ARGUMENTA OECONOMICA
No 2 (49) 2022
ISSN 1233-5835; e-ISSN 2720-5088

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FORECASTING THE INSTABILITY OF POLISH BANKS

The paper presents a formalised procedure of the identification of financial stability EWI (Early Warning Indicators) for the Polish banking sector, in which a two-step procedure was applied. First, the author used a logit model to estimate of the biggest Polish banks' probabilities of default (PDs). Next, the calculated individual banks' PDs were used to prepare aggregated domestic banking system stability. In the last step, employing a set of multivariate Markov-switching models with distributed lags (MMSM-DL), the author applied this measure to identify EWI from the candidate macro, private and public debt, banking sector, financial markets and property prices indicators. The best performing EWI were selected with application of area under the receiver operating characteristic (AUROC) metrics and compared with an output of a popular logistic regression (LR) model.

To the best author's knowledge, this article presents for the first time a fully formalised analytical framework based on the MMSM-DL approach that combines microprudential and macroprudential data for the Polish banks financial stability EWI identification. Moreover, the survey supports the hypothesis that the Polish banking sector is stable with use of a formalised econometric procedure.

Keywords: macroprudential analysis, early warning indicators (EWI), Markov-switching models, AUROC (Area Under the Receiver Operating Characteristic)

JEL Classification: C34, C49, E32, G21
DOI: 10.15611/aoe.2022.2.06

Quote as: Łupiński, M. (2022). Forecasting the instability of Polish banks. *Argumenta Oeconomica*, 2(49).

1. INTRODUCTION

Early warning indicators (EWI) of financial stability are important tools of analysis used in macroprudential policymaking. By signalling with substantial advance symptoms of an incoming financial crisis, they provide financial supervisors with the appropriate time span needed to effectively apply supervisory instruments which allow to diminish the negative impact of financial distress on financial institutions. To appropriately fulfil their role, EWI should: 1) signal instabilities in the early stages of development, 2) discriminate clearly future crisis from non-crisis periods (optimal

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balance between false positive and true positive rate), 3) consider the specificity of the local financial sector, 4) be based on widely recognized indicators, 5) be selected using transparent procedure. Considering the recurrent character of banking crises (Baron et el., 2018), the author is convinced that the proposed EWI will be useful tool in forecasting the stability of the Polish banking sector.

In this paper the author presents a formalised procedure of the EWI identification of financial stability for the Polish banking sector, in which a two-step procedure was applied. First, a logit model was used to estimate of the biggest Polish banks' probabilities of default (PDs). Next, the calculated individual banks' PDs were used to prepare aggregated domestic banking system stability. In the last step, applying a set of multivariate Markov-switching models with distributed lags (MMSM-DL), the author employed this measure to identify EWI from the candidate macro, private and public debt, banking sector, financial markets and property prices indicators. The best performing EWI were selected with the application of the area under the receiver operating characteristic (AUROC) metrics and compared with an output of a popular LR model.

To the best of the author's knowledge, this article presents for the first time a fully formalised analytical framework based on the MMSM-DL approach that combines microprudential and macroprudential data for Polish banks financial stability EWI identification. Moreover, the survey supports the hypothesis that the Polish banking sector is stable with the use of a formalised econometric procedure.

The article consists of seven parts. Section 2 presents a general idea of early warning indicators and their importance for micro and macroprudential policymaking. Section 3 provides a literature overview on EWI and the determinants of economic and financial crises. Section 4 describes the dataset used in the survey, while Section 5 presents the two-step EWI identification procedure. Sections 6 and 7 describe the results and discuss the possibility of their practical application.

2. EARLY WARNING INDICATORS AND THEIR IMPORTANCE FOR PRUDENTIAL POLICY MAKING

The 2007+ crisis expanded prudential policy making with a macro perspective. The macroprudential policy is aimed at diminishing the impact of systemic risk that causes a loss in confidence and increased uncertainty about the functioning of the financial system and its parts (Smaga, 2014). As this kind of risk stems mainly from the cyclical character of the financial system, it seems crucial to provide decision makers with the tools able to identify different states of the financial cycle. To simplify the analysis, a vast majority of researchers assume that the economy can be in three phases: a normal state, a boom and a crisis. *Ex-post* all the states are identifiable, but in real-time they unfortunately cannot be observed directly. During a crisis, the banking sector loses its stability and cannot efficiently perform its crucial economic functions, namely effective financial resources and financial risk allocation as well as settling payments. The early warning indicators are supposed to give decision makes an insight into the current phase of the financial cycle, and assess possible banking sector instability to apply in advance macroprudential policy instruments such as countercyclical capital buffers or dynamic provisioning, reducing the negative impact of an incoming crisis.

There are several important criteria of EWI that should be taken into account when searching for the optimal ones, the most important being its appropriate timeliness. Optimal EWI should signal incoming crisis early enough to give time for effective policy actions. Some researchers suggest that EWI should start to signal a crisis at least half a year before its outbreak (Drehmann and Juselius, 2013). However, optimal EWI should not inform about a crisis too early as there are costs connected with macroprudential policy implementation. The second important ideal EWI's feature is stability; stable EWI show policymakers clear trends and allow them to be more decisive in their actions.

Two additional valuable characteristics of EWI are robustness and easy interpretability. Robustness means that their crisis signalling ability should not depend on different time series samples or crisis dating methodologies. Easy interpretability is closely connected with strong conceptual underpinnings of EWI that allow to provide the public with justifiable explanations of the taken policy actions.

In the real world, the signals from EWI can mislead policymakers. For example, they can introduce credit tightening when in fact there is no serious risk of financial system instability. Moreover, it is also almost impossible to assess the expected costs and benefits of implementing macroprudential policy instruments, namely estimate policymakers' utility function. In such cases, it is reasonable to use the second-best approach analysing the area under the receiver operating characteristic. The mathematical properties of the AUROC function allow to use curve metrics as a good proxy for the EWI quality measure. Bearing in mind the described advantages (Pepe, Janes and Longton, 2009)., AUROC was used to evaluate the performance of the EWI selected in this research.

In the macroprudential perspective, the Polish banking sector is currently perceived as well-balanced and stable. The assets to GDP ratio is 90% (compared with 272% for euro area), and loans to GDP and deposits/GDP ratios are 50% and 54%, respectively (89% and 85% for euro area countries; National Bank of Poland, 2018). The Polish banking sector is dominated by commercial banks aimed at maximising the profits of their shareholders. In 2017 commercial banks owned almost 65% of the total assets of financial institutions in Poland, whilst in the same year cooperative and affiliating banks reported 7% of the total financial assets (National Bank of Poland, 2018). Taking into account the Polish banking sector structure, EWI should be selected using the stability indicators based on granular data gathered from the biggest commercial banks and aggregated time series describing the general condition of the financial sector.

The most important components of an individual bank's stability indicator are probabilities of default (PDs). For the ten biggest Polish banks their current PDs can be mapped from ratings published by rating agencies (Moody's, Fitch and S&P). However, for the smaller banks PDs can only be estimated with a rating model. This model links the probability of default of the specific bank with a set of individual financial variables using a logistic function. The estimation of the model requires the application of the Polish banking sector distress events database. The records of this database are compiled from the history of Polish banks insolvencies and information about their participation in the stability support programmes. The banking sector distress database covers the period 2007-2018.

3. LITERATURE REVIEW

3.1. Causes of banking crises

The literature on the causes of banking crises is broad and constantly evolving. In the first wave of research, many academics focused on the consequences of panic and individual runs on the banks in the wake of a series of negative opinions (Bryant, 1980, Chari and Jagannathan, 1988). This literature also points out substantial macroeconomic shocks triggering market failures, causing massive assets losses of individual banks, followed by their insolvency (Gorton, 1998). Some researchers emphasised the role of unstable macro polices (Lindgren et al., 1996), mainly expansionary monetary and fiscal (Reinhart and Rogoff, 2009), as the prime cause of cyclical private debt accumulation, followed by the rapid growth of non-performing loans in commercial banks. Loose monetary policy was perceived as the main source of cheap money, inflating assets price bubbles (Brunnermeier, 2001) causing banking crises (Rochet, 2008).

After the outbreak of the 2007+ financial crisis, many authors tried to analyse the connections of the mentioned trend with the liberalisation of supervisory and regulatory principles. They found that the commercial banks' self-regulation approach was inappropriate to curb the negative external effects (Calomiris, 2010). The weak regulations led to the miscalculation of the banks' assets fair value, magnifying bank lending and credit quality procyclicality (Laux and Leuz, 2010; Schularick and Taylor, 2012). Simultaneously, the scale of the 2007+ crisis was related to rapid spillovers of systemic risk that affected banks operating in different jurisdictions (Alter and Beyer, 2014; Hautsch et al., 2015; Laeven and Valencia, 2018).

3.2. Systemic financial stability

To analyse systemic financial stability academic researchers used a broad scope of econometric and statistical methods. Some of them tried to capture the marginal contribution of individual financial entities to the general risk of the financial system employing the CoVaR framework (Adrian and Brunnermeier, 2008, 2016; Brunnermeier et al., 2012; Castro and Ferrari, 2014; López-Espinosa et al., 2012; Weiß and Mühlnickel, 2014). This approach compares cumulated system-wide losses caused by systemically important institutions, or their group failure, and the financial output of the system being in a normal condition.

Alternative idea of systemic financial stability analysis uses information included in financial market data. The Systemic Expected Shortfall (SES) model was applied to compute the expected value of individual institution undercapitalisation when the systemic risk spillovers occur and when the whole financial system is undercapitalised (Acharya, 2009; Acharya et al., 2017). There is also a formalised SRISK framework based on the SES model that measures systemic risk with the capital shortfall of a particular financial institution caused by severe market negative shock, focusing on the key institution's parameters such as its size, leverage and interconnectedness (Laeven et al., 2014, 2016). Moreover, the Component Expected Shortfall (CES) procedure extends the SES approach to directly measure the contribution of the individual institution to the system-wide systemic risk (Banulescu and Dumitrescu, 2015).

3.3. Early warning indicators literature

The first simple financial EWI were used in the late 1970s to detect currency crises (Bilson, 1979). In the 1990s, Frankel & Rose (1996) described formalised frameworks to find EWI signalling FX market crises, banking sector instabilities and interlinkages between these events. The initial early warning measures were constructed with univariate methods (Kaminsky et al., 1998). The next stage of EWI's development introduced multivariate models (Alessi and Detken, 2011; Frankel and Saravelos, 2010; Gerdrup, Kvinlog, and Schaanning, 2013; Giese et al. , 2014; Rose and Spiegel, 2009), among which the most popular were multinomial probit/logit and factor models. The quality check of the computed EWI was carried out with signal-to-noise ratio minimisation procedure or with the application of policymakers' loss function.

The further development of EWI's construction methods concentrated on extending input datasets and applying new statistical and econometric methods to substantially improve the quality of the estimated measures (Bussiere and Fratzscher, 2006, Frankel and Saravelos, 2010; Rose and Spiegel, 2009). The introduction of new estimation techniques included the application of non-linear Markov-switching models (Abiad, 2003) and network frameworks to capture systemic risk propagation across the financial system (Elsinger et al., 2006). Some researchers also tried to use panel methods to estimate aggregated (macroprudential) EWI based on individual (microprudential) input time series (Jahn and Kick, 2012). This research tries to adopt the last-mentioned approach which considers the unique futures of the Polish banking sector and the dataset's availability.

4. THE DATA

The survey described in the paper used two main groups of input time-series:

1) microprudential dataset depicting the Polish banks' financial situation (FINREP/COREP package),

2) macroeconomic and macroprudential dataset gathering thirty time series divided into five groups:

a) macreoconomic,

b) private/public debt,

c) banking sector,

d) financial markets,

e) property prices.

The time range of the data used covered the period of ten years, from 2007 to 2018.

4.1. Microprudential data

To select or prepare high quality early warning indicators, a reference database of the financial crisis is needed. For most European countries, researchers can use the European System of Central Banks Heads of Research Database. Fortunately (but unfortunately for the survey performed by the author) during the last twenty years the Polish banking sector was not touched by a financial crisis. Instead of using certain dates of financial distress, the author used an approach based on individual probabilities of default for the Polish biggest banks. This approach applied the methodology proposed in the scoring systems prepared for the US and German banking sector. The US federal depository regulators with their CAMEL framework, Moody's RiskCalc Model and Bundesbank savings banks scoring systems are based on microprudential data classified into four key groups: capital adequacy, credit risk sensitivity, market risk sensitivity and profitability. The individual banks' data used in the survey are shown in Table 1.

Table 1

Microprudential dataset used in the survey

Data group	**Capital adequacy**	**Credit risk sensitivity/ concentration**	**Market risk sensitivity**	**Profitability**
1	2	3	4	5
Variables	• Tier 1 capital ratio (MI_TIER1) • Total bank reserves to assets ratio (MI_TBRTAR)	• Customer loans to total assets ratio (MI_CLTTAR) • Loan loss provisions to total loans ratio (MI_LLPTLR)	• Net results from transactions with foreign currencies to income ratio (MI_NRTFCIR) • Net results from transactions	• Cost to income ratio (MI_CIR) • EBIT to equity capital ratio (MI_EBITCR) • Return on equity (MI_ROE)

1	2	3	4	5
		• Large credit expositions to total credit ratio (MI_LCETCR) • Nonperforming loans to total loans ratio (MI_NLTLR)	with derivatives to income ratio (MI_NRTDIR) • Stocks to total assets ratio (MI_STAR)	• Share of fee income (MI_SFI)

Source: own study.

4.2. Macro data

Theoretical considerations and empirical evidence show that macroeconomic variables can represent directly unobservable expectations of real economic development. Negative shocks sourced in the real sphere of the economy can induce negative consequences for a particular country's financial system, and especially for its banking sector. Among the most important measures of expected aggregate demand power are the purchasing managers' index (PMI) and the gross capital formation indicator. Both indicators signal real economy overheating that very often implies banking sector instability. The rest of the macroeconomic dataset embraced nominal and real GDP, the unemployment rate, the real effective exchange rate (REER) and the current account balance time series. The above-mentioned time series were taken from the National Bank of Poland internal databases and provided by external vendors (Polish Central Statistical Office, private agencies).

4.3. Private and public debt data

Financial data analysis shows that there is a strong link between rapid public and private debt expansion and banking sector instability (Aldasoro et al., 2018). This is main reason why the majority of the EWI research frameworks include the following indicators:

- nominal total credit to non-financial sector/non-financial corporations/households,
- nominal bank credit to non-financial sector/non-financial corporations/households,
- nominal public debt,
- debt service ratio of all agents/non-financial sector/non-financial corporations/households,
- gaps and ratios of the above variables compared with GDP.

It is worth noting that nominal total credit to non-financial sector/non-financial corporations/households indicators are also used as crucial measures of risk in many professional applications such as supporting macroprudential policy-makers in the process of setting appropriate countercyclical capitals buffer for the local banking sector. Therefore, nominal total credit gap to GDP ratio is often applied as the benchmark for simple univariate approaches.

4.4. Banking sector data

This part of the dataset consisted of four aggregated time series describing the financial condition of the Polish banking sector. They address different risks affecting local institutions, namely:

- credit risk: ratio of non-performing loans to total gross loans time series.
- interest rate and assets structure risk: share of wholesale financing time series (measure of the banking sector interconnectedness),
- solvency risk: leverage ratio and average banking sector credit default swap (CDS) premia time series.

4.5. Financial market data

The next crucial analysed phenomenon was the possible contribution of interbank transmission channels to systemic risk spillovers. To measure the influence of the situation on the wholesale money market, the author used the spread of the 10Y government bonds yield over WIBOR 3M (3-month Warsaw Interbank Offered Rate). The decreasing spread represented the growing awareness of commercial banks of the future prospects of their counterparts trying to acquire short-term liquidity. The study tried to capture the impact of the negative shocks stemming from country risk with sovereign CDS. The author also used nominal equity prices to examine general sentiment of the investors.

As described in the previous section, the author tried to ascertain whether Polish banking sector EWI is prone to negative spillovers effects generated by financial institutions' balance sheets dependencies. The last financial crisis also showed the importance of the international channels of instability transmission. As is it not easy to quantify the impact of the Polish banks' foreign exposures on the fair values of their balance sheets, the study used the second-best solution of including into the database as a proxy of the international risk measure, the forward-looking VIX index computed on the S&P stock market index options, assuming that higher expected implied volatility is correlated with higher possible instability in the international financial markets.

4.6. Property prices data

The 2007+ crisis provided the strong proof of the correctness of the thesis that the rapid growth of the property prices can induce a business cycle boom and build strong credit action imbalances that ultimately affect banks' solvency. In 2007 and 2008, residential property prices and rental rates in Poland were booming, but they were not high enough to create a serious systemic risk for the banking industry. However, ten years later the situation was somewhat different, as more and more cheap money was invested in commercial property projects and many individual investors enjoyed higher returns for their savings by buying small flats for rental purposes. Therefore, the author tried to capture the process of building potential imbalances by observing a set of property market indicators, namely nominal and real residential property prices, nominal commercial property prices, ratio of nominal residential property prices to nominal income and ratio of nominal residential property price to nominal rent. All the series described above were taken from the Bank for International Settlements Property Price Statistics Database. To sum up the data section, all the potential EWI are presented in Table 2.

Table 2

The dataset used for EWI selection

Macro	**Private/public debt**	**Banking sector**	**Financial markets**	**Property prices**
• PMI • Gross capital formation • Nominal GDP • Real GDP • Unemployment rate • Nominal M3 • REER • Current account balance	• Nominal total credit to non-financial sector/non-financial corporations/ households • Nominal bank credit to non-financial sector/non-financial corporations/ households • Nominal public debt • Debt service ratio all agents/non-financial sector/ non-financial corporations/ households • Gaps and ratios of above variables to GDP	• Ratio of non--performing loans to total gross loans • Leverage ratio • Share of wholesale financing • Average bank CDS premia	• Spread of the 10Y government bonds yield over WIBOR 3M • Nominal equity prices • Sovereign CDS premia • Bloomberg VIX index	• Nominal residential property prices • Real residential property prices • Ratio of nominal residential property prices to nominal income • Ratio of nominal residential property prices to nominal rent • Nominal commercial property prices
Polish Central Statistical Office, Markit Group Institute for Supply Management of Financial Activity	National Bank of Poland	National Bank of Poland, ACI Poland, WSE Benchmark	National Bank of Poland, and Bloomberg	Bank for International Settlements, National Bank of Poland

Source: own study.

5. IDENTIFICATION OF EARLY WARNING INDICATORS

5.1. Introduction to the applied framework

The two biggest financial crises of the 20th and 21st century took by surprise the majority of economic policy decision makers. Most of them were lulled by the general good sentiment of the financial markets, or were unable to distinguish information about incoming serious negative shocks from the stream of relevant and irrelevant data provided daily. The observed serious consequences of the lack of proper preventive decisions drew the attention of academic researchers and practitioners to an early warning framework that allows to identify in advance signals of imbalance, that finally could trigger a financial crisis. The *a priori* separation of future signals of vulnerability and non-vulnerability requires a series of critical assumptions and choices that can seriously affect the quality of the results. To deal with this complexity, it is advisable to create a conceptual framework for EWI identification. This approach allows to investigate the impact of the different assumptions and modelling scenarios on the characteristics of the built indicators and make some amendments according to changing data characteristics.

The procedure of the EWI identification can be divided into three key parts:

1. initialisation of a framework,
2. model building and quality assessment,
3. interpretation of the obtained results.

The first phase embraces dataset quality checking and transformation, setting general goals of the surveys, selecting models and making assumptions for the models planned to be applied. In the second step, specifications of the previously selected models are determined and then the models are sequentially estimated

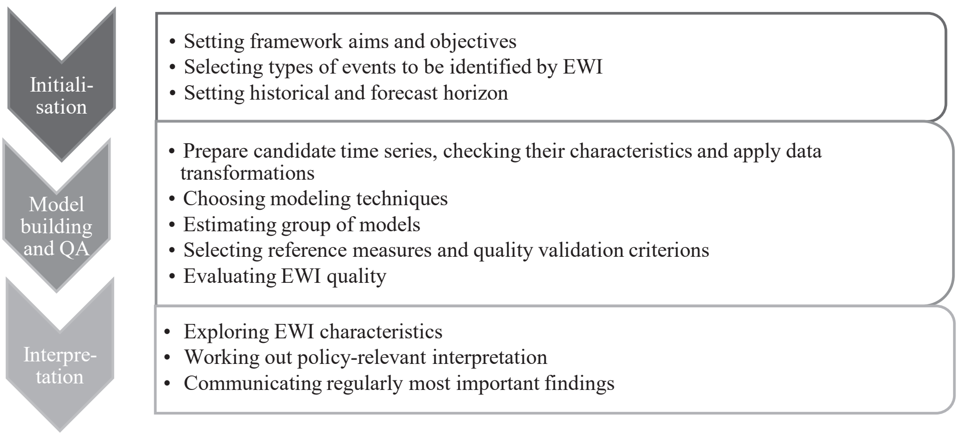

Fig. 1. General overview of the conceptual EWI framework

Source: own study.

and validated. The last phase deals with gained results analysis and development of optimal communication methods to policymakers and the public. The general overview of the EWI conceptual framework is depicted in Figure 1.

The complete procedure of EWI identification consists of the following steps:

- Prerequisites
  - analyse the financial cycle with different sets of filters: Hodrick-Prescott, Christiano-Fitzgerald and Baxter-King;
  - apply data transformations.
- Estimation and quality analysis
  - select time-series subsets from the initial database;
  - using selected time-series estimate MMSM-DL models and their competitors: the univariate and LR model;
  - evaluate the quality of the univariate time series and models' output using the AUROC / psAUROC statistics and decision-makers preferences function.

5.2. Individual bank rating model

The bank rating model used in the survey allowed to compute the probability of default of each financial entity considered in the analysis $P(y_{i,t} = 1)$. The group of lagged individual bank's measures ($BI_{i,t-1}$) and financial time series (F_t) were used as an input to the population-averaged logit model:

$$P\left(y_{i,t} = 1\right) = \frac{e^{\alpha + \beta BI_{i,t-1} + \gamma F_{t-1}}}{1 + e^{\alpha + \beta BI_{i,t-1} + \gamma F_{t-1}}}. \tag{1}$$

The individual banks measures were taken from a microprudential dataset showing Polish banks' financial situation; $P(y_{i,t} = 1)$ was derived from the proprietary dataset of Polish banks' instability events.

5.3. Multivariate Markov-switching models with distributed lags

The macroeconomic and macroprudential time series included in the database revealed dramatic structural breaks during the last financial crisis and in the pre-crisis period. Due to the strong cyclical character of the analysed variables is seems to be appropriate to analyse their dynamics with nonlinear models. To capture time-series irregular oscillations, the author considered several parametric and nonparametric models. As the reference analytical framework, multivariate Markov-switching models with distributed lags was chosen.

The Markov-switching models are well known in the econometric analysis of economic and financial time series. Hamilton (1989) explained the relationship between changes in hidden regimes and dynamics of US GDP cycles using their univariate version. The multivariate approach to modelling structural breaks in time series, Markov-switching vector autoregression models (MS-VAR) were presented by Clements and Krolzig (1998). Kim and Nelson (1998) proposed a general form of the multivariate Markov-switching analytical structure.

The next generation of multivariate Markov-switching models combines their canonical structure with the distributed lags approach. This kind of models was applied by Billio and Cavicchioli (2014). In building this class of models, the author assumed that ($N \times 1$) vector of expected values of the observed time series (y_t) depends on the last r regimes ($r \geq 0$), each with possible M states (s_t, $M \geq 0$). The migration between states is described by transition probabilities:

$$p_{ij} = \Pr\left(s_t = j | s_{t-1} = i\right),\ i, j = 1, \ldots, M. \tag{2}$$

In further analysis, individual transition probabilities were gathered in the $M \times M$ matrix $P = (p_{ij})$.

All the states considered in the reference model can be represented by the ($M \times 1$) vector ξ_t, whose m-th element equals 1 if $s_t = m$, and 0 otherwise. The intercept term of the model is defined as

$$\nu_t = \xi_t - E\left(\xi_t | \xi_{t-1}\right) \tag{3}$$

and is computed using the formula

$$\nu_t = \sum_{j=1}^{r}\sum_{m=1}^{M} \nu_{jm} I\left(s_{t-j} = m\right), \tag{4}$$

where $I(\times)$ is the indicator function.

The N-dimensional MMSM(r, M) – DL(p) model ($p \geq 0$), denoted also as MMSM-DL(r, M, p), can be described by equation

$$\phi_{s_t}\left(L\right) y_t = \sum_{j=1}^{r} \nu_{j,s_{t-j}} + \Sigma_{s_t} u_t, \tag{5}$$

where $u_t \sim IID\left(0, I_N\right), \phi_{s_t}\left(L\right) y_t = \phi_{0,s_t} + \phi_{1,s_t} L + \ldots + \phi_{p,s_t} L^p$, $\phi_{0,s_t} = I_N, \phi_{p,s_t} \neq 0,$ while $\left|\phi_{s_t}\left(z\right)\right|$ have all their roots strictly outside the unit circle. The first state-space representation of process (4) can be written in the form

$$\begin{cases} \phi\left(L\right)\left(\xi_t \otimes I_N\right) y_t = \sum_{j=1}^{r} \Lambda_j \xi_{t-j} + \Sigma\left(\xi_t \otimes I_N\right) u_t, \\ \xi_t = P' \xi_{t-1} + \nu_t, \end{cases} \tag{6}$$

where $\Lambda_j = \left(\nu_{j1} \ldots \nu_{jM}\right)$, $\Sigma = \left(\Sigma_1 \ldots \Sigma_M\right)$, $\phi\left(L\right) = \left[I_N + \phi_{1,1} L + \phi_{p,1} L^p + \ldots + I_N + \phi_{1,M} L + \phi_{p,M} L^p\right]$ or alternatively (and in a more complicated form) as

$$\begin{cases} \tilde{\phi}\left(L\right)\left(\delta_t \otimes I_N\right) y_t + \phi\left(L\right)\left(\pi \otimes I_N\right) y_t = \sum_{j=0}^{r} \Lambda_j \pi + \sum_{j=0}^{r} \tilde{\Lambda}_j \pi + \tilde{\Sigma}\left(\delta_t \otimes I_N\right) u_t + \Sigma\left(\pi \otimes I_N\right) u_t, \\ \delta_t = F + \delta_t, \end{cases} \tag{7}$$

where $\tilde{\Lambda}_j = \left(\nu_{j1} - \nu_{jM} \ldots \nu_{jM-1} - \nu_{jM}\right)$, $\tilde{\Sigma}_j = \left(\Sigma_1 - \Sigma_M \ldots \Sigma_{M-1} - \Sigma_M\right)$, δ_t is (M-1) vector formed by the columns, except the last one given by $\zeta_t - \pi$ and $\tilde{\phi}(L) = \left[(\phi_{1,1} - \phi_{1,M})L + \ldots + (\phi_{p,1} - \phi_{p,M})L^p + \ldots + (\phi_{1,M-1} - \phi_{1,M})L + (\phi_{1,M-1} - \phi_{1,M})L^p\right]$.

To evaluate the quality of the proposed early warning indicators prepared with the MMSM-DL approach, they were confronted with two kinds of indicators:

- naïve univariate measures,
- output of logistic regression (LR) model transforming input time-series to crisis probabilities, with two possible states: crisis (1) and non-crisis (0).

5.4. Quality analysis

As the last stage of the empirical survey, the identified EWI were validated with the AUROC procedure proposed by Drehmann and Juselius (2013). It is assumed that the analysed EWI signals in advance a financial distress period when it exceeds a specified threshold (TR). Finally, the financial sector instability ('default') is shown as (D) or not (ND). Hence, the possible output of the EWI quality check for each period in the analysed time span can be presented in a 'confusion matrix' (Table 3).

Table 3

Output of the EWI quality analysis for each period of time span

	No destabilisation	**Destabilisation**
Indicator below a threshold (TR) – no signal generated	TN: true negative	FN: false negative
Indicator above a threshold (TR) – signal generated	FP: false positive	TP: true positive

Source: own elaboration.

Based on this table, FPR i.e. false positive rate (noise rate, type II error rate), is defined as $\frac{FP}{TN+FP}$ and TPR, true positive rate (signal rate), equals $\frac{TP}{FN+TP}$, whereas FNR is computed as $\frac{FN}{FN+TP}$. The area under the receiver operating characteristic curve is the area under the plot of $TPR = f(FPR(TR))$ for each possible TR, and is measured with simple statistics ranging [0,1].

Moreover, the confusion matrix can be used to define the decision-makers preferences function

$$PF(\theta) = \theta \frac{D}{D+ND} FNR + (1-\theta) \frac{ND}{D+ND} FPR, \tag{8}$$

where θ is a preference parameter. This function can also be used to compute a partial standard, with AUROC (psAUROC as AUROC in specified regions of ROC curve for $\theta < x$).

6. RESULTS

According to the procedure described in the previous section, the author first estimated probabilities of default for each individual Polish commercial bank (i) from the biggest twenty entities in each period (t) from the time between 2007 and 2018. Table 4 shows the regression statistics of the estimated PDs.

Table 4

Regression statistics of PDs of the twenty biggest Polish commercial banks

Variables	***t*-statistics (*** p < 0.01, ** p < 0.05, * p < 0.1)**
MI_TIER1	–0.1296*** (–3.913)
MI_TBRTAR	–1.1135*** (–11.378)
MI_CLTTAR	0.0815*** (3.613)
MI_LLPTLR	0,2466** (2.772)
MI_LCETCR	0,6495* (1.816)
MI_NLTLR	0,3621** (2.314)
MI_NRTFCIR	0.0415 (0.283)
MI_NRTDIR	0.0128 (0.131)
MI_STAR	–0,0014*** (–2,842)
MI_CIR	0,0376 (0,089)
MI_EBITCR	–0.0756*** (–10.351)
MI_ROE	–0.1672*** (–12.986)
MI_SFI	0.0197*** (2.914)
Number of institutions	20
Number of observations	12480

Source: own computations.

To prepare input data to the multivariate Markov-switching model with distributed lags (MMSM-DL) used in the second step of the analysed statistics, the author standardised PDs of the analysed banks and combined them with the corresponding stock market indexes to compute the Polish banking sector stability index (BSI). This procedure allowed to combine the micro (individual banks) and macroprudential (systemic) dimension of the stability analysis. Moreover, applying

MMSM-DL provided the possibility for the identification and forecasting of possible turning points for general banking stability.

The estimation of the MMS-DL model was preceded with the analysis of the financial cycle characteristics of the candidate EWI and reference series. The analysis was based on results on output of the Hodrick-Prescott, Christiano-Fitzgerald and Baxter-King detrending procedure. For reference time series and relevant measures of the bank credit-to-GDP gap, the financial cycle characteristics were compared with the same analysis performed for the US and seven EU countries (the Czech Republic, France, the UK, Spain, Hungary, Germany and Greece). Figure 2 reveals substantial discrepancies between the financial cycle time spans observed in the analysed economies. In the case of Poland and the US, the cycle lasted only approximately ten quarters, while for Germany and Greece the cycle time span was two times longer.

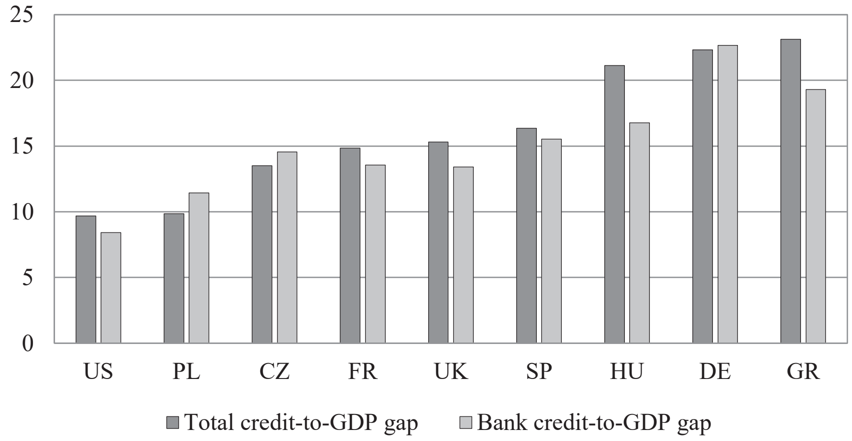

Fig. 2. Length of financial cycles (quarters) in Poland, the US and selected EU countries

Source: own computations.

In the key part of the research the author tried to select the time series and find the models that were most useful for predicting the aggregated banking sector stability index. The top six trivariate models (taking into account the AUROC criterion) are presented in Table 5; all of them were estimated using the MMSM-DL approach.

The most popular variables used in the estimation of the most efficient models were selected from the group of banking credit and banking sector data (Table 6). A statistical analysis of the whole population of estimated analytical structures indicated that the macroeconomic time series can also be used as early warning indicators of distress in the Polish banking sector.

Table 5

EWI: top six trivariate models

Model	AUROC	sdAUROC	Prob. TR for $\theta = 0.7$	TPR	FPR
MMSM-DL(4,4,4): Bank credit (YoY g.r.), Spread of the 10Y government bonds yield over WIBOR 3M, Debt service ratio (YoY g.r.)	0.89	0.010	0.38	0.80	0.32
MMSM-DL(4,2,4): Bank credit (YoY g.r.), Average bank CDS premia, Ratio of non-performing loans to total gross loans (YoY g.r.)	0.88	0.010	0.35	0.82	0.31
MMSM-DL(4,4,4): Bank credit (YoY g.r.), Spread of the 10Y government bonds yield over WIBOR 3M, GDP (YoY g.r.), Ratio of non-performing loans to total gross loans (YoY g.r.)	0.86	0.009	0.31	0.82	0.38
MMSM-DL(4,2,4): Spread of the 10Y government bonds yield over WIBOR 3M, Average bank CDS premia, Ratio of non-performing loans to total gross loans (YoY g.r.)	0.86	0.009	0.28	0.81	0.30
MMSM-DL(4,2,4): Total credit (YoY g.r.), Average bank CDS premia, Ratio of non-performing loans to total gross loans (YoY g.r.)	0.85	0.008	0.29	0.80	0.33
MMSM-DL(4,4,4): Debt service ratio (YoY g.r.), Average bank CDS premia, Ratio of non-performing loans to total gross loans (YoY g.r.)	0.82	0.008	0.30	0.82	0.25

Source: own computations.

Table 6

EWI: inclusion of variables into models, top ten variables with statistically significant coefficients

Variable	MMSM-DL(4,4,4)	Models Average AUROC	MMSM-DL(4,2,4)	Models Average AUROC
Bank credit (YoY g.r.)	88.41%	0.84	86.37%	0.80
Spread of the 10Y government bonds yield over WIBOR 3M	85.56%	0.80	85.25%	0.79
Ratio of non-performing loans to total gross loans (YoY g.r.)	83.92%	0.78	84.83%	0.79

Debt service ratio (YoY g.r.)	80.32%	0.76	81.95%	0.77
Average bank CDS premia	78.33%	0.75	79.52%	0.75
Nominal equity prices (YoY g.r.)	76.79%	0.73	77.66%	0.75
PMI (YoY g.r.)	70.43%	0.72	70.13%	0.75
Nominal GDP (YoY g.r.)	65.74%	0.71	63.87%	0.73
Nominal M3 (YoY g.r.)	60.78%	0.70	61.56%	0.72
Current account-to-GDP ratio (YoY g.r.)	48.67%	0.70	46.81%	0.70

Source: own computations.

In the next step the estimated trivariate models were confronted with naïve univariate models. The following table 7 presents the characteristics of the top ten such models.

Table 7

EWI: top ten univariate models

Variable	**AUROC**	**sdAUROC**	**psAUROC**	**Prob. TR for $\theta = 0.7$**	**TPR**	**FPR**
Bank credit-to-GDP gap	0.80	0.013	0.87	0.33	0.76	0.27
Spread of the 10Y government bonds yield over WIBOR 3M	0.78	0.013	0.86	0.33	0.79	0.26
Total credit-to-GDP gap	0.77	0.012	0.85	0,32	0.76	0.29
Debt service ratio (YoY growth rate)	0.74	0.012	0.83	0,32	0.71	0.29
Ratio of non-performing loans to total gross loans (YoY g.r.)	0.74	0.011	0.87	0.33	0.73	0.28
PMI	0.69	0.010	0.83	0.31	0.76	0.30
Average bank CDS premia	0.69	0.011	0.80	0.29	0.74	0.29
Nominal M3 (YoY g.r.)	0.67	0.010	0.83	0.27	0.69	0.30
Nominal residential property prices	0.66	0.011	0.82	0.30	0.74	0,32
Ratio of nominal residential property prices to nominal rent	0.66	0.011	0.79	0.31	0.73	0.38

Source: own computations.

The results of the AUROC evaluation show that the trivariate models performed significantly better than their single variable competitor. The composite EWI were better in eliminating false signals of incoming crisis and forecast accurately future distress in the Polish banking sector.

CONCLUSIONS

The obtained results allowed to conclude that in the considered time span (2007-2018), the Polish banking sector was macroprudentially stable. However, on the microprudential level the proposed procedure identified a narrow group of banks prone to instability. In the case of a strong negative shock, these can turn into systemic risk catalysts.

The performed analysis was based on a group of financial stability EWI that could be used as useful tools by local macroprudential policymakers to detect in advance financial distress in the Polish banking sector. The strongly formalised characteristics of the framework applied in this paper gives the mentioned policymakers a solid base for communication of the macroprudential and microprudential conditions of the Polish banking sector, allowing them also to explain the sources and consequences of potential instabilities.

The EWI identification procedure applied in the survey combines microprudential and macroprudential perspectives of the banking sector analysis. The primary input to the used framework was the individual banks dataset, which first allowed to compute these banks' probabilities of default, followed by the aggregated Polish banking sector stability index. This measure is then used to select, with the help of multivariate Markov-switching models with distributed lags, a group of reliable early warning indicators.

According to the obtained results, the indicators based on multivariate models were useful for forecasting financial distress. The indicators identified with multivariate MMSM-DL models perform better in forecasting financial stabilities than their univariate competitors (89% vs. 80% according to the AUROC criterion). Moreover, the indicators identified with nonlinear models are better (ca 8 p.p.) in predicting financial crises than benchmark LR models. The best-performing trivariate MMSM-DL models were estimated with bank credit, spread of the 10Y government bonds yield over WIBOR 3M, ratio of non-performing loans to total gross loans, debt service ratio, average bank CDS premia, nominal equity prices and PMI time series. The same indicators were also good predictors of future instability when applied individually. In this case, the univariate models gained an AUROC statistics range from 80% (bank credit time series) to 69% (PMI indicator).

The identified EWI and obtained results allow to conclude that the key sources of instability of some Polish biggest banks are internal. This allows to formulate some advice for Polish microprudential (the Polish Financial Supervision Authority, UKNF) and macroprudential policymakers (the Polish Financial Supervision Authority, the National Bank of Poland and the Ministry of Finance), regarding which instruments to use to curb risk stemming from excessive credit risk appetite, inappropriate interest rate term structure and excessive sensitivity to the credit cycle.

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Received: February 2020, revised: February 2022