How Effective is Macroeconomic Imbalance Procedure (MIP) in Predicting Negative Macroeconomic Phenomena?

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Abstract:

Purpose: The evaluation of the predictive power of Macroeconomic Imbalance Procedure (MIP) indicators is crucial for coordinating the economic policies of the EU countries. MIP is one of the pillars of the economic crisis prevention procedure.
Design/Methodology/Approach: Using the Bayesian model averaging (BMA) framework, we compare different models where lagged MIP indicators try to explain several macroeconomic variables associated with crises.
Findings: The results show that the importance of MIP indicators between 2001 and 2017 was diversified. In the case of annual real GDP growth, including a 1-year lagged house price index, nominal unit labor cost, real effective exchange rate (1-year change), and export market share in the model improves the model's explanatory power most. For explaining inflation rate, export market share (again), and house price index is valid.
Practical Implications: The construction of the MIP procedure should be simplified, as not all indicators have a fundamental capability of predicting excessive imbalances which result in crisis events. Indicators are relevant to the current economic priorities of the EU, which do not have a significant capacity to anticipate crisis phenomena should be excluded from the Alert Mechanism.
Originality/Value: We use the Bayesian model averaging (BMA) framework BMA that directly deals with heterogeneity by finding a combination of regressors that account for it to the greatest extent within a conditioning set of information. Consequently, BMA appears to be ideally suited for finding robust determinants of "crisis" variables.

Keywords: Macroeconomic Imbalance Procedure, Bayesian model averaging, early warning system.

JEL Classification: E02, E61, C25.
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1. Introduction

To enable efficient coordination of economic policies of the EU Member States and to prevent excessive macroeconomic imbalances in the EU, support structural reforms, create more jobs and growth, and foster investment, the European Semester was introduced. The Macroeconomic Imbalance Procedure (MIP) is a critical step in the European Semester. The goal of the MIP is to identify and prevent potentially harmful macroeconomic imbalances that could adversely affect economic stability in the EU.

According to the official European Commission (EC) website, the scoreboard aims to trigger in-depth studies and analyses to determine whether potential imbalances identified in the early warning system are benign or problematic (European Commission, 2011). This paper continues the research on the ability or degree of suitability of MIP indicators to foresee negative phenomena in the economy. Using the Bayesian model averaging (BMA) framework, we compare the different models, where lagged MIP indicators explain several macroeconomic variables associated with crises. The results show that the importance of MIP indicators between 2001 and 2017 is diversified, and only one (long-term unemployment rate) has no significance.

2. Literature Review

The following scoreboard MIP indicators are currently in use: current account balance [CAB3yr], net international investment position [NIIP], real effective exchange rate, 1-year % change [REERtp] and 3-year % change [REERtpi], export market share [ExMark5yr], nominal unit labour cost index [NULC3yr], house price index [HousePriceIn], private sector credit flow consolidated [PSCFc], private sector debt consolidated [PSCDc], general government gross debt [GenGovDbt], unemployment rate [UR3yr], total financial sector liabilities unconsolidated [TFSLnc], activity rate change (% of total population aged 15-64) [ActRateCh], long-term unemployment rate change (% of active population aged 15-74) [LTUR3yr], and youth unemployment rate change (% of active population aged 15-24) [YUR3yr]. For details concerning definitions of MIP indicators see "Macroeconomic Imbalance Procedure Scoreboard" and Erhart *et al.* (2018).

Before introducing the Macroeconomic Imbalance Procedure (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 government deficits (3% of GDP) and government debt levels (60% of GDP). Unfortunately, as Ioannou and Stracca (2014) show, the Stability and Growth Pact has positively contributed to the government's primary balance only before the introduction of the euro, but not after that. The problem of the ineffectiveness of the Pact has been addressed, among other things, by Bergman *et al.* (2016) and Hallerberg *et al.* (2007).

MIP should not be understood as a classical Early Warning System (EWS). Its purpose is not to quantify the probability of a crisis. It is intended to signal and monitor the build-up of macroeconomic imbalances that lead to the classically understood crisis phenomena. Despite this, the European Commission and most researchers consider the MIP scoreboard an EWS and analyze it as a classic EWS.

Neither legal documents nor the EC provides an exact definition of macroeconomic imbalance. This is politically understandable and allows for certain flexibility but makes it very difficult to evaluate the effectiveness of the MIP procedure. Another obstacle in the analysis is that the MIP is only an element of the EU Member States' broad coordination mechanism of economic policies, which is the European Semester. The MIP is intended to prevent imbalances within the Member States and across them (Mazzocchi and Tamborini, 2021). Regular monitoring of the alert indicators (summarized each spring in the form of the Alert Mechanism Report - AMR) 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 prepares recommendations for corrective actions. The Commission shall, after that, recommend that the Council requires the country submission of a corrective action plan detailing measures to address their challenges which should be implemented within a given period.

According to Domonkos *et al*. (2017), MIP-focused studies may be divided into two categories. The first one discusses the procedure of the MIP (its legal, institutional, and political aspects as well as the willingness of Member States to implement the recommendations of the EC), and the second one analyses the indicators included in the scoreboard, especially their ability to predict crises. We have concentrated on the rarely investigated area of research - empirical studies on the predictive relevance of MIP indicators. Most of those studies used various types of signal approaches that implement a database of indicators. A particular hand signals a crisis when its level exceeds a pre-defined alarm threshold.

Using various crises definitions, the authors have reached considerably different conclusions. Knedlik (2014) found that current account, net international investment position, and nominal unit labor costs were the most valuable predictors of a debt crisis. However, Mazzocchi and Tamborini (2021) point out that a current account surplus is not expected to be a clear and present danger for stability in the MIP framework. Csortos and Szalai (2014) argued that only the current account deficit and the unemployment rate had sent accurate alarm signals relatively more often than false ones in case of a crisis event defined as a GDP gap. Boysen-Hogrefe *et al.* (2015) found that private sector credit flow, house prices, and personal 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). An extensive

review of papers on the subject can be found in the report published by the Joint Research Centre (Erhart *et al.,* 2018).

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) demonstrated that credit-to-GDP, equity, and property price gaps, in percent relative to trends, can detect the build-up of risks of upcoming banking distress in an economy. Sohn and Park (2016) examined EWS of the banking crisis and bank-related stock returns and found that credit growth is more informative in predicting bank sector crisis than the credit-to-GDP gap. Their findings have been confirmed to a large extend by Geršl and Jašová (2018).

This paper aims to determine which MIP indicators are systematically good predictors of unfavorable movements in certain variables, usually associated with crises. We define concerns broadly, in terms of both financial and real symptoms, as:

- downturn in GDP,
- (high) inflation,
- (strong) depreciation or devaluation of the home currency,
- downturn in stock exchange index.

The rationale behind the selection of dependent variables relies on literature. Mishkin (2011a; 2011b) recognizes GDP contraction as a symptom of the (economic) crisis, often accompanied by an increase in unemployment. Domonkos *et al.* (2017) use the output gap (deviation of real GDP from potential GDP) as a crisis indicator, even if the precise calculation of potential output is somewhat ambiguous. Siranova and Radvanský (2018) use deviations of the real GDP growth from its five-year average by more than one standard deviation to capture crisis periods.

According to Crockett (1996), a crisis must have a measurable effect on actual activity and the rate of inflation. High inflation is associated with macroeconomic instability and impacts the real return on assets, discouraging savings and incentivizing borrowing, increasing the likelihood of experiencing a crisis (Caggiano *et al.,* 2016). Even in the Eurozone, existing data suggest that relatively high inflation in the periphery has led to those countries' exports growing more expensive than exports from lower inflation eurozone economies. Both the current account and financial account-driven narratives of the crisis envision such inflation (Fuller, 2018). Sometimes high inflation rates reflect an increase in exchange market pressure (Barkbu, Eichengreen, and Mody, 2012).

Claessens and Kose (2013) differentiate between four types of financial crises-sudden stops, debt crises, banking crises, and currency crises. The latter means a sharp depreciation or devaluation. The definition of significant devaluation or depreciation ranges from 15% to more than 30% across the different studies (Šmídková *et al.*,

2012), but in the EU countries, much less severe weakening of currency could be considered as crisis-like.

Waelti (2015), addressing sudden stops, recognizes the weakening of home currency as a crisis indicator, along with sovereign debt distress, stock market crashes. Construction of the exchange market pressure index, a weighted average of monthly exchange rate changes against major currencies, may be attributed to Kaminsky, Elizondo, and Reinhart (1998). The crisis was identified when the index was above its mean by more than three standard deviations. Berg, Borensztein, and Pattillo (2005) define (currency) crisis as a situation when a weighted average of one-month changes in the exchange rate and reserves more than 3 (country-specific) standard deviations above the country average.

We follow Frankel and Saravelos (2012), who use little local currency percentage change versus the US dollar as a crisis measure. Stock market drop, measured by a falling index, is another clear sign of a crisis. For example, Frankel and Saravelos (2012) use equity market returns in domestic stock market benchmark indices over the same period as above, adjusted for the volatility of returns, as crisis indicators. Also, Rose and Spiegel (2012) consider percentage change in the national stock market, collected from federal sources, as one of the observable indicators of the crisis. Lo Duca *et al*. (2017) apply a more complex approach combining significant asset price correction with banking, currency, and sovereign risk materialization. Fu *et al.* (2020) deal with a stock market crisis, it occurs when the CMAXt ratio (the current stock index divided by the maximum stock index level for the period up to time t) falls sharply enough.

Of course, other events may indicate a crisis (Mızrak and Yüksel, 2019 for a comprehensive overview of the literature on financial problems). For example, Catão and Milesi-Ferretti (2014) focus on defaults and rescheduling events and events associated with ample IMF support. Similarly, Christofides, Eicher, and Papageorgiou (2016) observe whether a country requested access and received IMF approval. Such events are rather extreme from the EU perspective. Knedlik (2014) 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. But anyway, four phenomena considered in this paper are unambiguously synonymous with symptoms of a crisis.

This paper aims to identify MIP indicators that may be considered robust explanatory variables for four selected crisis indicators. The MIP variables selected by the European Commission reflect general opinions on which imbalances may be dangerous for economic stability. However, we cannot expect any single early warning signal for all dimensions of the crises (Christofides, Eicher, and Papageorgiou, 2016). Hence, it can be hypothesized that some of the MIP indicators have greater predictive strength than others for one or more crisis dimensions. Their identification could have practical implications for the reaction function of the

European Commission. The Commission understands the concept of macroeconomic imbalances in a very broad way. Meanwhile, studies show that it is difficult to identify a methodology to compare the effectiveness of different alert systems (Candelon *et al.,* 2012). In our opinion, it is even more challenging to assess the efficacy of an early warning system when the definition of a crisis (in this case - an imbalance) is not precise. Therefore, it was necessary to check the relevance of individual indicators in predicting different types of crises.

Crisis-related indicators, constituting MIP variables themselves (e.g., unemployment, excessive government debt), were of course not considered as dependent variables.

3. Research Methodology

The Bayesian model averaging (BMA) framework compares the different models and their assessment based on empirical grounds. In the literature, country heterogeneity in the data is dealt with using random or fixed-effects models. Those models are well fit when a single theory is tested at a time, and unexpected and fixed effects serve as a way of covering up the ignorance about the sources of heterogeneity (Wooldridge, 2010). On the other hand, BMA deals with heterogeneity directly by finding a combination of regressors that accounts for it to the greatest extent within a conditioning set of information. Consequently, BMA appears to be ideally suited for finding robust determinants of "crisis" variables. BMA assumes the following general form of the model:

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

where j=1, 2,..,m denotes the number of the model, y_j is a vector $(n \times 1)$ of the values of the dependent variable, α_j is a vector of intercepts, β_j is a vector $(K \times 1)$ of unknown parameters, X_j is a matrix $((N * T) \times K)$ of explanatory variables, whereas ε_j is a vector of residuals which are assumed to be conditionally homoscedastic and normally distributed, $\varepsilon \sim N(0, \sigma^2 I)$. N denotes the number of cross-sections (28 EU-countries), T the length of the analyzed period (17 years), and K is a total number of regressors (MIP indicators). For the space of all models, unconditional posterior distribution of coefficient β is given by (Moral-Benito, 2016):

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

where: $P(\beta|M_j, y)$ is the conditional distribution of coefficient β for a model M_j, and PMP is the posterior probability of the model. Using the Bayes' theorem, PMP can be expressed as (Masanjala and Papageorgiou, 2008):

$$PMP = \frac{L(y|M_j) * P(M_j)}{\sum_{j=1}^{2^K} l(y|M_j) * P(M_j)}, \tag{3}$$

where $L(y|M_j)$ is model specific marginal likelihood and $P(M_j)$ is prior probability of model M_j.

The value of the coefficient β is characterized by a normal distribution with zero mean and variance $\sigma^2 V_j$, hence:

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

It is assumed that the prior variance matrix V_j is proportional to the covariance in the sample:

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

where g is the proportionality coefficient, proposed by (Zellner, 1986). Fernandez, Ley, and Steel (2001) proposed the so-called 'benchmark prior':

$$g = \frac{1}{\max(n, k^2)}, \tag{6}$$

where $\frac{1}{n}$ is known as *UIP* – unit information prior (Kass and Wasserman, 1995), whereas $\frac{1}{k^2}$ is convergent to *RIC* – risk inflation criterion (Foster and George, 1994).

To specify prior model probability, non-informative priors are utilized. For the binomial model prior (Sala-i-Martin e*t al.*, 2004):

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

where EMS denotes expected model size, while k_j is the number of covariates in a given model. When $EMS = \frac{K}{2}$, it turns into a uniform model prior $(P(M_j) \propto 1)$ – priors on all the models are equal to $\frac{1}{2^K}$ (Eicher *et al.*, 2011). Binomial-beta model prior is given by (Ley and Steel, 2009):

$$P(M_j) \propto \Gamma(1 + k_j) * \Gamma\left(\frac{K-EMS}{EMS} + K - k_j\right). \tag{8}$$

When $EMS = \frac{K}{2}$ probability of each model size is equal $(= \frac{1}{K+1})$.
Using the PMPs in the role of weights allows for the calculation of unconditional posterior mean and standard deviation of the coefficient β_i. Posterior mean (PM) of the coefficient β_i, independently of the space of the models, is given by:

$$PM = E(\beta_i|y) = \sum_{j=1}^{2^K} P(M_j|y) * \hat{\beta}_{ij}, \tag{9}$$

where $\hat{\beta}_{ij} = E(\beta_i|y, M_j)$ is the value of the coefficient β_i estimated for the model M_j. The data was normalized before estimation, so the posterior means can be used to assess relative importance of the regressors. The posterior standard deviation (PSD) is equal to:

$$PSD = \sqrt{\sum_{j=1}^{2^K} P(M_j|y) * V(\beta_j|y, M_j) + \sum_{j=1}^{2^K} P(M_j|y) * [\hat{\beta}_{ij} - E(\beta_i|y, M_j)]^2}, \quad (10)$$

where $V(\beta_j|y, M_j)$ denotes the conditional variance of the parameter for the model M_j (Beck, 2019).

Posterior inclusion probability (PIP) is the probability of including the variable in the model after seeing the data. It is calculated as (Doppelhofer and Weeks, 2009):

$$PIP = P(x_i|y) = \sum_{j=1}^{2^K} 1(x_i = 1|y, M_j) * P(M_j|y), \quad (11)$$

where $x_i = 1$ signifies including the variable x_i in the model.

The posterior probability of a positive sign of the coefficient in the model, $P(+)$ is calculated in the following way (Beck, 2017):

$$P(+) = \begin{cases} \sum_{j=1}^{2^K} P(M_j|y) * CDF(t_{ij}|M_j), & if \quad E(\beta_i|y) > 0 \\ 1 - \sum_{j=1}^{2^K} P(M_j|y) * CDF(t_{ij}|M_j), & if \quad E(\beta_i|y) < 0 \end{cases} \quad (12)$$

where CDF denotes cumulative distribution function, while $t_{ij} \equiv (\hat{\beta}_i/\widehat{SD}_i|M_j)$.

4. Results

The benchmark prior rule (Fernandez *et al.*, 2001) given in equation (6) dictated the choice of the Unit Information Prior (Kass and Wasserman, 1995). Consequently, all the results reported in this section were obtained with UIP g prior and uniform model last (Ley and Steel, 2009), the combination advocated by Eicher, Papageorgiou, and Raftery (2011).

The robustness of the results was assessed using the absolute value of the ratio of posterior mean to posterior standard deviation (PM/PSD). Raftery (1995) considers a regressor robust if the ratio above is greater than 1, which suggests that the inclusion of the variable in the model improves the model's explanatory power. Masanjala and Papageorgiou (2008) propose a more stringent critical value of 1.3, corresponding to a frequentist 90% confidence interval. The results obtained by the application of BMA are presented in Tables 1-4. Different MIP indicators may be considered robust explanatory variables for other dependent variables.

Table 1. *BMA statistics, dependent variable: annual real GDP growth rate.*

Variable	PIP	PM	PSD	PM/PSD	P(+)
HousePriceIn	1,000	0,345	0,056	6,132	1,000
NULC3yr	1,000	0,310	0,070	4,443	0,000
REERtp	0,988	0,181	0,051	3,559	0,000
ExMark5yr	0,987	0,230	0,069	3,329	1,000
ActRateCh	0,726	0,092	0,069	1,345	1,000
GenGovDbt	0,584	0,091	0,089	1,016	0,000
PSCFc	0,540	0,068	0,073	0,932	0,000
CAB3yr	0,486	0,068	0,081	0,835	1,000
YUR3yr	0,179	0,031	0,087	0,361	0,999
TFSLnc	0,161	0,015	0,041	0,359	1,000
LTUR3yr	0,147	0,025	0,079	0,319	0,002
UR3yr	0,093	0,006	0,027	0,222	0,962
NIIP	0,076	0,003	0,022	0,125	0,370
PSCDc	0,057	0,001	0,013	0,064	0,335
REERtpi	0,056	0,001	0,015	0,074	0,883

Source: *Own research.*

In case of annual real GDP growth (Table 1), inclusion of 1-year lagged house price index, nominal unit labour cost, real effective exchange rate (1-year change) and export market share in the model improves most the explanatory power of the model.

Table 2. *BMA statistics, dependent variable: annual inflation rate.*

Variable	PIP	PM	PSD	PM/PSD	P(+)
ExMark5yr	1,000	0,284	0,048	5,865	1,000
HousePriceIn	1,000	0,323	0,053	6,078	1,000
NULC3yr	1,000	0,283	0,055	5,114	1,000
REERtpi	1,000	0,224	0,044	5,036	0,000
CAB3yr	0,999	0,289	0,074	3,926	0,000
YUR3yr	0,993	0,227	0,081	2,806	1,000
NIIP	0,829	0,136	0,079	1,727	1,000
PSCFc	0,798	0,111	0,071	1,572	1,000
PSCDc	0,507	0,055	0,063	0,874	0,000
TFSLnc	0,409	0,044	0,061	0,720	1,000
ActRateCh	0,321	0,027	0,046	0,595	0,000
LTUR3yr	0,217	0,032	0,074	0,435	0,015
UR3yr	0,127	0,010	0,033	0,293	0,008
REERtp	0,056	0,001	0,012	0,103	0,001
GenGovDbt	0,053	0,001	0,013	0,071	0,134

Source: *Own research.*

For explanation of inflation rate (Table 2), again export market share and house price index are useful.

In order to foresee the stock exchange market change (Table 3), the house price index and the real effective exchange rate (3-years change) should be included in the model.

Table 3. *BMA statistics, dependent variable: annual stock exchange index change.*

Variable	PIP	PM	PSD	PM/PSD	P(+)
HousePriceIn	0,809	0,158	0,098	1,610	0,000
REERtpi	0,794	0,132	0,084	1,572	1,000
TFSLnc	0,672	0,122	0,102	1,200	1,000
CAB3yr	0,647	0,118	0,102	1,163	1,000
PSCFc	0,612	0,097	0,091	1,069	0,000
NIIP	0,326	0,046	0,077	0,600	1,000
PSCDc	0,171	0,016	0,042	0,374	0,000
UR3yr	0,107	0,009	0,035	0,247	0,954
YUR3yr	0,086	0,006	0,027	0,202	0,062
NULC3yr	0,084	0,005	0,027	0,195	0,056
GenGovDbt	0,075	0,004	0,023	0,170	0,046
LTUR3yr	0,074	0,004	0,023	0,159	0,086
REERtp	0,071	0,003	0,022	0,123	0,779
ExMark5yr	0,070	0,003	0,020	0,148	0,932
ActRateCh	0,052	0,001	0,013	0,078	0,939

Source: *Own research.*

Table 4. *BMA statistics, dependent variable: average exchange rates relative to the U.S. dollar*

Variable	PIP	PM	PSD	PM/PSD	P(+)
NIIP	1,000	0,481	0,074	6,541	0,000
CAB3yr	0,999	0,305	0,064	4,797	1,000
UR3yr	0,996	0,298	0,076	3,924	0,000
ActRateCh	0,985	0,187	0,055	3,421	1,000
PSCDc	0,985	0,197	0,057	3,421	0,000
GenGovDbt	0,713	0,113	0,086	1,314	1,000
ExMark5yr	0,132	0,012	0,038	0,307	0,002
REERtpi	0,080	0,004	0,021	0,201	0,000
REERtp	0,074	0,003	0,019	0,186	0,000
LTUR3yr	0,072	0,004	0,025	0,171	0,994
TFSLnc	0,062	0,002	0,016	0,116	0,867
PSCFc	0,059	0,002	0,016	0,120	0,001
NULC3yr	0,056	0,001	0,018	0,053	0,746
YUR3yr	0,056	0,001	0,018	0,045	0,677
HousePriceIn	0,050	0,000	0,012	0,001	0,748

Source: *Own research.*

Table 4 shows that in case of devaluation / depreciation quite different variables are at work: net international investment position, current account balance, 3-year average unemployment rate, activity rate change and private sector debt, consolidated.

Table 5 shows the values which have absolute value of the ratio of posterior mean to posterior standard deviation (PM/PSD) above 1. Double parentheses indicate that absolute values of the ratio of posterior mean to posterior standard deviation (PM/PSD) are above 1.3 and single parentheses, between 1 and 1.3. The sign shows

the direction of influence on four dependent variables, based on posterior probability of a positive sign of the coefficient in the model [P (+)].

Table 5. *Variables with PM/PSD indicator above 1*

MIP variable Crisis indicator (decline or increase)	GDP (decline)	Inflation (increase)	Stock exchange index (decline)	Exchange rate (increase)
Activity rate	((+))↓			((+))↑
Current account balance		((–))↓	(+)↓	((+))↑
Export market share	((+))↓	((+))↑		
General government gross debt	(–)↑			((+))↑
House price index	((+))↓	((+))↑	((–))↑	
Long-term unemployment rate				
Net international investment position		((+))↑		((–))↓
Nominal unit labour cost index	((–))↑	((+))↑		
Private sector credit flow, consolidated		((+))↑	(–)↑	
Private sector debt, consolidated				((–))↓
Real effective exchange rate (1-year change)	((–))↑			
Real effective exchange rate (3-years change)		((–))↓	((+))↓	
Total financial sector liabilities, non-consolidated			((+))↓	
Unemployment rate				((–))↓
Youth unemployment rate		((+))↑		

Source: *Own research.*

In addition, we indicate by arrows (↑ and ↓), whether an increase or decrease of the variable in a row would forerun a "crisis". For example, first row suggests, that relationship between activity rate and GDP as well exchange rate is positive ((+)). This means: a decline (↓) in activity rate may be associated with prospective GDP fall, but an increase (↑) in activity rate may weaken the home currency.

Accordingly, we may conclude which changes in MIP indicators could be associated with consecutive deterioration of economic situation, i.e.: fall in GDP, (too) high inflation, fall in stock exchange index and rise in exchange rate (devaluation / depreciation). While fall in GDP and stock exchange index should be always perceived as "bad", rising inflation and weaker home currency – not necessarily, especially when inflation is below 2% and home currency depreciates only slightly restoring competitiveness of the economy. Keeping this in mind we try to identify which changes of MIP indicators precede (but not necessarily cause) "unfavourable" changes in GDP, inflation, stock exchange index and exchange rate.

Decline in GDP may be expected when the following MIP variables are rising, general government debt, nominal unit labour cost index and real effective exchange rate (1-year change). Also falling activity rate, export market share and house price index are signs of upcoming decrease in GDP. All these six MIP variables should require special attention.

Higher inflation may be observed the following year, when export market share, house price index, net international investment position, nominal unit labor cost index, private sector credit flow (consolidated), and youth unemployment rate rise. The same effect could bring two a little bit contradictory events: the deterioration in the current account balance (more extensive utilization of foreign savings) and the fall in the real effective exchange rate, 3-years change (rising competitiveness emerging from the depreciation of the home currency and relatively low domestic inflation compared with major trading partners). A deterioration in the current account balance, a fall in the real effective exchange rate (3-years change) and total financial sector liabilities (non-consolidated), as well as rising house price index and private sector credit flow (consolidated), are associated with a decline in stock exchange index.

Depreciation/devaluation of home currency may be expected when net international investment position, private sector debt (consolidated), and unemployment rate are falling. General government gross debt and activity rate are rising, and the current account balance is improving. Most of these relationships, except NIIP and government debt, are not convincing from the theoretical point of view.

Only a few MIP indicators exhibit clear-cut ability to forecast two crisis phenomena. Rising general government debt seems to adversely influence GDP growth and weakness of currency against the US Dollar. The nominal unit labor cost index coincides with consecutive GDP fall and rising inflation while increasing private sector credit flow (consolidated) – with higher inflation and stock exchange index drop. The behavior of a real effective exchange rate (3-years change) is a puzzle – one would expect the opposite relationships. Changes of other MIP indicators (activity rate, current account balance, export market share, house price index, NIIP) signal both crisis and non-crisis events. Accordingly, they cannot be classified as "bad" or "good." Private sector debt (consolidated), long-term unemployment rate, youth unemployment rate, and especially long-term unemployment rate are the worst indicators of upcoming crisis events.

5. Conclusions

Using the Bayesian model averaging (BMA) framework, we identified several MIP indicators, which may be considered robust explanatory variables for four dependent variables, usually associated with crises: fall in GDP and stock exchange index, rising inflation, and home currency depreciation/devaluation. Only three MIP indicators exhibit clear-cut and expected ability to forecast two crisis phenomena: rising general government debt, nominal unit labor cost index, and private sector credit flow (consolidated). The relationship between real effective exchange rate (3-years change) and "crisis events" is not expected and requires detailed investigation. The remaining MIP indicators are signaling either both crisis and non-crisis events (activity rate, current account balance, export market share, house price index, NIIP), or just one crisis phenomenon (private sector debt (consolidated), real effective exchange rate (1-

year change), unemployment rate and youth unemployment rate), but not always in a usual manner.

MIP is a procedure much more complicated than classical EWS used to assess the probability of a crisis in an economic sector (e.g., the banking sector) or bankruptcy of an individual enterprise. The original selection of MIP indicators was not a comprehensive study confirming the predictive power of individual indicators acting as a coherent system but rather a literature review of each hand individually. This is confirmed, among other things, in the Commission's occasional paper (European Commission, 2012). The individual indicators were selected to reflect the European Commission's priorities in coordinating and harmonizing Member States' economic policies and to be consistent with the pre-existing regulations on public finance discipline, originating partly from the Stability and Growth Pact.

Specifically, key policy messages to EC for improving the performance of the European semester (in particular – MIP) are as follows:

(1) Our findings suggest that the construction of the MIP procedure should be simplified, as not all indicators have a fundamental capability of predicting excessive imbalances which result in crisis events. Indicators that are relevant to the current economic priorities of the EU, which do not have a significant capacity to anticipate crisis phenomena, should be excluded from the Alert Mechanism Report. Still, they may continue to be monitored in the other steps of the European Semester framework. Such optimization of the procedure shall contribute to the transparency of the MIP procedure and should facilitate both its future evolution and the effectiveness of the recommendations made based on AMR.

(2) Special attention should be given to the following MIP indicators: general government debt, nominal unit labor cost index, and private sector credit flow (consolidated).

(3) A literature survey indicates that almost every researcher understands the concept of excessive imbalance differently. That is why we decided to study the four most significant areas affected by excessive imbalances and, consequently, crisis phenomena. The Commission should propose a uniform interpretation of "excessive imbalances" because only then will it be possible to honestly evaluate the effectiveness of the MIP procedure over time and possibly optimize it.

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