Equilibrium. Quarterly Journal of Economics and Economic Policy
Volume 15 Issue 1 March 2020
p-ISSN 1689-765X, e-ISSN 2353-3293
www.economic-policy.pl

ORIGINAL ARTICLE

Citation: Biegun, K., & Karwowski, J. (2020). Macroeconomic imbalance procedure (MIP) scoreboard indicators and their predictive strength of "multidimensional crises". *Equilibrium. Quarterly Journal of Economics and Economic Policy*, *15*(1), 11–28. doi: 10.24136/eq.2020.001

Contact to corresponding author: jacek.karwowski@ue.wroc.pl; Wroclaw University of Economics and Business, Faculty of Economics and Finance, Finance Department,ul. Komandorska 118/120, 53-345 Wrocław, Poland

Received: 31.01.2020; Revised: 14.02.2020; Accepted: 7.03.2020; Published online: 28.03.2020

Krzysztof Biegun
Wroclaw University of Economics and Business, Poland
orcid.org/0000-0002-4888-6600

Jacek Karwowski
Wroclaw University of Economics and Business, Poland
orcid.org/0000-0003-2754-5003

Macroeconomic imbalance procedure (MIP) scoreboard indicators and their predictive strength of "multidimensional crises"

JEL Classification: *E02; E61; C25*

Keywords: *macroeconomic imbalance procedure; economic crisis; multidimensional crisis; ordered probit model*

Abstract

Research background: The evaluation of the predictive strength of MIP indicators in relation to crises is extremely important for the process of coordinating the economic policies of the EU countries. MIP is one of the pillars of the economic crisis prevention procedure. Predictive power of individual indicators has not been tested before their introduction.
Purpose of the article: Evaluation of the predictive strength of fourteen MIP indicators in relation to multidimensional crises in the EU countries.
Methods: We used ordered probit model to test the ability of MIP indicators to correctly predict episodes of "multidimensional crises" (as defined by the authors) in the period between 2008 and 2017 in all EU Member States.
Findings & Value added: We defined "multidimensional crises", combining several negative phenomena into one limited dependent variable. This work is also novel in its application of probit regression to test the predictive strength of MIP indicators with an ordered probit model. We identified five MIP variables which were statistically significant in predicting "multidimensional crises" for all EU countries: net international investment position, nominal unit labour cost index, house price index, private sector credit flow and general government gross debt. Other variables turned out to be less important or not effective in crises prediction.

Introduction

To enable more efficient coordination of economic policies of the Member States (MS) and joint response to crises spreading all over the European Union (EU), the European Semester (ES) was introduced. It is supposed to become a tool that will allow MS to ensure sound public finances (avoiding excessive government debt), prevent excessive macroeconomic imbalances in the EU, support structural reforms and foster investment. The ES incorporates three separate processes that work in parallel (Efstathiou & Wolff, 2018):

1. fiscal surveillance based on the Stability and Growth Pact (SGP),
2. Macroeconomic Imbalances Procedure (MIP),
3. coordination of EU countries' economic and employment policies, as foreseen in the Treaty on the Functioning of the EU.

The research problem and the main purpose of the study focused our attention to the MIP — framework created to prevent and correct imbalances in the Member States regarding both financial stability and macroeconomic aspects.

The starting point for MIP was the realization that large macroeconomic imbalances built-up in the euro area in the pre-crisis years and the EU lacked instruments to even monitor such imbalances. That's why several (14) scoreboard MIP indicators have been set (see Table 1). According to the official website of the European Commission, the aim of this scoreboard is to trigger in-depth studies and analyses to determine whether potential imbalances identified in the early-warning system are benign or problematic. The composition of the scoreboard indicators may evolve over time. The Commission can organize missions with the European Central Bank — if appropriate — to conduct the in-depth reviews (European Commission, 2011).

The purpose of this paper is to evaluate the predictive strength of MIP indicators in relation to events which we call "multidimensional crises", in all EU countries, using ordered probit model. The problem is extremely important for the process of coordinating the economic policies of the EU MS, as the MIP is one of the pillars of the economic crisis prevention procedure. The exponential pace of work on the implementation of the procedure has meant that the predictive power of individual indicators has not been tested before their introduction. This paper is novel in the way aggregate crisis variables are applied, measuring the intensity of the crisis, and in its use of an ordered probit model for the data analysis, formerly utilised for predicting corporate liquidity or currency crises.

The paper is organised as follows. After providing a short review of literature on economic and financial crises, the main features of the MIP are introduced. The research methodology and data features are reviewed in the next section. After providing concept of crises implemented in the paper, we present ordered probit model results. The paper concludes with a reflection on policy relevant findings.

Literature review

"Economic crisis" is usually understood as a downturn in GDP, accompanied by an increase in unemployment (Mishkin, 2011b, p. 56). Several authors track "abnormal data" and declare that a crisis is above or below a certain threshold (De Scheemaekere *et al.*, 2015, pp. 1–12). Domonkos *et al.* (2017, pp. 32–52) as well as Beck (2013, p. 30; 2019 p. 251) use the deviation of real GDP from potential GDP (output gap) as a crisis indicator. This approach is rather one-dimensional. In addition, precise calculation of potential output is quite difficult and ambiguous. Others focus on crisis periods that are captured by deviations of the real GDP growth from its five-year average by more than one standard deviation (Siranova & Radvanský, 2018, pp. 335–352).

On the other hand, "financial crisis" is very often understood as "a major collapse of the financial system, entailing inability to provide payments services or to allocate credit to productive investment opportunities" (Oesterreichische Nationalbank, 2001, p. 92). Claessens and Kose (2013, pp. 1–65) more precisely distinguish between four types of financial crises: currency crises; sudden stop (or capital account or balance of payments) crises; debt crises; and banking crises. Catão and Milesi-Ferretti (2014, pp. 11–32) focus on major external crises (defaults and rescheduling events as well as events associated with large IMF support).

Kaminsky *et al.* (1998, p. 16) constructed the exchange market pressure index — a weighted average of monthly exchange rate changes against U.S. dollar or per deutsche mark. Periods in which the index was above its mean by more than three standard deviations were defined as crises.

Other very comprehensive approach is represented by Knedlik (2014, pp. 157–166), who defines crises as years in which spreads of yield on long-term government bonds over AAA rated long-term government bonds in the euro area exceed their mean by more than one standard deviation. An overview of literature on financial crises can be found in Mızrak and Yüksel (2019, pp. 33–50).

Early warning indicators serve as a useful starting point for identifying systemic risks. Many studies find that specific indicators that breach certain critical thresholds can help to identify unsustainable booms before a crisis actually develops. For example, Borio and Drehmann (2009) demonstrated that credit-to-GDP, property price and equity price gaps, in per cent relative to trends, are able to detect the build-up of risks of future banking distress in an economy. These indicators performed reasonably well also out of sample, as indicated by their ability to point to potential banking distress ahead of the current crisis. Aldasoro *et al.* (2018) calculated individual thresholds for four household and cross-border debt indicators in 26 jurisdictions. The critical thresholds, if breached, should raise concern about financial stability.

Kaminsky (1998) identified several indicators of financial crises, belonging to such groups as overborrowing, bank runs, loose monetary policy, balance of payments problems and growth slowdown. An indicator is said to "signal" a crisis in a period if in that period the indicator crosses the critical cut-off. She also proposed composite indicators to keep track of the number of signals being issued in the different sectors of the economy, as the first step in the construction of a system of early warning.

The MIP procedure has been of interest to researchers for the last few years. The research on the MIP and — more broadly — the European Semester may be divided into several areas. Some of them deal with the issue of political consensus needed for effective coordination of the economic policies of EU countries, others address the distribution of competences between the EU institutions and Member States and the efficiency of the decision-making process. Another area of research is that of the effectiveness of the recommendations issued by the Commission. We have focused on the least frequently addressed research area — empirical studies on the predictive relevance of MIP indicators. Most of those studies used various types of signal approach. They use a database of indicators. A particular indicator signals a crisis when its level exceeds a particular cut-off. Using different definitions of crisis events, authors came to significantly different conclusions. Csortos and Szalai (2014) found that only current account deficit and the unemployment rate had the prediction ratios better than the ratios of false signals in case of a crisis event defined as a GDP gap. Knedlik (2014) argued that current account, net international investment position and nominal unit labour costs were the best predictors of a debt crisis. Boysen-Hogrefe *et al.* (2015) found that house prices, private sector debt and private sector credit flow were best predictors of the future crises. Private sector debt and current account balance were the best performing indicators in case of a crisis event as a GDP gap, according to Domonkos *et al*.

(2017). An overview of these papers can be found in the report published by the Joint Research Centre (Erhart *et al*., 2018).

This work is aimed at identifying MIP indicators which may be considered robust explanatory variables for our aggregated crisis variable. Fourteen MIP variables were selected by the European Commission in quite an arbitrary manner; they rather reflect general opinions on which imbalances may be dangerous for economic stability, but lack one common theoretical background. Accordingly, as Christofides *et al*. (2016) show, we cannot expect any single early warning signal for all dimensions of the crises. That is why we decided to measure the intensity of the crises using one aggregated variable. This leads us to the hypothesis that some of the MIP indicators have greater predictive strength then others, for all or almost all severity levels of crisis. Their identification could have practical implications for the reaction function of the European Commission.

Following "Regulation (EU) No 1176/2011 of the European Parliament and of the Council of 16 November 2011 on the Prevention and Correction of Macroeconomic Imbalances" (2011) we assume that "imbalances" mean any trend giving rise to macroeconomic developments which are adversely affecting, or have the potential to adversely affect, the proper functioning of the economy of a Member State or of the economic and monetary union, or of the Union as a whole (Table 1).

Research methodology

In this work, we chose to define a financial crisis by episodes of financial instability — a situation in which economic performance is potentially impaired by fluctuations in the price of financial assets or in the ability of financial intermediaries to meet their contractual obligations. In addition, we consider monetary instability, understood as instability in the general level of prices. It is important that financial or monetary instability (as well as crisis) must be capable of having a measurable effect on economic performance: real activity and/or the rate of inflation (Crockett, 1996, pp. 531–568). Both effects will be included in the measure, indicating the severity of a crisis. We test the ability of MIP indicators to correctly predict episodes of "multidimensional crises" in the period between 2008 and 2017.

We propose the concept of "multidimensional crisis" based on several economic indicators (Table 2). If a certain threshold is exceeded, it counts as a "single crisis" (1). Accordingly, "multidimensional crisis" may reach level 1, 2, 3, 4 or 5 in a quarter. If a crisis has occurred more often than once a quarter of the year, the maximum value from all quarters is taken as a crisis indicator. Selection of indicators, and especially their thresholds, may be regarded as arbitrary, but to a great extent relies on literature (Claessens & Kose, 2013; Mishkin, 2011a) as well as on experience. The rationale behind it is a severe and painful phenomenon not only in economic but also in personal terms.

We test two sets of thresholds. Set 1 relies on statistical distributions of crisis indicators and set 2 is based on an expert opinion on what a crisis is. The database created by Reinhart and Rogoff (n.d.) was not used, as it covers crises only till 2010. Implementation of another database, ECB/ESRB EU crises database (Lo Duca *et al*., 2017, pp. 1–56), gave absolutely unsatisfactory results.

Set 1

We investigate the distributions of four crisis indicators in the period 2008–2017. Thresholds values are defined as mean values plus or minus one, two or three standard deviations (Table 3).

For the decline in GDP we set first threshold not as just a mean value (1.17%), but 0%; 1% GDP growth is hardly perceived as a crisis. Three other thresholds are calculated as mean minus one, two and three standard deviations (4.02%).

For inflation the mean value is 1.77%, which is pretty close to the commonly accepted level of price stability of around 2%. Other three thresholds are: mean plus one, two and three standard deviations (2.27%).

The first threshold devaluation/depreciation of the exchange rate against USD is set relatively low, below 1% (mean value), but three other ones reach approx. 6%, 11% and 16%.

For stock market decline, we define the first threshold at the mean, equal minus 0.04%. Next thresholds are more severe, reaching over –36% at level 4.

Restrictions on cash withdrawals are always defined as 1 if imposed or 0 otherwise.

Set 2

In general, setting threshold levels is challenging. If they are set too high, e.g. the decline in GDP over 30%, only very serious crises, if any, would be recognized. If they are set too low, e.g. a stock exchange index change by –2%, crises could be reported every second quarter. Our "multidimensional crisis" in its standard expert version covers:

1. Fall of GDP, defined as decrease by more than 10% on yearly basis; a GDP drop by over 10% is something extraordinary in the European Union.
2. High inflation, eroding value of savings and making investment decisions difficult; price increase by 10% or more will be regarded as "crisis", inflation over 10% is seldom experienced in the European Union nowadays, but is mentioned as rather extraordinary level reached during the Great Inflation during the 1970s (ECB, 2010, p. 99).
3. High depreciation / devaluation of home currency against USD, defined as increase in exchange rate (either average of observations through period or end of period values compared with previous period) by more than 15%; 15% depreciation / devaluation was set arbitrarily, considering 30% year-on-year proposed by (Laeven *et al*., 2012, pp. 1–32), which has never been reached by any EU country in the period under investigation, and relatively stable exchange rate EUR/USD.
4. Severe stock market decline, understood as decrease of broad stock market index by more than 20% quarterly; during the 2008–2009 crisis the S&P500 index dropped by over 20% in the last quarter 2008, and DAX by almost 20%,
5. Instability of banking system, manifested by restrictions on cash withdrawals.

Other thresholds (Table 4) are set 20% lower or higher starting from the standard version, until extreme (e.g. 14% inflation) or almost "normal" values (e.g. –8% stock market index decline) are reached.

Of course, there are other symptoms of the crisis, like a decline in employment or exploding government debt (Reinhart & Rogoff, 2009, pp. 466–472), but they were included in MIP as leading indicators.

We proceed as follows.

First, for every year (2008–2017), we calculate "multidimensional crisis": a combination of several negative consequences of financial and real crises, as described above. Each negative event counts as "1", otherwise "0". This is an extension of probit model applied by Mızrak and Yüksel (2019, pp. 33–50). We ignore averted and potential crises on purpose.

Second, we prepare panel data for the period 2007–2016 and for all 28 EU countries (14 MIP indicators for every year and country; explanatory variables).

Third, we proceed to construct ordered probit model, where the crisis variable is regressed on a set of MIP indicators, lagged by one year, to check for the ability of MIP indicators to issue a warning about upcoming crisis. Such selection of data and a lag of the explained variable is the closest to the actual European Semester procedure. The overall model selection evidence reflects that the first lag of the explanatory variables is superior compared with longer lags. With longer lags the predictive accuracy appears to diminish.

The ordered probit models have come into fairly wide use as a framework for analysing inherently ordered outcomes or responses (e.g. ratings) (Greene, 2000, p. 736). It is in line with the probit regression analysis put forward by Frankel and Rose (1996). The ordered probit model is currently considered the best practice when dealing with outcomes that are categorical in nature (Osborne, 2015, p. 17). It is a generalization of the probit model to the case of more than two outcomes of a dependent variable for which the potential values have a natural ordering, as “no crisis” (0), “minor crisis” (1), “big crisis” (2), and so on.

In this paper we use probit regression to assess the predictive strength of indicators arbitrarily selected by the Commission. The probit model is robust to the violation assumptions that OLS regression can be influenced e.g. by the assumption of normal distribution of residuals and homoscedasticity, so it seems to be the best choice for this task.

In line with Wooldridge (2010, pp. 504–505, 508), our ordered probit model for crisis ($\mathrm{cr}_{i,t}$), conditional on explanatory variables $\mathbf{v}_{i,t}$ can be derived from a latent variable model. Assume that a latent variable $\mathrm{cr}^*_{i,t}$ is determined by

$$\mathrm{cr}^*_{i,t} = \mathbf{v}_{i,t-1}\,\boldsymbol{\beta} + e_{i,t}, \quad e_{i,t}|\mathbf{v}_i \backsim \mathrm{Normal}(0,1), \quad t = 1,\ldots,\mathrm{T} \qquad (1)$$

where $\mathbf{v}_{i,t}$ is a vector (1×14) of independent variables (fourteen MIP indicators) for a country i (i = 1,2,…,28) and a year t (t = 1,2,…,10); $\boldsymbol{\beta}$ is a vector (14×1) of regression coefficients.

Let $\alpha_1 < \alpha_2 < \ldots < \alpha_5$ be unknown cut points, and define

$$\begin{aligned} \mathrm{cr}_{i,t} &= 0 \quad \text{if } \mathrm{cr}^*_{i,t} \le \alpha_1 \\ \mathrm{cr}_{i,t} &= 1 \quad \text{if } \alpha_1 < \mathrm{cr}^*_{i,t} \le \alpha_2 \\ &\vdots \\ \mathrm{cr}_{i,t} &= 5 \quad \text{if } \mathrm{cr}^*_{i,t} > \alpha_5 \end{aligned} \qquad (2)$$

The data set includes the panel values of dependent “multidimensional crisis” variables $\mathrm{cr}_{i,t}$ (0 to 5) and fourteen explanatory MIP variables ($\mathbf{v}_{i,t}$, yearly observations for 28 European Union economies) covering the periods from 2008 to 2017 and 2007 to 2016, respectively.

Our data sources are:

- for MIP indicators: EUROSTAT, Directorate-General for Economic and Financial Affairs ("Statistical Annex of Alert Mechanism Report 2018" 2017), data were used as available in the report,
- for GDP change: IMF (International Financial Statistics),
- for inflation: BIS (long consumer price index),
- for exchange rate against US dollar: BIS (long series on US dollar bilateral nominal exchange rates),
- for stock market indexes: stock exchange data, www.stooq.com, www.finance.yahoo.com, www.investing.com,
- for restrictions on cash withdrawals: Internet search.

During the data preparation process, we decided to leave some outlier observations — their elimination would deprive us of key data on crisis phenomena. Despite the robustness of the probit model, this may have some influence on the results obtained. Probit regression is all the more effective the larger the data set is.

Results

First, we looked at the correlation matrix between regressors (pairwise correlation coefficients — Pearson's product-moment correlation for the selected variables). Just in one case (V13 and V14, long-term unemployment rate and youth unemployment rate) the correlation coefficient reached 0.87. The second largest (in absolute value) was negative correlation -0.57 between V2 and V10 (net international investment position and unemployment rate). 5% critical value (two-tailed) is equal 0.1181 for n = 276. Most of correlation coefficients were significant (178 of 196). The goal of our research was to evaluate the existing MIP procedure, so we kept all the variables in the model.

Second, we looked at episodes of "multidimensional crises" that took place in sample countries between 2008 and 2017. Depending on the threshold levels applied, several crises' severity levels have been reached (0 — no crisis, and 1, 2, 3, 4 or 5). In order to test the forecasting ability of the dependent variables we used values lagged by one year.

Results for the set 1 thresholds are presented in Table 5. Variables 2, 5 and 7 are statistically significant, to a great extent at the 1% level, and all have the same signs across all thresholds. Others are significant only at selected thresholds.

Results for the set 2 thresholds are presented in Table 6. This time MIP variables 2, 5, 6, 7, 9 seem to have strong predictive strength. All parameters have the same sign and are significant at 1% (***) or 5% (**) level. Other variables are never significant (variable 1) or only for specific threshold levels.

Our test results show that:

- the variables 2, 5, 6, 7, 9 are almost always statistically significant at 1% or 5% level (sometimes at 10% level); they have predictive strength for “small” as well “serious” crises,
- variables 4 and 11 and 12 are also statistically significant in most cases,
- variables 1, 3, 8, 10, 13 and 14 seem to be obsolete or not very effective in crises prediction. This is not that obvious in case of current account balance, real effective exchange rate and private sector debt;
- all parameters of significant variables have expected signs.

Discussion

Now, we will formulate some remarks on the most relevant variables.

V2. According to our results, the increasing international investment position (NIIP) tends to diminish the probability of crisis, which may not be so obvious. To see why, we should 1) look at the functional categories of assets and liabilities and 2) realize that an increase of NIIP may be result of increasing assets or decreasing liabilities.

International assets and liabilities may be decomposed into: direct investment, portfolio investment, financial derivatives other than reserves and employee stock options, and other investment and reserve assets (IMF, 2009, p. 14, 120). Increase in international assets may be interpreted as an increase in (international) savings which constitute a certain buffer against crises. Negative signs and significance suggest that an increase in assets diminishes the probability of crisis next year, which is expected. It is less obvious, however, that a similar effect may be caused by a decrease of foreign investments in the economy. Foreign investment withdrawal could potentially be a sign of expected crisis but it is not; parameters of variable 2 are clearly negative. Lower foreign investments mean lower liabilities to other countries, which eventually should be repaid.

Interestingly, improvement in current account (variable 1), is not statistically significant. Typically, highly negative NIIPs result from persistently high current account deficits (European Commission, 2012, p. 9), which, *per se*, have statistically no influence on ability to predict “crisis” (variable 1). The more negative the NIIP to GDP, the more country becomes vulnerable to volatility in international financial markets. If international assets (and NIIP) decrease, probability of crisis increases. Decrease of NIIP may be also caused by foreign capital inflow into the economy. It may be reversed in case of any deterioration in the economy.

Catão and Milesi-Ferretti (2014), Knedlik (2014) as well as Siranova and Radvanský (2018) have also shown that NIIP is one of the significant explanatory variables for crises. Positive and stable values of NIIP (and also current account balance) are important for macroeconomic stability of EU countries (Kološta *et al.*, 2018).

V5. The scoreboard incorporates a nominal unit labour costs (ULC) indicator in view of monitoring developments in price and cost competitiveness across EU Member States. The ULC measures the average cost of labour per unit of output. A rise in an economy's nominal unit labour costs corresponds to a rise in labour costs that exceeds the increase in labour productivity. This can potentially be a threat to an economy's cost competitiveness, if other costs (e.g. cost of capital) are not adjusted in compensation (European Commission, 2012, p. 14). Large and sustained increases in ULCs may lead to the erosion of competitiveness, and — as our results show — to "multidimensional crisis". Parameters for all considered threshold levels are positive, as expected. This is in line with the results of Knedlik (2014), who found this variable useful in predicting the debt crisis.

V6. House price index is the scoreboard indicator which measures the year-on-year change in house prices, deflated by the Eurostat consumption deflator. A rapidly rising house price index is usually a certain proxy for an upcoming crisis. This is commonly accepted wisdom and confirmed by our data analysis. Our results to some extent confirm the results of previous studies (Borio & Drehmann, 2009; Boysen-Hogrefe *et al.*, 2015), who also considered house price important.

V7. Private sector credit flow, consolidated, is the scoreboard indicator, which measures private sector credit flows expressed in percent of GDP, and it includes loans and securities other than shares. It is a flow counterpart of private sector debt (which is a stock indicator). Positive sign of parameters is confirmed by a wide body of economic literature (e.g. Gourinchas & Obstfeld, 2011), which identifies quickly expanding credit as one of the best predictors of financial or banking crises. Also Frankel and Rose (1996) found that currency crashes tend to occur when, *inter alia*, domestic credit growth is high. Excessive creation of money *ex nihilo* tends to trigger wrong asset allocation, higher import demand, capital inflows and contributes to the widening of current accounts deficits. In addition, credit growth to the non-tradable, in particular housing, sector crowds out resources from the tradable sector (European Commission, 2012, p. 20).

V9. General government gross debt in percent of GDP is one of the commonly accepted imbalance indicators. In the EU–narration "general government debt is assessed for its contribution to the general indebtedness of a Member State, being thus looked at together with private sector debt". Our results confirm that rising government debt is "bad" in a sense that it is negatively associated with the occurrence of crises, "small" and "big". Interestingly, rising private debt cannot be statistically associated with upcoming crises.

Conclusions

In order to prevent or contain future crises in the EU it is essential to be able to accurately predict their occurrence. We set out to assess the ability of MIP indicators to predict the risk of excessive macroeconomic imbalances in the EU. We tested the predictive strength of all MIP 14 indicators considered for evaluating the macroeconomic stability of the EU member countries.

We were able to identify five MIP variables which were statistically significant in predicting "multidimensional crises" for all EU countries: net international investment position, nominal unit labour cost index, house price index, private sector credit flow and general government gross debt. The other variables turned out to be less important or not effective in crises prediction; their significance in the MIP procedure should be re-evaluated.

However, we are aware that our approach has limitations; e.g. the results could be sensitive to how a crisis is defined. Other variables than our five, indicating the crises, could also be considered. In addition, early warning indicators may be different for well and less developed countries.

In any case, the scoreboard proposed by the European Commission and optimized with a probit model should be considered — at its best — as a tool for an initial evaluation. A more detailed economic evaluation of the imbalances in the Member State always has to follow.

References

Aldasoro, I., Borio, C., & Drehmann, M. (2018). Early warning indicators of banking crises: expanding the family. *BIS Quarterly Review, March*.

Beck, K. (2013). Determinants of business cycles synchronization in the European Union and the Euro Area. *Equilibrium. Quarterly Journal of Economics and Economic Policy*, *8*(4). doi: 10.12775/equil.2013.025.

Beck, K. (2019). What drives business cycle synchronization? BMA results from the European Union. *Baltic Journal of Economics*, *19*(2). doi: 10.1080/1406099x.2019.1652393.

Borio, C., & Drehmann, M. (2009). Assessing the risk of banking crises - revisited. *BIS Quarterly Review*, *March*.

Boysen-Hogrefe, J., Jannsen, N., Plödt, M., & Schwarzmüller, T. (2015). An empirical evaluation of macroeconomic surveillance in the European Union. *Kiel Working Paper* (Vol. 2014). doi: 10.1111/j.1467-6346.2007.00779.x.

Catão, L. A. V, & Milesi-Ferretti, G. M. (2014). External liabilities and crises. *Journal of International Economics*, *94*. doi: 10.1016/j.jinteco. 2014.05.003.

Christofides, C., Eicher, T. S., & Papageorgiou, C. (2016). Did established early warning signals predict the 2008 crises? *European Economic Review*, *81*. doi: https://doi.org/10.1016/j.euroecorev.2015.04.004.

Claessens, S., & Kose, M. A. (2013). Financial crises: explanations, types, and implications. *IMF Working Paper*, *28*.

Crockett, A. (1996). The theory and practice of financial stability. *Economist*, *144*(4). doi: https://doi.org/10.1007/BF01371939.

Csortos, O., & Szalai, Z. (2014). Early warning indicators: financial and macroeconomic imbalances in Central and Eastern European countries. *MNB Working Papers*, 2.

De Scheemaekere, X., Oosterlinck, K., & Szafarz, A. (2015). Identifying economic crises: insights from history. *Financial History Review*, *22*(1). doi: 10.1017 /S0968565015000025.

Domonkos, T., Ostrihoň, F., Šikulová, I., & Širaňová, M. (2017). Analysing the relevance of the MIP scoreboard's indicators. *National Institute Economic Review*, *239*(1). doi: 10.1177/002795011723900112.

ECB (2010). The "great inflation": lessons for monetary policy. *Monthly Bulletin*, *May*.

Efstathiou, K., & Wolff, G. (2018). Is the European Semester effective and useful? *Bruegel Policy Contribution*, *09*. Retrieved form http://bruegel.org/wp-content/uploads/2018/06/PC-09_2018_2.pdf.

Erhart, S., Becker, W., & Saisana, M. (2018). *The macroeconomic imbalance procedure - from the scoreboard and thresholds to the decisions*. Publications Office of the EU. doi: https://doi.org/10.2760/038148.

European Commission (2011). EU economic governance "Six Pack" - state of play. *28 September* (Issue September 2010). http://europa.eu/rapid/press-release_MEMO-11-647_en.htm.

European Commission (2012). Scoreboard for the surveillance of macroeconomic imbalances. *European Economy Occasional Papers*, *92*. doi: 10.2765/20196.

Frankel, J. A., & Rose, A. K. (1996). Currency crashes in emerging markets: an empirical treatment. *International Finance Discussion Papers , Board of Governors of the Federal Reserve System (U.S.), 534*.

Gourinchas, P. O., & Obstfeld, M. (2011). Stories of the twentieth century for the twenty-first. *American Economic Journal: Macroeconomics*, *4*(1). doi: 10.1257 /mac.4.1.226.

Greene, W. H. (2003). *Econometric analysis.* Pearson Education, Inc.

IMF (2009). *Balance of payments and international investment position manual*.

Kaminsky, G. (1998). Currency and banking crises: the early warnings of distress. *International Finance Discussion Paper, Board of Governors of the Federal Reserve System (U.S.), 629*.

Kaminsky, G., Lizondo, S., & Reinhart, C. M. (1998). Leading indicators of currency crises. *IMF Staff Papers, 45*(1).

Knedlik, T. (2014). The impact of preferences on early warning systems - the case of the European Commission’s Scoreboard. *European Journal of Political Economy, 34*(1174). doi: 10.1016/j.ejpoleco.2014.01.008.

Kološta, S., Kráľ, P., & Flaška, F. (2018). Alternative measures of macroeconomic imbalances in the EU – design and verification. *E+M Ekonomie a Management, 22*(1). doi: 10.15240/tul/001/2019-1-003.

Laeven, L., & Valencia, F. (2012). Systemic banking crises database: an update. *IMF Working Paper, WP/12/163*.

Lo Duca, M., Koban, A., Basten, M., Bengtsson, E., Klaus, B., Kusmierczyk, P., Lang, J., Detken, C., & Peltonen, T. (2017). A new database for financial crises in European countries. *Occasional Paper Series, 13*. doi: 10.2849/119019.

Mishkin, F. S. (2011a). Monetary policy strategy: lessons from the crisis. *NBER Working Paper Series, 16755*.

Mishkin, F. S. (2011b). Over the cliff: from the subprime to the global financial crisis. *Journal of Economic Perspectives*, *25*(1). doi: 10.1257/jep.25.1.49.

Mızrak, F., & Yüksel, S. (2019). Significant determiners of Greek debt crisis: a comparative analysis with Probit and MARS approaches. *International Journal of Finance & Banking Studies, 8*(3). doi: 10.20525/ijfbs.v8i3.834.

Oesterreichische Nationalbank (2001). *Financial stability report 2*.

Osborne, J. W. (2015). *Best practices in logistic regression*. SAGE Publications Ltd. doi: 10.4135/9781483399041.

Regulation (EU) No 1176/2011 of the European Parliament and of the Council of 16 November 2011 on the prevention and correction of macroeconomic imbalances. (2011). Official Journal of the European Union, *2011*(1176).

Reinhart, C. M., & Rogoff, K. S. (n.d.). Dates for Banking Crises, Currency Crashes, Sovereign Domestic or External Default (or Restructuring), Inflation Crises, and Stock Market Crashes (Varieties). Retrieved from https://www.carmenreinhart.com/data/browse-by-topic/topics/7/.

Reinhart, C. M., & Rogoff, K. S. (2009). The aftermath of financial crises. *American Economic Review*, *99*(2). doi: 10.1257/aer.99.2.466.

Siranova, M., & Radvanský, M. (2018). Performance of the macroeconomic imbalance procedure in light of historical experience in the CEE region. *Journal of Economic Policy Reform*, *21*(4). doi: 10.1080/17487870.2017.1364642.

Statistical Annex of Alert Mechanism Report 2018. (2017). Commission Staff Working Document (Issue SWD(2017) 661 final).

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data*. Cambridge, MA, London: The MIT Press.

Acknowledgements

"The project is financed by the Ministry of Science and Higher Education in Poland under the programme "Regional Initiative of Excellence" 2019–2022 project number 015/RID/2018/19 total funding amount 10 721 040,00 PLN".

Annex

Table 1. MIP scoreboard indicators

Variable	Indicator	Unit
V1	Current account balance (% of GDP)	3-year average
V2	Net international investment position	% of GDP
V3	Real effective exchange rate (42 trading partners, HICP deflator)	3-year % change
V4	Export market share (% of world exports)	5-year % change
V5	Nominal unit labour cost index (2010=100)	3-year % change
V6	House price index (2015=100), deflated	1-year % change
V7	Private sector credit flow, consolidated	% of GDP
V8	Private sector debt, consolidated	% of GDP
V9	General government gross debt	% of GDP
V10	Unemployment rate	3-year average
V11	Total financial sector liabilities, non-consolidated	1-year % change
V12	Activity rate (% of total population aged 15-64)	3-year change in p.p.
V13	Long-term unemployment rate (% of active population aged 15-74)	3-year change in p.p.
V14	Youth unemployment rate (% of active population aged 15-24)	3-year change in p.p.

Source: “Statistical Annex of Alert Mechanism Report 2018” (2017, p. 8). Data source are Eurostat, IMF and Directorate-General for ECFIN.

Table 2. Crisis indicators

Description	Crisis threshold level	Comment
1. Decline in GDP	Over a%, year-on-year change	Major commonly accepted indicator of crisis
2. High inflation	Over b%, year-on-year change	Inflation, if high, has obvious negative effects on the whole economy
3. High devaluation / depreciation of home currency against USD	Over c% quarterly (either average or end of period)	Erosion of own currency with possible negative effects on exchange rate stability, confidence in home currency, foreign reserves etc.
4. Severe stock market decline	Local stock exchange major index change, over d%, end of quarter against end of previous quarter	May cause high losses of investors in stocks; major indicator of financial crisis
5. Restrictions on cash withdrawals	If imposed in specific quarter	Sign of financial instability; painful for citizens

Table 3. Set 1 crisis thresholds (in %)

Variables	Level 1	Level 2	Level 3	Level 4
1. Decline in GDP	0	–2,84	–6.86	–10.87
2. High inflation	1.77	4.03	6.30	8.57
3. High devaluation / depreciation of home currency against USD*	0.70 0.73	5.56 6.35	10.43 11.97	15.29 17.58
4. Severe stock market decline	–0.04	–12.24	–24.44	–36.64

Note: *First figure refers to quarter average, second one to end-of-period value.

Table 4. Set 2 crisis thresholds (in %)

Variables	Level 1	Level 2	Level 3	Level 4 (standard)	Level 5	Level 6
1. Decline in GDP	–4	–6	–8	**–10**	–12	-14
2. High inflation	4	6	8	**10**	12	14
3. High devaluation /depreciation of home currency against USD*	6 6	9 9	12 12	**15** **15**	18 18	21 21
4. Severe stock market decline	–8	–12	–16	**–20**	–24	–28

Note: *First figure refers to quarter average, second one to end-of-period value.

Table 5. Signs of statistically significant parameters for different threshold levels (set 1)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Level 1 146 (52.9%)		– ***			+ ***		+ ***	– **		– ***	+ **	– ***		
Level 2 N 133 (48.2%)		– ***	+ **		+ ***	+ ***	+ ***	– **	+ **		+ *	– ***		+ ***
Level 3 195 (70.7%)		– ***		+ *	+ ***	+ ***	+ ***		+ ***		+ **			
Level 4 247 (89.5%)		– ***		+ **	+ **	+ *	+ *		+ **					

Note: Numbers below "Level" indicate number of cases "correctly predicted"; N indicates that the null hypothesis: "error is normally distributed" couldn't be rejected at 5% significance level.

Table 6. Signs of statistically significant parameters for different threshold levels (set 2, expert version)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Level 1 N 142 (54.1%)		– ***	+ **		+ ***	+ ***	+ ***	– ***	+ ***	– *	+ **	– ***		+ ***
Level 2 N 163 (59.1%)		– ***	+ **	+ *	+ ***	+ ***	+ ***		+ ***		+ ***	– ***		+ **
Level 3 N 196 (71.0%)		– **		+ **	+ ***	+ ***	+ ***		+ ***		+ **	– **		
Level 4 233 (84.4%)		**– *****		**+ *****	**+ *****	**+ *****	**+ *****		**+ *****					
Level 5 243 (88%)		– ***		+ *	+ ***	+ ***	+ ***		+ ***			– *		
Level 6 N 250 (90.6%)		– ***			+ ***	+ ***	+ ***		+ ***			– ***	+ **	