EKONOMIA I PRAWO. ECONOMICS AND LAW
Volume 23, Issue 1, March 2024
p-ISSN 1898-2255, e-ISSN 2392-1625
www.apcz.umk.pl/EiP

ORIGINAL ARTICLE
received 12.06.2023; revised 20.03.2024; accepted 31.03.2024
Citation: Biegun, K., Dahl, M., & Karwowski, J. (2024). Predictive strength of Macroeconomic Imbalance Procedure indicators. *Ekonomia i Prawo. Economics and Law*, 23(1), 23–45. https://doi.org/10.12775/EiP.2024.002.

Predictive strength of Macroeconomic Imbalance Procedure indicators

KRZYSZTOF BIEGUN

corresponding author
Wroclaw University of Economics and Business, Faculty of Economics and Finance, Finance Department, ul. Komandorska 118/120, 53-345 Wrocław, Poland
krzysztof.biegun@ue.wroc.pl
orcid.org/0000-0002-4888-6600

MARTIN DAHL

Lazarski University in Warsaw, Faculty of Economics and Management, Institute of International Political and Economic Relations, Poland
m.dahl@lazarski.edu.pl
orcid.org/0000-0003-1978-7045

JACEK KARWOWSKI

Wroclaw University of Economics and Business, Faculty of Economics and Finance, Finance Department, Poland
jacek.karwowski@ue.wroc.pl
orcid.org/0000-0003-2754-5003

Abstract

Motivation: The Macroeconomic Imbalance Procedure (MIP) is a key step in the European Semester, aimed at the coordination of the economic policies of the EU Member States to prevent excessive macroeconomic imbalances in the EU and support structural reforms. The MIP was originally envisaged as a legal tool for crisis prevention, allowing macroeconomic imbalances to be detected and then remedied, but is also used as an Early Warning System. However, the real strength of MIP indicators to predict crises has not been proved in practice and is widely contested in the literature.

Aim: Fourteen scoreboard ("main") and 28 auxiliary MIP indicators are currently in use. This paper is aimed at the assessment of the power of all MIP indicators in predicting crises.

Results: The added value of our research is to test the MIP's ability to predict changes in GDP, which may be considered as a proxy for the deterioration or improvement of the economic situation. Very little investigation has been done in this area so far. In addition, to our knowledge, no research papers have investigated the relevance of auxiliary MIP indicators. Our results show that only four main indicators (house price index, nominal unit labour cost index, general government sector debt, and export market shares) and another four auxiliary indicators (residential construction as percentage of GDP, activity rate, people living in households with very low work intensity, and export performance against advanced economies) seem to be able to predict the upcoming crises.

Keywords: macroeconomic imbalance procedure; MIP; crisis forecasting; European semester; economic policy
JEL: F15; F36; F47; G01; C11

1. Introduction

The Macroeconomic Imbalance Procedure (MIP) is intended to signal and monitor the build-up of macroeconomic imbalances that lead to the classically understood crisis phenomena. Despite this, both the European Commission (EC) itself and most researchers consider the MIP scoreboard as an Early Warning System (EWS) and analyse it as a classic example of EWS.

Before the introduction of the MIP, the EU monitored economic developments within the economies of member states through the Stability and Growth Pact. This framework now operates in tandem with the MIP and sets thresholds on both government deficits (3% of GDP) and government debt levels (60% of GDP). However, due to the changes in economic conditions brought about by the COVID-19 crisis, since 2020 the surveillance cycle of the European Semester is being temporarily adjusted to ensure the effective implementation of the Recovery and Resilience Facility, and this will also affect the implementation of the Macroeconomic Imbalance Procedure.

Unfortunately, as Ioannou and Stracca (2014) have demonstrated, the Stability and Growth Pact made a positive contribution to the government primary balance only before the introduction of the euro, but it has not since. The problem of the ineffectiveness of the Pact has been addressed, inter alia, by Bergman et al. (2016) and Hallerberg et al. (2007). Pierluigi and Sondermann (2018) have claimed that the common set of rules and practices in place before the inception of the crisis has failed to bring about sufficient reforms in particular in the most vulnerable Member States in the run-up to the financial crisis Moreover. According to Casagrande and Dallago (2021), since 2007 the EU has experienced a deterioration of stability and cohesion from economic, political, and social perspectives.

Neither legal documents nor the EC provide an exact definition of macroeconomic imbalance. This is politically understandable and allows for a certain flexibility, but this makes it very difficult to evaluate the effectiveness of the MIP procedure.

Another obstacle in the analysis is the fact that the MIP is only an element of the broad coordination mechanism of the economic policies of EU Member States, the European Semester. Regular monitoring of the level of alert indicators (summarised each spring in the form of the Alert Mechanism Report) is the first step of the MIP procedure. In the case of potential imbalances being identified, the EC prepares an in-depth report on the indicated country and issues recommendations for corrective actions.

The Commission shall thereafter recommend that the Council requires of each country the submission of a corrective action plan detailing measures to address their challenges which should be implemented within a given period.

Our paper is structured as follows. We first review the literature on the predictive power of MIP in relation to crises, which are very differently defined by the authors. However, to our knowledge, no research papers have investigated the relevance of all MIP indicators, either main or auxiliary. Our goal is to look at the ability of all available indicators to predict a change in GDP, which is a proxy for the deterioration (or improvement) of the economic situation in every EU Member State under investigation. Accordingly, we treat the changes in the abovementioned MIP indicators as signals of looming crisis rather than as imbalance. Real GDP growth, one of the auxiliary variables, is regarded by us as a dependent variable, a proxy for the improvement or deterioration of the economic situation in every Member State.

Next, the predictive power of the MIP indicators on assessment of the GDP growth rate of 26 European Union countries is examined using Bayesian model averaging.

The following section, Results, provides an identification and overview of relatively few MIP indicators which have the predictive power of identifying upcoming crises in a systematic way. Next section includes closing observations.

2. Literature review

According to Domonkos et al. (2017), MIP-focused studies may be divided into two categories. The first discusses the procedure of the MIP (its legal, institutional, and political aspects as well as the willingness of Member States to actually implement the recommendations of the EC). MIP today may be regarded a broader instrument seeking to make interventions through a range of economic and social indicators (Hansen & Lovering, 2022). The second analyses the indicators included in the scoreboard, especially their ability to predict crises.

We have concentrated on a seldom-investigated area of research: empirical studies on the predictive relevance of MIP indicators. Most of those studies have used various types of the signal approach which implement a database of indicators. A particular indicator signals a crisis when its level exceeds a pre-defined alarm threshold. The disadvantage of the signal approach is its inability to show statistical significance for the derived thresholds (Dany-Knedlik et al., 2021).

One of the challenges in assessing the effectiveness of the Macroeconomic Imbalance Procedure (MIP) as a tool for identifying and addressing potential economic crises, is the lack of a clear definition of excessive imbalances within the MIP regulations. This presents a significant obstacle for researchers seeking to evaluate the performance of the MIP in identifying imbalances and crisis-prone situations. In order to effectively analyse the MIP's ability to anticipate and counteract economic crises, it is necessary to establish a clear and operational definition of excessive imbalances.

The literature review reveals a variety of perspectives on the concept of crisis. According to Mishkin (2011a; 2011b), a decrease in GDP can be considered a symptom of an economic crisis, often accompanied by a rise in unemployment. Domonkos et al. (2017) use the output gap, defined as the deviation of actual GDP from potential GDP, as an indicator of crisis, acknowledging the challenges associated with calculating potential output. Siranova and Radvanský (2018) propose using the deviation of real GDP growth rate from its five-year average by more than one standard deviation as a crisis indicator.

Biegun and Karwowski (2020) introduced the concept of a "multidimensional crisis" based on several economic indicators, such as the decline in GDP, inflation, devaluation or depreciation of the national currency against the USD, the decline in the main index of the local stock exchange and the introduction of restrictions on cash withdrawals. They identified a crisis event when the level of any of the indicators exceeded certain thresholds. This approach allowed them not only to identify crises, but also to classify their severity.

Using various definitions of crisis, the authors have reached considerably different conclusions. An overview of these papers can be found in the report published by the Joint Research Centre (Erhart et al., 2018). For example, Knedlik (2014) has found that current account, net international investment position, and nominal unit labour costs were the most useful predictors of a debt crisis. Meanwhile, Csortos and Szalai (2014) have argued that only the current account deficit and the unemployment rate have sent true alarm signals relatively more often than false ones in the case of a crisis event defined as a GDP gap. Next, Boysen-Hogrefe et al. (2015) have found that private sector credit flow, house prices, and private sector debt were the best indications of 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). This is in line with Kaminsky (1998), who identified several indicators of financial crises, such as growth slowdown, loose monetary policy, overborrowing, bank runs, and balance of payments problems. Also Borio and Drehmann (2009) have demonstrated that credit-to-GDP, equity, and property price gaps, in per cent relative to trends, are able to detect the build-up of risks of upcoming banking distress in an economy. Finally, Sohn and Park (2016) have examined the EWS of banking crisis and bank related stock returns and found that the credit growth is more informative in predicting bank sector crisis than the credit-to-GDP gap. Their findings have been confirmed to a large extent by Geršl and Jašová (2018). Biegun and Karwowski (2020) 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. This paper is part of a stream of publications (e.g., Koll & Watt, 2022) that point to the need for MIP reform. However, it should be noted that the directions of the suggested modifications largely depend on how the authors perceive the purpose of the MIP.

3. Methods

Fourteen scoreboard ("main") and 28 auxiliary MIP indicators are currently in use (see Table 1 for the full list of scoreboard indicators). Details concerning the definitions of MIP indicators can be found in Erhart at al. (2018) and Eurostat (2023a; 2023b).

This research is aimed at the assessment of the predictive power of macroeconomic imbalance procedure of all MIP indicators in predicting crises. Real GDP growth, one of the auxiliary variables, is regarded by us as a dependent variable, a proxy for the improvement or deterioration of the economic situation in every Member State. We have looked at GDP growth rates with a one-year delay. The remaining 41 indicators, which we treat as independent variables, may be divided into six groups (the classification is our own).

The use of GDP changes as a proxy is motivated by the inherent ambiguity in the concept of macroeconomic imbalance. Neither legal documents nor the European Commission provide a precise definition of macroeconomic imbalance. This lack of a clear definition makes it challenging to evaluate the effectiveness of the MIP procedure directly. Therefore, we have chosen to use GDP changes as a proxy, as it is a well-established, widely accepted, and quantifiable indicator of economic performance and stability.

External imbalances are related to the specific balance of payment positions (flows). Current account or more exactly current account plus capital account (=net lending/borrowing) measures the net resources that the economy makes available to the rest of the world (if positive) or receives from the rest of the world. Foreign direct investment (as flows or stocks) shows how a country is dependent on inbound investment or can generate outbound investment abroad. Meanwhile, export shares changes measure how the economies depend on the demand from abroad and net trade in energy products — on the energy prices.

Furthermore, net international investment position (stock) measures the difference between the external financial assets and liabilities of a country.

Another group of indicators may be labelled "international competitiveness" because they measure how an economy performs in comparison with the rest of the world (changes in terms of trade, real exchange rate, unit labour cost, labour productivity, fixed capital formation, and domestic expenditure on research and development).

Indebtedness is potentially another source of micro- and macroeconomic instability that may lead to a crisis. Several indicators belong to this group: private sector credit flow and debt, household debt, non-performing loans of domestic and foreign entities, financial sector liabilities, general government debt, and consolidated banking leverage. Excessive indebtedness potentially poses a threat to economic agents and the economy as a whole.

Changes in real estate prices (house price indices) and residential construction may be regarded as a proxy for a growing property bubble.

The situation of the labour market is characterised by eight MIP indicators: activity rates, the three-year average unemployment rate, long-term unemployment rates, and youth unemployment rates. One might expect that the situation of the labour market has a low predictive ability with respect to crises, but in fact the relationship is the opposite: higher unemployment will follow an economic downturn. In fact, unemployment was introduced merely to contextualise "real" macroeconomic imbalances. As a result, breaching the early warning threshold on the unemployment indicator did not trigger further Commission analysis in the form of an In-Depth Review (IDR), unlike other indicators like the current account, private debt, or unit labour costs (Hansen & Lovering, 2022).

The last group of MIP indicators measures poverty, e.g., the proportion people at risk of poverty or social exclusion or severely materially deprived people as a percentage of the total population. Again, they are signs of a crisis which had already occurred, a kind of evidence of growing macroeconomic imbalances.

It may be hypothesised that only a few MIP indicators have the predictive power of identifying upcoming crises in a systematic way, and they belong to the following groups:

- "international competitiveness", because deteriorating competitiveness limits growth opportunities and "external imbalances" because these indicators may be evidence of declining competitiveness;
- indebtedness, because rising debt is a sign of the inability to balance revenues and expenses in the long run; and
- real estate prices as a sign of a bubble following too loose monetary or fiscal policy.

The investigation uses the panel of 26 European Union Member States (the full data set was not available for Croatia and Romania) over the 2007–2018 (MIP indicators are the independent variables) and 2008–2019 (GDP year-to-year change is the dependent variable) period. Prior 2007, many MIP indicators were not available, and inclusion of 2019 would not help to foresee a fall in GDP in 2020 which occurred due to the COVID-19 pandemic.

Unfortunately, the data for five indicators were not available for selected countries and years. The variables that had to be dropped are crossed out in Table 2. It seems that only three of them could add value to our analysis; all of them belong to the "Indebtedness" group.

The predictive power of the MIP indicators on assessment of the GDP growth rate of 26 European Union countries is examined using Bayesian model averaging. BMA assumes the following general form of the model:

$$y_j = \alpha_j + \beta_j X_j + \varepsilon_j, \tag{1}$$

where j (j=1, 2, ..., m) stands for the model's number, y_j is the vector including the explained variable values, α_j is the vector of intercept terms, β_j is the vector of unknown parameters, X_j is the matrix of MIP indicators, and ε_j is the vector of residuals which are assumed to be independent and normally distributed, $\varepsilon \sim N(0, \sigma^2 I)$ and conditionally homoscedastic. Moreover, each model M_j had a binary vector ascribed to it $(K\times1)\phi=(\phi_1, \phi_2, ..., \phi_K)$, where zero signifies that a given regressor does not appear in the model, while 1 means that there is a variable in the model, with K being the total number of potential regressors.

Given the model space, the unconditional posterior distribution of coefficient β is estimated in the following way:

$$P(\beta | y) = \sum_{j=1}^{2^K} P(\beta | M_j, y) \times P(M_j | y), \tag{2}$$

where $P(\beta|M_j,y)$ denotes the coefficient β's conditional distribution for a given model M_j and $P(M_j|y)$ represents the model's posterior probability. According to Bayes' theorem, the posterior model probability, $P(M_j|y)$, is computed in the following way:

$$PMP = p(M_j | y) = \frac{l(y | M_j) \times p(M_j)}{p(y)} = \frac{l(y | M_j) \times P(M_j)}{\sum_{j=1}^{2^K} l(y | M_j) \times P(M_j)}. \tag{3}$$

PMP (Posterior Model Probability) is proportional to the product of marginal likelihood of M_j, $l(y|M_j)$ and a discrete prior, $P(M_j)$. Because $p(y) = \sum_{j=1}^{2^K} l(y | M_j) \times P(M_j)$, model weights can be treated as probabilities.

The first step of applying BMA involves the specification of the prior structure. The coefficient β is normally distributed, with zero mean and variance being $\sigma^2 V_j$; thus:

$$P(\beta | \sigma^2, M_j) \sim N(0, \sigma^2 V_j), \tag{4}$$

where V_j is the prior variance matrix related to the covariance in the following way:

$$V_j = \left(gX_j'X_j\right)^{-1}, \tag{5}$$

where g denotes the proportionality coefficient. The g-prior, developed by Zellner (1986), is commonly utilised in BMA implementations. The so-called "benchmark prior" (Fernández, et al., 2001) has dictated the choice of risk inflation criterion (RIC) proposed by Foster and George (1994) for the dataset at hand. Additionally, unit information prior (UIP) put forward by Kass and Wasserman (1995) was employed in the main results.

This paper employs two main estimation procedures. Since the analysed dataset is characterised by the presence of multicollinearity and functional interdependence between independent variables, this paper extends the standard BMA structure in two ways using dilution priors. First, the model prior is augmented by means of multicollinearity prior. Second, the paper utilises the tessellation prior through the Metropolis–Hastings algorithm. The detailed description of both methods is provided below.

The first procedure involves augmenting the binomial model prior (Ley & Steel, 2009; Sala-i-Martin et al., 2004) with the expression correcting for multicollinearity (George, 2010):

$$P\left(M_j\right) \propto \left|R_j\right|^{0.5} \left(\frac{EMS}{K}\right)^{k_j} \times \left(1 - \frac{EMS}{K}\right)^{K-k_j}, \tag{6}$$

where EMS is the expected model size; k_j denotes the number of covariates for model j; the total number of regressors is represented by K; and $|R_j|$ denotes the determinant of the correlation matrix comprising all the regressors from each estimated model j. With $EMS=k/2$, it turns into uniform model prior; priors on all the models are all equal ($P(M_j) \propto 1$). With the increase in the degree of multicollinearity between the regressors, the value of $|R_j|$ approaches 0 and, consequently, the prior for a given model decreases. MC^3 (Markov Chain Monte Carlo Model Composition) sampler by Madigan et al. (1995) is applied to decrease the model space. To analyse the chain's convergence, this paper estimates the correlation coefficient between the analytical and MC^3 posterior model probabilities from the best 10,000 models.

The second approach is based on the binomial-beta model prior proposed by Ley and Steel (2009):

$$P\left(M_j\right) \propto \Gamma\left(1 + k_j\right) \times \Gamma\left(\frac{K - EMS}{EMS} + K - k_j\right), \tag{7}$$

with EMS being equal to $k/2$, the probability of model j size is $1/(K+1)$. This paper uses the MCMC search and the "Spinner Process" to implement dilution and tessellation, respectively. The latter involves the following steps for obtaining samples from a subspace of models $P_v(M_j)$ (George, 2010):

- obtain a sample of size k from K;
- generate $Y^* \sim N_n(0, I)$, where Y^* can be regarded as "imaginary data";
- choose the covariance matrix with sample size being $k_j = k$ that is "closest" to Y^*;
- choose model j which has the largest R^2 in the regression of generated Y^* on the covariance matrix.

When implementing the second approach, the correlation coefficient between analytical and MC^3 posterior model probabilities is not enough to evaluate the chain's convergence. Therefore, the estimation procedure was conducted ten times with various numbers of iterations and burnins. The estimation results were not found to be quantitatively and qualitatively different from the results presented in this paper.

The unconditional posterior mean (PM) of the coefficient β_i can be estimated using the PMPs as weights:

$$PM = E(\beta_i | y) = \sum_{j=1}^{2^K} P(M_j \quad y) \times \hat{\beta}_{ij} \tag{8}$$

where $\hat{\beta}_{ij} = E(\beta_i | y, M_j)$ is the OLS estimator of β_i from model M_j. The posterior standard deviation (PSD) is obtained in the following way:

$$PSD = \sqrt{\sum_{j=1}^{2^K} P(M_j | y) \times V(\beta_j | y, M_j) + \sum_{j=1}^{2^K} P(M_j | y) \times \left[\hat{\beta}_{ij} - E(\beta_i | y, M_j)\right]^2}, \tag{9}$$

where $V(\beta_j | y, M_j)$ is the conditional variance of the β_i coefficient from model M_j. To better capture the relative impact of the determinants on the macroeconomic imbalance procedure indicators, standardised coefficients were calculated along with BMA statistics based on their values. Standardised posterior mean is denoted by SPM, whereas standardised posterior standard deviation is represented by SPSD[1].

The main BMA statistics of interest in the context of model selection is the posterior inclusion probability (PIP) or the posterior probability of the inclusion of the regressor in the model after seeing the data:

$$PIP = P(x_i | y) = \sum_{j=1}^{2^K} 1(\varphi_i = 1 | y, M_j) \times P(M_j | y), \tag{10}$$

where $\varphi = 1$ indicates the inclusion of the regressor x_i. The prior inclusion probability is equal to 0.5 in both employed estimation procedures. If the obtained PIP exceeds than 0.5, a regressor is considered to be robust. However, Kass and Raftery (1995) have proposed a more detailed classification scheme with the robustness being weak, positive, strong, or decisive when posterior inclu-

[1] See Doppelhofer and Weeks (2009) for the details.

sion probability is between 0.5 and 0.75; 0.75 and 0.95; 0.95 and 0.99; or 0.99 and 1, respectively[2].

To check the posterior probability of the coefficient's positive sign, $P(+)$, the following equation is used:

$$P(+) = P[sign(x_i) \mid y] = \\ = \begin{cases} \sum_{j=1}^{2^K} P(M_j \mid y) \times CDF(t_{ij} \mid M_j), \; if \; sign[E(\beta_i \mid y)] = 1 \\ 1 - \sum_{j=1}^{2^K} P(M_j \mid y) \times CDF(t_{ij} \mid M_j), \; if \; sign[E(\beta_i \mid y)] = -1 \end{cases}, \tag{11}$$

where *CDF* is the cumulative distribution function, whereas $t_{ij} \equiv \left(\hat{\beta}_i / \widehat{SD}_i \mid M_j\right)$.

Details about the BMA can be found in Beck (2017; 2019; 2020; 2021) and Hoeting et al. (1999); g-prior structure in Eicher et al. (2011), Fernández et al. (2001), and Ley and Steel (2009; 2012); model prior structure in Ley and Steel (2009); and dilution priors in George (2010).

The utilization of Bayesian model averaging (BMA) in the context of the European Semester can enhance the accuracy of economic forecasts by incorporating expert knowledge through the application of prior distributions. This method has been shown to improve the performance of forecasting models, as it takes into account the uncertainty surrounding model selection and weighting. Furthermore, BMA can also provide a more robust assessment of forecast uncertainty, as it accounts for the potential model misspecification. Overall, the implementation of BMA in the European Semester process can lead to more informed policy decisions and a more efficient use of resources.

However, it is important to note that the application of BMA in the context of the European Semester is dependent on the availability of data. Specifically, this methodology requires adequate data on model parameters and prior distributions in order to be implemented effectively. This can be a challenge, as data availability and quality can be limited for certain countries or for specific time periods. In the absence of sufficient data, alternative forecasting methods may need to be employed. Despite this limitation, the use of BMA can still provide valuable insights and improvements in economic forecasting, particularly when data availability is sufficient.

[2] The results presented in the main text went through vast robustness checks in terms of different specifications of model prior, g prior, and number of iterations used. The results presented in the main text are very robust to manipulations in both prior structure and are virtually immune to changes in the number of iterations above 1,000,000.

4. Results

Detailed calculation results are shown in Table 3 and 4. Only a few indicators should be systematically included in the model and accordingly seem to be good predictors of upcoming crises (Table 1).

There are only eight variables (of 36) with the posterior inclusion probability (PIP) of including them in the model after seeing the data with >0.5 (with a one-year lag). If the obtained PIP is greater than 0.5, a regressor is considered robust. For every variable in the Table 1, the first row refers to dilution prior method and the second one for tessellation prior. If the PIP for a given method was <0.5, the cell is empty. All data are taken from Appendices 2 and 3.

The PM column shows the statistic posterior mean of the coefficient β_i, independently of the space of the models. PSD is the posterior standard deviation. The standardised posterior mean is denoted by SPM, whereas the standardised posterior standard deviation is represented by SPSD. P(+) is the probability of a positive sign of the coefficient in the model; if equal or close to 1.0000, it indicates a positive relationship, and if it is equal or close to 0.0000, it is negative.

Auxiliary variables are written is italics. In addition, we have performed similar calculations with a two-year lag; the variables which were able to predict a change in GDP two years in advance are written in bold.

Now we will describe the variables which seem to be most effective in predicting crises. Before we start, we must make note of two important caveats.

Firstly, the relationships summarised in Table 1 are not necessarily about causality. We are simply saying that some MIP variables should be included in a model to properly precede either a decline or an increase in GDP.

Secondly, a decline in GDP is only one manifestation of the crisis. Other unfavourable phenomena are also possible, such as a strong weakening of the national currency, high inflation, or the barely-measurable instability of the banking sector.

There are five MIP indicators which seem to be significant for both methods, dilution, and tessellation. They are marked in bold in Table 1.

The first and most important indicator, HPI (house price index, deflated — 1 year % change, or real house price index), is the main MIP variable, which should be included in every model explaining GDP behaviour. It is calculated as the ratio between the house price index (HPI) and the national accounts deflator (DEFL) for private final consumption expenditure (households and non-profit institutions serving households, NPIs).

Meanwhile, the Eurostat HPI captures price changes of all residential properties purchased by households (flats, detached houses, terraced houses, etc.), both new and existing, independent of their final use and their previous owners. Only market prices are considered; self-build dwellings are therefore excluded. The land component is included.

The scoreboard indicator is the year-on-year growth rate of the deflated house price index (reference year 2015=100) and is calculated using the formula:

$$\frac{\frac{HPI_t}{DEFL_t}-\frac{HPI_{t-1}}{DEFL_{t-1}}}{\frac{HPI_{t-1}}{DEFL_{t-1}}}\times 100. \tag{12}$$

This indicator measures inflation in the house market relative to inflation in the final consumption expenditure of households and NPIs. More specifically, it measures how the prices in the house market (relative to the national accounts deflator for private final consumption expenditure) are accelerating compared to the previous year. This means that if the prices of residential properties are rising faster than prices of consumption (goods and services), but the discrepancy is stable, the MIP indicator will be zero. It issues a warning only when the divergence is accelerating. Our results do not confirm the common belief that property prices rising faster than headline inflation is a sign of upcoming crisis. Instead, the opposite sequence is suggested: rising property prices are ahead of increasing GDP at least one year in advance. Both variables occur in parallel.

Another indicator belonging to the same group (real estate prices) is RC (residential construction as a percentage of GDP). This is the only auxiliary indicator that is characterised by a PIP value above 0.5 for both dilution and tessellation methods. This tracks the actual construction (not sales) of housing and is part of gross fixed capital formation (GFCF). GFCF consists of resident producers' acquisitions (less disposals) of fixed assets during a given period plus certain additions to the value of non-produced assets realised by the productive activity of producer or institutional units. The higher the share of RC, the higher the possibility of crisis (fall in GDP) the following year. RC is more related to the real economy than the previous one (HPI deflated), which refers to the prices.

NULC (nominal unit labour cost index — 3-year % change) is the main indicator with the second-best PIP value. NULC index is defined as the ratio of labour cost to labour productivity, where labour cost is the ratio of the compensation of employees (current prices) to the number of employees, and labour productivity is the ratio of gross domestic product (at market prices in millions; chain-linked volumes reference year=2010) to total employment.

The scoreboard indicator is the percent change of nominal unit labour cost (NULC) over three years and is calculated using the formula:

$$\frac{NULC_t - NULC_{t-3}}{NULC_{t-3}}. \tag{13}$$

Our results confirm the expected relationship: rising labour costs negatively influence competitiveness and, as a result, GDP. However, this indicator is not calculated relative to foreign countries. It solely indicates that rising labour cost relative to labour productivity is a negative phenomenon (assuming other countries do not follow this scheme).

GGSD (general government sector debt — % of GDP) is the main MIP indicator which represents the indebtedness group. General government gross debt (GGGD) means total gross debt at nominal value outstanding at the end of the year and consolidated between and within the sectors of general government in the following categories: currency and deposits, debt securities, and loans. Basic data are expressed in national currency and converted into euros using end-year exchange rates for the euro provided by the European Central Bank. The MIP headline indicator is expressed as a percentage of GDP and is calculated as:

$$\frac{GGGD_t}{GDP_t} \times 100. \tag{14}$$

Unlike the previous indicators, GGSD is the result of decisions of the authorities of individual countries, not of economic processes. We demonstrate that the rise in public debt usually precedes the crisis. This can be taken as an argument against the policy of excessive indebtedness. However, one should be careful in making conclusions; perhaps the authorities usually see the symptoms of a crisis and then take action resulting in an increasing public debt. There is also a possibility that public debt is not so much causing a crisis (GDP decline), but accompanying negative phenomena in the economy, which eventually lead to a decline in economic activity. In any case, an increase in public debt in relation to GDP should always be a warning signal for economic authorities.

The ART [activity rate (15–64 years) — % point change (t, t–3)] has a PIP above 0.5 only when the dilution method was applied. The activity rate is the percentage of the economically active population aged 15–64 of the total population of the same age. According to the definitions of the International Labour Organisation, people are classified as employed, unemployed, or economically inactive. The economically active population (also called the labour force) is the sum of employed and unemployed persons. Inactive persons are those who were neither employed nor unemployed during the reference week. This MIP indicator is the three-year change in percentage points. The result of our research is not surprising; one might expect that an increase in the percentage of economically active people leads to an increase in GDP.

The next three indicators were significant only for the tessellation prior method.

PLH (People living in households with very low work intensity — % of total population aged 0–59, 3-year change in pp) is the only statistically significant variable which represents the group of people living in poverty. This auxiliary indicator measures the number of people aged 0–59 living in households where the adults (aged 18–59) worked less or equal to 20% of their total work potential during the past year. Students are excluded. Our results suggest that a rising share of people living in households with very low work intensity precedes an increase in GDP. We consider this to be completely unintuitive and contrary to expectations.

At this point, it is worth emphasising that the results of our study should not serve as a sole reason to negate the conclusions of the Council that social and labour market indicators are not relevant for identifying macro-financial risks (Council of the EU, 2016). Rather, the chosen research method allows us to conclude that the inclusion of the ART and PLH variables improves the model's ability to predict fluctuations in the GDP growth rate over the period under study.

EMS5 (export market shares — 5 years % change, main indicator) is calculated by dividing the exports of the country (EXP_c) by the total exports of the world (EXP_{world}). Therefore, the indicator measures the degree of importance of a country within the total exports of the world. For the calculation at current prices, the market share refers to the world trade (world export market share). The rationale for using this main indicator is to measure trade competitiveness and to capture non price competitiveness. A country might lose shares of export market not only if exports decline but most importantly if its exports do not grow at the same rate of world exports and its relative position at the global level deteriorates.

To capture the structural losses in competitiveness that can accumulate over longer time periods, the MIP scoreboard indicator is the percentage change of export market shares (of goods and services) over five years and is calculated as follows:

$$\frac{\frac{EXP_{c,t}}{EXP_{world,t}} - \frac{EXP_{c,t-5}}{EXP_{world,t-5}}}{\frac{EXP_{c,t-5}}{EXP_{world,t-5}}} \times 100. \tag{15}$$

Increasing ESM5 allows to expect GDP growth in the next year, which seems understandable.

The SOECD (export performance against advanced economies — 5-year % change, auxiliary indicator) is similar to the previous indicator but relates to the share of OECD exports only. Interestingly, our calculations suggest a negative sign of the coefficient in the model. This would mean that a growing share of a country's exports in the exports of OECD countries would precede a decline in GDP in the following year. This rather strange relationship is difficult to explain, especially in the context of what has been stated above concerning the EMS5 variable. If both correlations were to prove true, we would have to deal with the following situation: the exports of a given country increased in relation to its exports five years ago faster than world exports in the same period, and at the same time slower than exports of OECD countries:

$$\frac{EXP_{c,t}}{EXP_{world,t}} - \frac{EXP_{c,t-5}}{EXP_{world,t-5}} > 0 \text{ or } \frac{EXP_{c,t}}{EXP_{c,t-5}} > \frac{EXP_{world,t}}{EXP_{world,t-5}}, \tag{16}$$

and

$$\frac{EXP_{c,t}}{EXP_{OECD,t}} - \frac{EXP_{c,t-5}}{EXP_{OECD,t-5}} < 0 \text{ or } \frac{EXP_{c,t}}{EXP_{c,t-5}} < \frac{EXP_{OECD,t}}{EXP_{OECD,t-5}}. \tag{17}$$

Put together:

$$\frac{EXP_{world,t}}{EXP_{world,t-5}} < \frac{EXP_{c,t}}{EXP_{c,t-5}} < \frac{EXP_{OECD,t}}{EXP_{OECD,t-5}}. \tag{18}$$

In such a configuration, one should expect GDP growth in a given country supported by both variables (EMS5 and SOECD). Similarly, our model shows that GDP is likely to decline if the growth in OECD countries' exports is the lowest, the country's exports growth is higher, and world exports rise at the fastest possible pace. It is quite obvious that such relationships (increases in the country's exports "between" OECD growth and the world) do not have to be systematic and heavily depend on exchange rates.

5. Conclusion

The aim of this paper was to assess the predictive power of macroeconomic imbalance procedure all MIP indicators in predicting crises, especially the auxiliary, which are most often omitted in the literature. Real GDP growth, one of the auxiliary variables, was regarded by us as the dependent variable, a proxy for improvement or deterioration of economic situation in every Member State.

The predictive power of the MIP indicators on assessment of GDP growth rate of 26 European Union countries was examined using Bayesian model averaging.

Our results show that only four main indicators [HPI (house price index, deflated — 1 year % change), NULC (nominal unit labour cost index — 3 years % change), GGSD (general government sector debt — % of GDP), EMS5 (export market shares — 5 years % change)], and another four auxiliary indicators [RC (residential construction as % GDP), ART (activity rate (15–64 years) — % point change (t, t–3)), PLH (people living in households with very low work intensity — % of total population aged 0–59, 3-year change in pp), SOECD (export performance against advanced economies — 5-year % change) seem to be able to predict upcoming crises. However, in some cases the relationship between the indicator and GDP change is surprising and not easy to justify.

Our research shows that only a few MIP indicators out of the 14 main and 28 auxiliary indicators can predict negative changes in economic activity. Others do not have any substantial predictive strength and their inclusion does not enhance the effectiveness of the MIP tool in identifying increasing macroeconomic imbalances. Furthermore, the predictive power of these indicators remains negligible, regardless of the variable used as a proxy for crisis or excessive macroeconomic imbalances. This is in line with the results of other researchers who have shown that only selected variables are able to predict upcoming imbalance, which in turn can lead to the crisis situations, however defined.

It can be inferred that many indicators were included in the MIP procedure not due to their predictive capabilities, but rather because of the specific importance of the areas to which they pertain in relation to the objectives of the European Commission at the time the procedure was established. While this approach may be understandable from a political and social perspective, it undermines the ability of the procedure to achieve its fundamental objective. It would therefore be recommended to separate those indicators that lack predictive power into a separate tool that will remain a part of the European Semester but will not impede the ability of MIP indicators to anticipate growing and potentially dangerous imbalances. Accordingly, it seems reasonable to recommend that the European Commission should reduce the number of crisis-related indicators and focus on those that show relatively strong links to changes in GDP. Of course, further research is needed to confirm the stability of these links over time.

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Acknowledgements

Author contributions: authors have given an approval to the final version of the article. Authors contributed to this work equally.

Funding: this research was fully funded by the Internal Research Grant of the Faculty of Economics and Finance of the Wrocław University of Economics and Business — MPK B701163.

Note: the results of this study were presented at *12th International Conference on Applied Economics Contemporary Issues in Economy* (June 29–30, 2023, Poland).

Appendix

Table 1.
Variables with posterior inclusion probability of including them in the model >0.5

Statistic	PIP	PM	PSD	SPM	SPSD	P(+)
HPI	1.000	0.147	0.025	0.347	0.059	1.000
	1.000	0.147	0.026	0.346	0.062	1.000
NULC	0.992	−0.116	0.029	−0.302	0.077	0.000
	0.978	−0.105	0.031	−0.274	0.081	0.000
GGSD	0.875	−0.020	0.011	−0.196	0.105	0.000
	0.932	−0.025	0.011	−0.250	0.106	0.000
RC	0.763	−0.261	0.174	−0.143	0.095	0.000
	0.545	−0.170	0.177	−0.093	0.097	0.000
ART	0.515	0.176	0.197	0.069	0.077	1.000
PLH						
	0.502	0.091	0.103	0.082	0.093	1.000
EMS5						
	0.776	0.128	0.079	0.722	0.447	0.999
SOECD						
	0.776	−0.118	0.074	−0.741	0.461	0.001

Source: Own preparation.

Table 2.
MIP scoreboard indicators: main and *auxiliary*

Variable	Description
real GDP — dependent variable	
	real GDP — 1 year % change
external imbalances — independent variables	
CAB	current account balance — % of GDP, 3-year average
NLB	*current plus capital account (net lending-borrowing) in % GDP*
NIP	net international investment position — % of GDP
	~~net international investment position excluding non-defaultable instruments in % GDP~~
EMS5	export market shares — 5-year % change
EMS1	*export market share, in volume — 1 year % change*
SOECD	*export performance against advanced economies — 5-year % change*
NTBEP	*net trade balance of energy products in % of GDP*
DIREF	*foreign direct investment in the reporting economy, flows in % of GDP*
DIRES	*foreign direct investment in the reporting economy, stocks in % of GDP*
international competitiveness — independent variables	
REER	real effective exchange rate, 42 trading partners — 3-year % change
REEREA	*real effective exchange rates — euro area trading partners — 3-year % change*
NULC	nominal unit labour cost index — 3-year % change
LP	*labour productivity — 1-year % change*
ULCP	*unit labour cost performance relative to euro area — 10-year % change*
TT	*terms of trade (goods and services) — 5-year % change*

Variable	Description
GFCF	*gross fixed capital formation in % GDP*
GDERD	*gross domestic expenditure on R&D in % of GDP*
indebtedness — independent variables	
PSCF	private sector credit flow, consolidated — % of GDP
PSD	private sector debt, consolidated — % of GDP
TFSL	total financial sector liabilities, non-consolidated — 1-year % change
GGSD	general government sector debt — % of GDP
	~~*gross non-performing loans of domestic and foreign entities in % of gross loans*~~
	~~*household debt, consolidated (including NPISH) in % of GDP*~~
	~~*consolidated banking leverage, domestic and foreign entities — total assets/total equity*~~
real estate prices — independent variables	
HPI	house price index, deflated — 1 year % change
	~~*house price index (2015=100), nominal — 3 year % change*~~
RC	*residential construction as % GDP*
labour market — independent variables	
AR	*activity rate (15–64 years) — % point change (t, t–3)*
ART	activity rate — % of total population aged 15–64
UR	unemployment rate — 3-year average
EI	*employment — 1 year % change*
LTURT	long-term unemployment rate — % of active population in the same age group, % point change (t, t–3)
LTUR	*long-term unemployment rate — % of active population aged 15–74*
YURT	youth unemployment rate — % of active population in the same age group, % point change (t, t–3)
YUR	*youth unemployment rate — % of active population aged 15–24*
poverty — independent variables	
PRPE	*people at risk of poverty or social exclusion — % of total population*
PRPAE	*people at risk of poverty after social transfers — % of total population*
SMDP	*severely materially deprived people — % of total population*
PLH	*people living in households with very low work intensity — % of total population aged 0–59*
YPEE	*young people neither in employment nor in education and training — % of total population aged 15–24*

Source: Eurostat (2023b).

Table 3.
Estimation results: dilution prior, one-year lag

Method	Dilution prior					
Statistic	PIP	PM	PSD	SPM	SPSD	P(+)
HPI	1.000	0.147	0.025	0.347	0.059	1.000
NULC	0.992	−0.116	0.029	−0.302	0.077	0.000
GGSD	0.875	−0.020	0.011	−0.196	0.105	0.000
RC	0.763	−0.261	0.174	−0.143	0.095	0.000
ART	0.515	0.176	0.197	0.069	0.077	1.000
PLH	0.353	0.058	0.088	0.052	0.080	1.000
EMS5	0.278	0.040	0.072	0.224	0.409	0.978
SOECD	0.277	−0.037	0.067	−0.231	0.422	0.016
GDERD	0.272	−0.177	0.337	−0.042	0.080	0.000
NLB	0.201	0.021	0.049	0.032	0.074	0.999
YPEE	0.198	0.025	0.057	0.028	0.065	1.000
PSCF	0.168	−0.004	0.010	−0.015	0.039	0.000
REEREA	0.161	−0.011	0.030	−0.017	0.047	0.000
GFCF	0.126	−0.017	0.051	−0.019	0.058	0.029
TT	0.119	0.009	0.030	0.009	0.032	0.964
PRPE	0.113	0.007	0.026	0.014	0.053	0.987
AR	0.113	−0.008	0.029	−0.011	0.039	0.035
LTURT	0.109	−0.019	0.070	−0.013	0.048	0.008
LP	0.104	0.012	0.045	0.009	0.033	1.000
CAB	0.092	0.009	0.034	0.013	0.051	0.971
SMDP	0.089	0.004	0.016	0.009	0.039	0.973
DIRES	0.069	0.000	0.000	0.003	0.018	0.909
ULCP	0.068	0.000	0.001	0.003	0.017	0.992
EI	0.067	−0.010	0.049	−0.007	0.032	0.013
PRPAE	0.059	−0.004	0.030	−0.004	0.030	0.277
NTBEP	0.057	0.000	0.029	0.000	0.016	0.574
PSD	0.051	0.000	0.001	0.000	0.014	0.568
DIREF	0.050	0.000	0.000	0.000	0.011	0.710
YURT	0.050	0.002	0.016	0.004	0.036	0.750
REER	0.047	0.000	0.014	0.001	0.024	0.247
NIP	0.044	0.000	0.001	0.000	0.015	0.556
EMS1	0.042	0.000	0.009	0.000	0.011	0.374
TFSL	0.039	0.000	0.004	0.000	0.013	0.691
YUR	0.035	0.000	0.007	−0.001	0.018	0.408
LTUR	0.035	0.000	0.023	0.000	0.019	0.564
UR	0.034	0.000	0.013	0.001	0.015	0.624

Source: Own preparation.

Table 4.
Estimation results: tessellation prior, one-year lag

Method	Tessellation prior					
Statistic	PIP	PM	PSD	SPM	SPSD	P(+)
HPI	1.000	0.147	0.026	0.346	0.062	1.000
NULC	0.978	−0.105	0.031	−0.274	0.081	0.000
GGSD	0.932	−0.025	0.011	−0.250	0.106	0.000
RC	0.545	−0.170	0.177	−0.093	0.097	0.000
ART	0.301	0.095	0.164	0.037	0.064	1.000
PLH	0.502	0.091	0.103	0.082	0.093	1.000
EMS5	0.776	0.128	0.079	0.722	0.447	0.999
SOECD	0.776	−0.118	0.074	−0.741	0.461	0.001
GDERD	0.242	−0.158	0.321	−0.037	0.076	0.000
NLB	0.145	0.014	0.040	0.021	0.061	0.998
YPEE	0.165	0.021	0.054	0.024	0.062	0.998
PSCF	0.113	−0.002	0.007	−0.009	0.031	0.000
REEREA	0.070	−0.004	0.019	−0.006	0.031	0.000
GFCF	0.253	−0.036	0.071	−0.041	0.080	0.006
TT	0.055	0.002	0.018	0.002	0.019	0.742
PRPE	0.108	0.018	0.086	0.037	0.174	0.977
AR	0.239	−0.023	0.047	−0.031	0.062	0.004
LTURT	0.084	−0.020	0.087	−0.013	0.060	0.038
LP	0.076	0.008	0.035	0.006	0.026	1.000
CAB	0.062	0.004	0.025	0.006	0.038	0.848
SMDP	0.115	−0.002	0.047	−0.005	0.114	0.789
DIRES	0.037	0.000	0.000	0.001	0.012	0.667
ULCP	0.053	0.000	0.001	0.002	0.015	0.969
EI	0.118	−0.021	0.070	−0.014	0.046	0.004
PRPAE	0.115	−0.023	0.091	−0.022	0.090	0.051
NTBEP	0.056	−0.005	0.033	−0.003	0.018	0.128
PSD	0.042	0.000	0.001	−0.001	0.014	0.263
DIREF	0.036	0.000	0.000	0.001	0.010	0.810
YURT	0.092	0.007	0.029	0.016	0.065	0.969
REER	0.037	0.000	0.012	0.000	0.019	0.241
NIP	0.039	0.000	0.001	0.000	0.014	0.460
EMS1	0.037	0.000	0.009	0.000	0.011	0.269
TFSL	0.040	0.000	0.004	0.001	0.013	0.785
YUR	0.033	0.000	0.007	0.000	0.019	0.566
LTUR	0.045	0.004	0.033	0.003	0.027	0.868
UR	0.031	0.001	0.017	0.001	0.019	0.756

Source: Own preparation.