented case, the functions at group centroids are far from each other (see Table 6), indicating sufficient discrimination between the solvent and insolvent group of countries and a low misclassification rate.

The final outcome of the analysis is the classification matrix (see Table 7), with hit ratios of 98.3% and 74.1% correctly recognised cases among solvent countries and sovereigns with liquidity problems, respectively. These results should be considered with caution considering the unequal sample size. Of the originally grouped observations, 97.9% (97.7% by leave one out cross-validation) were correctly classified, with 70.4% among insolvent sovereigns. Classification results are calculated based on prior probabilities considering each sample size.

The assumptions of variance-covariance matrix were verified with Box's M test. The null hypothesis assumes equality of matrices, so that the null hypothesis must be rejected with a significant p-value, signifying violation of one of the MDA assumptions. According to Chen and Peng (2014) MDA is robust on violation of normality or equality of variance-covariance matrix assumption. However, outliers have a bigger impact on the results obtained than does the violation of assumptions. Each case that is far from the centroid of the group to which it belongs is considered an outlier. The critical value, equal to 9.21, was calculated, as a numerical value from a chi-square distribution with a critical probability of 0.99 and 2 degrees of freedom. All data with a squared Mahalanobis distance to centroid larger than the critical value were removed from the analysis. With these assumptions, three cases were recognised as outliers (Bulgaria 2002, UK 1998–1999) and removed from the analysed data set.

The following Fisher's classification function coefficients were obtained (see Table 8) as a result of repeated analyses:

Table 8. Fisher's classification function coefficients after removal of outliers.

	Group	
	1	2
Population in millions	.015	.188
Volume of imports of goods and services, percentage change	.018	-.190
Volume of exports of goods and services, percentage change	.023	.140
Gross domestic product constant prices, percentage change	.108	-.251
Gross domestic product based on purchasing-power-parity (PPP) valuation of country GDP at current international dollars, in billions	.001	-.007
(Constant)	-.546	-9.396

Note: 1- non-bankrupt, 2-bankrupt.
Source: Authors' calculations.

Table 9. Classification results′ after removal of outliers.

			Predicted group membership		
Group			1	2	Total
Original	Count	1	1132	18	1150
		2	7	18	25
	%	1	98.4	1.6	100.0
		2	28.0	72.0	100.0
Cross-validated	Count	1	1131	19	1150
		2	8	17	25
	%	1	98.3	1.7	100.0
		2	32.0	68.0	100.0

Note: 1- non-bankrupt, 2-bankrupt.
Source: Authors' calculations.

Among countries with solvency difficulties in the original sample, the hit ratio remained on the same level (see Table 9). Cross-validation results among nations with solvency difficulties dropped by 2.4%. Data set adjustment has no impact on the overall classification ratio.

Whether the objective of the independence of explanatory variables has been achieved might be doubtful considering the use of macroeconomic data as an input factor in discriminant analysis. In order to dispel such doubts, all explanatory variables were analysed in terms of their differentiation ability. A correlation analysis was also conducted, as well as with an analysis of autocorrelation among errors. The coefficient of variation values for all data greater than 15% suggest, that the variables used have a high differentiation ability. The application of forward stepwise discriminant analysis resulted in optimal selection of the explanatory variables in terms of their explanatory power, differentiation ability, and significance for the model.

The independence of the explanatory variables was confirmed by the relatively small values of the Pearson intra-group correlation coefficients (see Table 10). However, to ensure proper model configuration and avoid highly correlated, redundant variables, principal component analysis (PCA) was performed. The Kaiser-Meyer-Olkin measure of sampling adequacy exceeded 0.5, with the significance level (p=0.000) of Bartlett's test of sphericity having satisfied the minimal requirements of the PCA. After the first iteration, all the included variables had communalities greater than 0.5, and no complex structure was recognised, indicating that no variables needed be removed from the analysis. No explanatory variable had a variance inflation factor greater than 3, showing no evidence of multicollinearity. However, the rejection of the null hypothesis of White's test suggests a possible

Table 10. Intra-group correlation of the explanatory variables used in the final MDA model.

	Volume of imports of goods and services, percentage change	Volume of exports of goods and services, percentage change	Population, in millions	Gross domestic product based on purchasing-power-parity (PPP) valuation of country GDP at current international dollars, in billions	Gross domestic product at constant prices, percentage change
Volume of imports of goods and services, percentage change	1.000	.605	.076	-.027	.431
Volume of exports of goods and services, percentage change	.605	1.000	–.013	-.063	.423
Population, in millions	.076	-.013	1.000	.824	-.025
Gross domestic product based on purchasing-power-parity (PPP) valuation of country GDP in current international dollars, in billions	-.027	-.063	.824	1.000	-.078
Gross domestic product at constant prices, percentage change	.431	.423	-.025	-.078	1.000

Source: Authors' calculations.

heteroscedasticity issue, which might bias the produced results. Following Hayes and Cai (2007), the authors have calculated heteroscedasticity-consistent standard errors to check how significant this impact is. The standard errors generated were insensibly higher than those obtained by the primary analysis and had no impact on the significance level of the explanatory variables. Additionally, a Durbin-Watson (DW) test was performed to detect serial autocorrelation errors. The value of the DW statistic (=1.774) hinted at uncorrelated residuals, confirming the quality of the results generated.

In view of the fact that the number of defaults is limited, it is not possible to perform an out of sample test, or to test separately emerging vs developed nations without increasing the bias in the uncontrolled way. To overcome this issue and to confirm the stability of the discrimination coefficients the bias corrected and accelerated bootstrap (BCa bootstrap) was applied. According to Chen and Peng (2014) this method is insensitive to the violation of the normality and equal variance assumption From the original data set 1000 bootstrap samples were drawn with replacement. The average result over all bootstrap samples has shown that the hit ratio among defaulted nations remained at the same level of 70.4%. The recognition rate among solvent nations has slightly increased by 0.5% and the overall hit ratio by ca. 0.2%. The Null Hypothesis, stating that the coefficients are equal to zero tested with support of the 95% BCa bootstrap confidence intervals, was rejected for all coefficients. Moreover, the original values were similar with those simulated via bootstrap method, which points at the stability of the discrimination coefficients.

5.2. Probit and logit

The results generated by probit and logit models for the same combination of explanatory variables, summarised in Table 11, have a high recognition rate of up to 99% among non-bankrupt countries. Unfortunately, the hit ratio among bankrupt countries is around 45% (48% and 44% under probit and logit models, respectively). The results of both models are validated by the Hosmer-Lemeshow goodness-of-fit test with p-values of above 0.05. Akaike information criterion (AIC) and Bayesian information criterion (BIC) values together with the Nagelkerke R^2 suggest a subtle advantage for the logit model. However, the differences between the two methods are minor. Both methods generate comparable results among healthy sovereigns; which model to use is only a matter of preference. The hit ratio reflected a visible difference for insolvent countries, where the probit model underperformed significantly.

5.3. Early warning

Comparison of the results generated by the models presented above cannot be based only on hits in the base year in which a crisis appears. Additional tests were performed for

Table 11. Summarised results of probit and logit models in the base year.

	Hosmer-Lemeshow test	p-Value	Nagelkerke R2	Cox-Snell R2	AIC	BIC	Bankrupt cases correctly estimated (%)	Non-bankrupt cases correctly estimated (%)
Logit	9.8253	0.2775	0.599	0.117	122.1	152.5	99.8	48.1
Probit	13.863	0.0853	0.582	0.114	126.4	156.9	99.6	44.4

Note: AIC – Akaike information criterion, BIC – Bayesian information criterion.
Source: Authors' calculations.

Table 12. Classification of results.

	T = 0		T = −1		T = −2	
	1	2	1	2	1	2
MDA	98.3	70.4	98.6	40.7	98.6	30.4
Logit	99.8	48.2	99.7	29.6	99.9	19.23
Probit	99.6	44.4	99.7	22.2	99.9	11.5

Note: MDA=multivariate discriminant analysis; T=0, base year in which crisis appears; T = -1, one-period lag, T = -2, two-period lag; 1=non-bankrupt; 2=bankrupt.
Source: Authors' calculations.

one- and two-periods-ahead predictive power. The results in Table 12 show that the ability to anticipate a crisis drops with time for all methods. However, the dynamic of the drop is smoother for discriminant analysis. The difference is especially noticeable in comparison with MDA, which consistently predicts crises better than the other two models do, almost alike for one- and two-period lags: 30% and 22%, respectively.

6. Conclusion

This article tries to shed light on whether a country`s financial disability can be predicted and what is the associated optimal combination of macroeconomic variables? In the applied analysis, the sample comprises 1178 observations based on data up to 2012 from 26 emerging and 20 developed countries. Discriminant analysis similar to other methods has shown 70% effectiveness in correct recognition of insolvency cases in the base year, after removal of the outliers. Logit and probit analyses yielded hit ratios of 48% and 44%, respectively. Manasse and Roubini (2009) found results of 74% for 37 market access countries from 1976 to 2001 and 69% for the period starting from 1990 based on logit analysis (Ciarlone & Trebeschi, 2005), as well as ratios of 50%, 56%, and 75% based on the binominal model, multinomial model, and CDS spreads, respectively. However, unlike in other studies (e.g., Ciarlone & Trebeschi, 2005), the debt/lending/revenue ratios were characterised by weak predictive power. In contrast, import, export, investment, population and GDP ratios have had the greatest predictive power. This outcome is in line with the findings presented in the report of (SESRIC, 2011), which underlined the importance of import, export and emigration in the process of formation of the European debt crisis. The lack of debt variable is in line with the argumentation presented by Rawkins (1992) and Ciarlone and Trebeschi (2005), for example, who observed that debt ratio is not a predictor of a sovereign default, but rather is an indicator of the pace of leaving the country out of crisis. However, the results presented above should be considered with caution because the total number of crisis episodes recorded for the selected sample is significantly lower than the number of 'non-crisis' events. Such disparity affects the number and quality of hit ratios. The authors share the opinion concerning data used for the analysis, i.e., for more accurate results, monthly or at least quarterly data should be investigated to facilitate a quick response to the first crisis signals. Moreover, no reliable results can be obtained for developed countries at present because of the application of a strict crisis definition (which does not include a financial or banking crisis) and the limited number of insolvency cases among developed countries. Considering its level and history of development, this region should be treated separately. The number of crises recognised among emerging countries confirm finding

(Pfister & Suter, 1987), that countries with a weak financial condition are the ones usually hit by crises and exposed to financial solvency difficulties.

Note

1. Lagged ratio of debt to export trend, ratio of imports to international reserves, and maturity of a country debt.

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