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Selecting appropriate countercyclical capital buffer for banking sector

Abstract

The paper proposes formal econometric framework, with background in economic and finance theories, that supports macroprudential policy decision-makers in the process of choosing appropriate value of the countercyclical buffer and proper timing for countercyclical buffer introduction (build-up) and resolution. The dedicated dataset, which consists of time series describing banking sector (e.g. share of wholesale financing), market risk (e.g. CDS of banks and sovereigns), real estate prices, and macroeconomic measures, was used to select the group of time series signalling, within the Multivariate Markov-Switching Model with Distributed Lags (MMS-DL) with an appropriate lead, the beginning and the end of the financial crisis phase, and to build the group of composite leading indicators of the private debt cycle. Different data transformation methods and different statistical data definitions were used to analyse the process of early warning signal extraction useful for countercyclical buffer operationalization. The constructed indicators were confronted with two kinds of competitors: the naïve univariate indicators and composite leading measures prepared with the help of Logistic Regression (LR) approach allowing to choose the most efficient analytical structure to support decision-makers.

Keywords: countercyclical capital buffer, macroprudential policy, multivariate Markov-switching model

JEL classification: C32, C58, G17, G21

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Ekonometryczna procedura selekcji odpowiedniego poziomu antycyklicznego bufora kapitałowego w polskim sektorze bankowym

Streszczenie

W artykule proponuje się osadzoną w teorii ekonomii i finansów sformalizowaną, ekonometryczną procedurę selekcji miar wspierających krajowych decydentów polityki makroostrożnościowej w procesie określania odpowiedniego poziomu i terminu wprowadzania antycyklicznego bufora kapitałowego. Przygotowany pierwotnie zbiór wejściowych szeregów czasowych, opisujących m.in. sytuację w sektorze bankowym (w tym udział finansowania hurtowego w pasywach banków), poziom ryzyka rynkowego (kwotowania obligacji skarbowych i CDS banków), sytuację na rynku nieruchomości i stan otoczenia makroekonomicznego, został użyty do wybrania, za pomocą przełącznikowych modeli Markowa wielu zmiennych z rozkładem opóźnień, grupy miar sygnalizujących z wyprzedzeniem początek i koniec okresów kryzysów finansowych oraz umożliwiających określenie przyszłej fazy cyklu akcji kredytowej. Właściwa estymacja i prognozowanie z wykorzystaniem wybranej grupy modeli zostały poprzedzone analizą przydatności alternatywnych metod kompilacji oraz klas transformacji wejściowych szeregów czasowych. Jakość uzyskanych w ten sposób wskaźników wyprzedzających kryzysu finansowego i faz cyklu kredytowego została określona na podstawie porównania z miarami obliczonymi na podstawie prostych modeli jednorównaniowych oraz modeli wielorównaniowych wykorzystujących regresję logistyczną.

Słowa kluczowe: bufor antycykliczny, polityka makroostrożnościowa, przełącznikowe modele Markowa wielu zmiennych z rozkładem opóźnień

Kod klasyfikacji JEL: C32, C58, G17, G21

1. Introduction

The last financial crisis (2008+) pointed out the importance of excessive growth of private credit and its procyclical behavior as the main sources of financial sector instability. Faced with new challenge on the field of crisis management Financial Stability Board (FSB) and Basel Committee of Banking Supervision (BCBS) recommended introduction of macroprudential supervision with main tasks focusing on private debt cycles and credit growth mitigation. As the most prominent tool for implementing this part of the macroprudential policy countercyclical BCBS recommended countercyclical buffer, CCB (BCBS, 2010a), arguing that additional capital gathered by financial institutions during boom phase could be utilized by them during bust period stabilizing in the macro-scale the inflow of the credit to the non-financial enterprises. Four years later (2014) regulations proposed by BCBS were implemented in Europe as one of the most important components of the CRR/CRD IV packages. Finally, at the end of 2015 European legislation concerning macroprudential policy and CCB as its main instrument was introduced to the Polish legal system.

BCBS recommendations and CRR/CRD IV packages define only the general framework of the macroprudential policy and CCB instrument. Considering substantially different characteristics of the particular jurisdictions responses to the last financial crisis operationalization of the CCB application was delegated to local supervisors. They are responsible for creating appropriate institutional and analytical framework, being capable of identification and quantification with appropriate lead future risk affecting local financial entities. In the case of Poland four main financial safety network institutions: National Bank of Poland, Ministry of Finance, Bank Guarantee Fund and Financial Supervision Authority joined their efforts in the form of Financial Stability Committee (FSC) to conduct the macroprudential policy. Analytical Framework of FSC is based on the experience and human capital of the cooperating bodies. However, general rules and models used as a background for CCB recommendations can currently (mid-2017) still be perceived as work in progress.

The paper proposes formal econometric framework, with background in economic and finance theories, that supports macroprudential policy decision-makers in the process of choosing appropriate value of the countercyclical buffer and proper timing for countercyclical buffer introduction (build-up) and resolution. The dedicated dataset consisting of time-series describing banking sector (e.g. share of wholesale financing), market risk (e.g. CDS of banks and sovereigns), real estate prices, and macroeconomic measures, was used to select the group of time series, signalling within the Multivariate Markov-Switching Model with Distributed Lags (MMS-DL) with appropriate lead, the beginning and the end of the financial crisis phase and to build the group of composite leading indicators of the private debt cycle. Different data transformation methods and different statistical data definitions were used to analyse the process of early warning signal extraction useful for countercyclical buffer operationalization. The constructed indicators were confronted with two kinds of competitors: the naïve univariate indicators and composite leading measures prepared with the help of Logistic Regression (LR) approach, allowing to choose the most efficient analytical structure to support decision-makers.

The article is organized as follow. Next section explores literature about macroprudential policy, financial cycles and leading indicators used for operationalization of countercyclical capital buffer. Then dataset used for CCB leading indicators construction is presented. The main part of the article describes Multivariate Markov-Switching Models used for computation of mentioned indicators and quality evaluation procedure applied for selection the most appropriate ones. In the last two sections the gained results are discussed, and conclusions and recommendations are formulated.

2. Literature review

There is a vast literature presenting macroeconomic and financial theories trying to explain financial cycles and source of financial distress. These theories entered mainstream economics mainly after the 2008+ crisis (Mendoza & Terrones, 2008, Borio & Drehmann, 2009, Jorda *et al.*, 2011, Bordo & Meissner, 2012, Schularick & Taylor, 2012). However, there are as well some samples of such works published in the end of the previous century (e.g. Kaminsky & Reinhart, 1999).

The concept and the role of macroprudential policy and its main instrument, countercyclical capital buffer, was primarily described in the discussion papers of Basel Committee of Banking Supervision (BCBS 2010a, 2010b). The application of countercyclical buffer was then explained in the papers of European Systemic Risk Board (ESRB, 2014) and BCBS (BCBS, 2015). The interest in the new kind of economic policy and its tools was also promptly expressed by academic researchers (Harmsen 2010, Repullo & Saurina 2011, CGFS, 2012, Juks & Melander, 2012).

Another group of papers tackle the subject of countercyclical buffer operationalization. The teams of academics and researchers from the central banks published series of papers with detailed presentation of databases and indicators used for analysis supporting decision process concerning setting adequate level of CCB. In this literature stream we can found papers of van

Norden (2011), Behn *et al.* (2013), Gerdrup *et al.* (2013), Swiss National Bank (2013), Castro *et al.* (2014), Drehmann & Juselius (2014), Giese *et al.* (2014) and Kalatie *et al.* (2015).

3. The database

The dedicated time series database was built and used as the starting point for the indicators selection procedure. Initial time series repository consisted of 270 variables: 60 indicators for each of the 9 countries included in the survey (Poland, Czech Republic, Hungary, Germany, France, Greece, Spain, United Kingdom, US) with the observations from the time span 1Q 1970 – 4Q 2015. For some countries (Poland, Czech Republic, Hungary, Greece) part of time series observations were available only for the last 25 years. However, the econometric models applied for the empirical analysis were flexible enough to cope with this issue. The scope of the described time series database is presented in Table 1.

The methods used in this paper for forecasting optimal CCB need also the reference database of the financial crisis dates. To make the gained results comparable with other surveys the author used dates from well-known European System of Central Banks Heads of Research Database. The graphical representation of this repository is showed by Graph 1. The financial crisis dates for the US were taken from Romer (2009).

Graph 1. The graphical representation of the database used for the financial cycles dates (the countries analysed in the paper highlighted with dark grey).
Source: European System of Central Banks Heads of Research Database with modifications of the author.

Table 1. The database used for the survey.

Private and public debt	Banking sector
• 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 • 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

Financial markets	Property prices	Macroeconomics
• Nominal 3M money market rate • Nominal long-term interest rates • Nominal equity prices • Sovereign CDS premia	• 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	• Nominal GDP • Real GDP • Unemployment rate • Nominal M3 • REER • Current account balance

4. Analytical frameworks

The analysis of the time series included in the database described in the previous section revealed that during the last financial crisis and in the pre-crisis time financial and macroeconomic time-series frequently exhibited dramatic structural breaks. Due to specific cyclical character of the analysed variables (e.g. substantial asymmetries in the cycles' phases) their dynamics should be analysed with nonlinear models. To analyse and forecast the time series, and to catch their irregular oscillations several parametric and nonparametric models were considered. For 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) used their univariate version to explain relationship between changes in hidden regimes and dynamics of US GDP cycles. Multivariate approach to modelling structural breaks in time-series, Markov-Switching Vector Autoregression models (MS-VAR), was presented by Krolzig (1997). Two years later Kim Nelson (1999) worked out general form of Multivariate Markov-Switching analytical structure.

The next generation of Multivariate Markow-Switching models, combining their structure with distributed lags approach, was proposed by Billio & Cavicchioli (2014). Building this class of models we assume that (Nx1) vector of expected value of the observed time-series (y_t) depends on the on the last r ($r \geq 0$) regimes, each with possible M states (s_t, $M \geq 0$).

The migration between states is defined by transition probabilities

$$p_{ij} = \Pr(s_t = j | s_{t-1} = i),\ i, j = 1, \dots, M, \tag{1}$$

which for the purpose of clarity can be gathered in the MxM matrix $P = (p_{ij})$.

All states considered within the analysed model can be represented by the (Mx1) vector ξ_t, of which m-th element equals to 1 if $s_t = m$, and otherwise equals to 0. The intercept term of the model is defined as

$$v_t = \xi_t - E(\xi_t | \xi_{t-1}), \tag{2}$$

and can be also computed with the formula

$$v_t = \sum_{j=1}^{r} \sum_{m=1}^{M} v_{jm}\, I(s_{t-j} = m), \tag{3}$$

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

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

$$\phi_{s_t}(L)y_t = \sum_{j=1}^{r} v_{j,\,s_{t-j}} + \Sigma_{s_t}u_t, \tag{4}$$

where $u_t \sim IID(0, I_N), \phi_{s_t}(L)y_t = \phi_{0,s_t} + \phi_{1,s_t}L + \cdots + \phi_{p,s_t}L^p$, $\phi_{0,s_t} = I_N, \phi_{p,s_t} \neq 0$. $|\phi_{s_t}(z)|$ have all their roots strictly outside the unit circle.

The first state-space representation of the process (4) can be written in the form

$$\begin{cases} \phi(L)(\xi_t \otimes I_N)y_t = \sum_{j=1}^{r} \Lambda_j \xi_{t-j} + \Sigma(\xi_t \otimes I_N)u_t \\ \xi_t = P'\xi_{t-1} + v_t \end{cases}, \tag{5}$$

where: $\Lambda_j = (v_{j1} \ldots v_{jM}), \Sigma = (\Sigma_1 \ldots \Sigma_M)$, $\phi(L) = [I_N + \phi_{1,1}L + \phi_{p,1}L^p + \cdots + I_N + \phi_{1,M}L + \phi_{p,M}L^p]$.

The described process has also alternative, much more complicated state-space representation given with the structure:

$$\begin{cases} \tilde{\phi}(L)(\delta_t \otimes I_N)y_t + \phi(L)(\pi \otimes I_N)y_t = \\ \sum_{j=0}^{r} \Lambda_j \pi + \sum_{j=0}^{r} \tilde{\Lambda}_j \pi + \tilde{\Sigma}(\delta_t \otimes I_N)u_t + \Sigma(\pi \otimes I_N)u_t, \\ \delta_t = F + \delta_t \end{cases} \tag{6}$$

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

The results of the analysis achieved with MMS-DL approach were confronted with two kinds of indicators: naïve univariate measures and output of Logistic Regression (LR) model, described with the formula

$$\Pr(CR_{i,t} = 1) = \frac{1}{1 + e^{-(\alpha + \beta' X_{i,t})}}, \tag{7}$$

transforming the input time series to crisis probabilities, with two possible states: crisis (1) and non-crisis (0).

5. Quality analysis of built indicators

To check the quality and compare countercyclical buffer forecast prepared with MMS-DL naïve univariate and LR models, we used the area under the receiver operating characteristic curve approach (AUROC) described in detail in the series of papers of Jorda & Taylor (2011), Jorda (2012) and Drehmann & Juselius (2014). Moreover, the decision-makers preferences function included in the works of Borio & Drehmann (2009) and Alessi & Detken (2011) was used. The computation of AUROC is based on the assumption that once exceeding a chosen threshold (denoted TR) the validated indicator should signal with a certain lead the outbreak of financial crisis and, hence, the need for countercyclical buffer accumulation. However, looking for historical data the crisis can materialize (noted C) or not (noted NC). The possible outcomes for N cases of such analysis (N = NC + NNC, number of crisis cases plus number of non-crisis cases) of this simple analysis can be gathered in the "confusion matrix":

Table 2. Possible outcomes of the quality analysis procedure (own preparations).

	No crisis	Crisis
Indicator stays below a threshold (TR) – no signal	A: True Negative	B: False Negative
Indicator stays above a threshold (TR) – no signal	C: False Positive	D: True Positive

Using this table the noise-to-signal ratio (NTSR) for the certain threshold TR can be computed:

$$\mathrm{NTSR(TR)} = \frac{\mathrm{FPR(TR)}}{\mathrm{TPR(TR)}}, \tag{8}$$

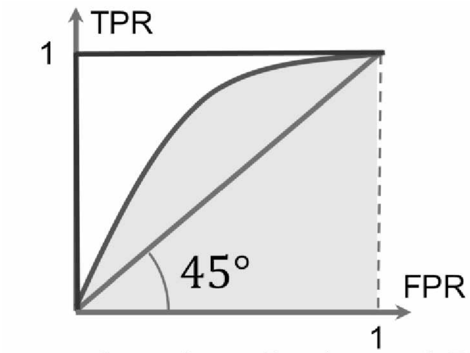
where FPR, false positive rate (noise rate, type II error rate), equals to $\frac{\mathrm{C}}{\mathrm{A+C}}$ and TPR, true positive rate (signal rate) is defined as $\frac{\mathrm{D}}{\mathrm{B+D}}$.

The area under the receiver operating characteristic curve is the area under the plot of the $\mathrm{TPR} = f(\mathrm{FPR(TR)})$ for each possible TR, and is measured with simple statistics ranging [0,1]

Based on the content of Table 2 the decision-makers preferences function can be defined as:

$$PF(\theta) = \theta \frac{NC}{NC+NNC} FNR + (1-\theta) \frac{NNC}{NC+NNC} FPR, \tag{9}$$

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



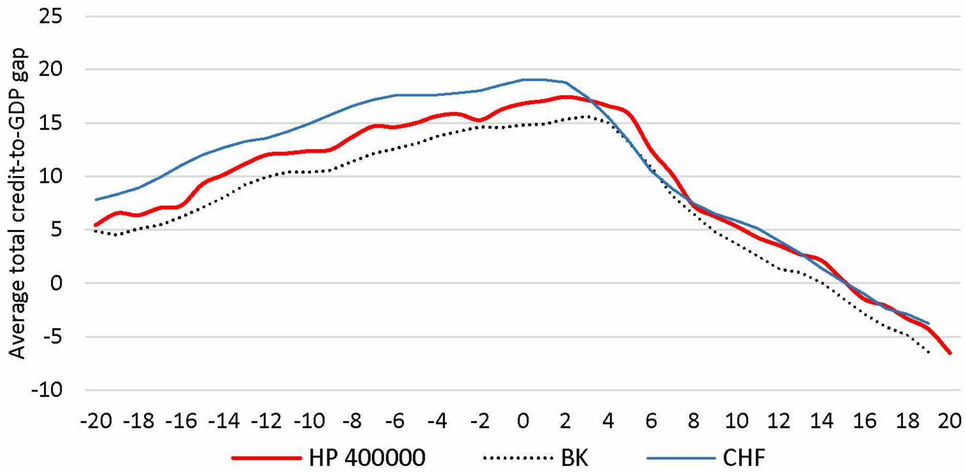
Graph 2. The sample of ROC curve (own preparations)

Summing up, the quality analysis section, the complete procedure of estimated countercyclical buffer indicators evaluation consists of the following steps:

- Prerequisites:
  - Analyse financial cycle with different set of filters: Hodrick-Prescott, Christiano-Fitzgerald, Baxter-King;
  - Transform time series: apply cyclical component extraction, differences;
- Estimation and quality analysis:
  - Select one/two/three elements time series subsets from initial database;
  - Using selected time series estimate MMS-DL models and their competitors: univariate and LR models;
  - Evaluate quality of univariate time series and models' output with AUROC and psAUROC statistics and decision-makers preferences function;

6. Results

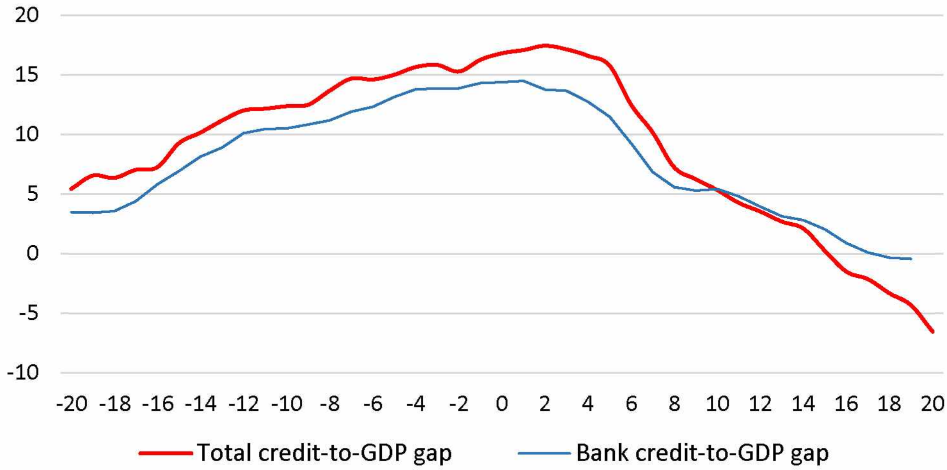
As it was mentioned in the section above the first part of the empirical survey was devoted to data transformation and cyclical components analysis. Significant trend component was visible in the majority of the input variables for each of the nine analysed countries. Hence the three different detrending methods, namely Hodrick-Prescott, Baxter-King and Chiristiano-Fitzgerald procedures were used to extract the cyclical factor. Application of these methods revealed a great heterogeneity of the impact of the cyclical component extraction methods on the original series. Graph 1 shows discrepancy in the average credit-to-GDP gap for each of three applied procedures (the plot time central point, noted with 0, is the 3rd quarter of 2008).



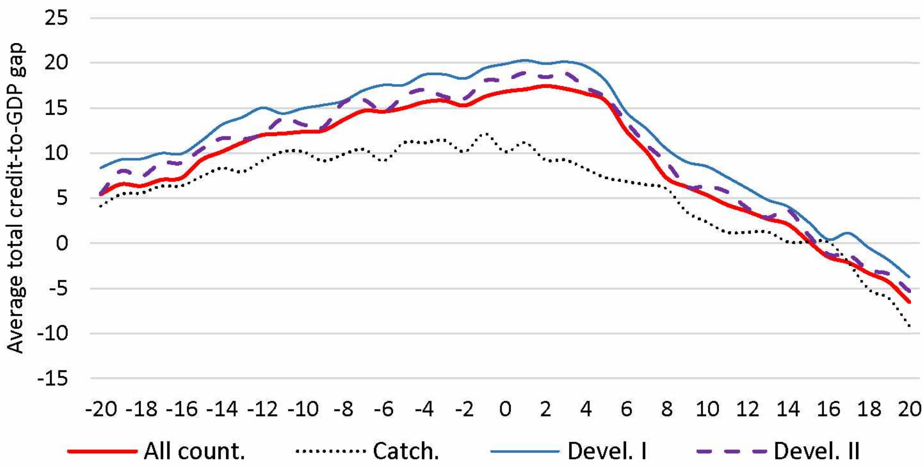
Graph 1. Impact of the different detrending methods on the average credit-to-GDP gap time-series.

Beside strictly technical impact on the obtained results the significant heterogeneity was also revealed among different series used as the credit cycle reference measures. Graph 2 shows the example of differences for different variables taken as credit cycle indicators.

The third kind of heterogeneity in the financial cycles was find where analysed time series were grouped for countries with different stages of economic and financial development. For the last financial crisis time series for catching-up countries (Poland, Czech Republic, Hungary, group called: Catch.) revealed cyclical characteristics which was substantially different from the characteristics of the series for developed countries "mildly" affected with the last financial crisis (Germany, France, United Kingdom, USA: group called Devel. I) and tackled strongly (Greece, Spain: group Devel. II) (see Graph 3).



Graph 2. Heterogeneity of credit cycles due to reference time series definition.



Graph 3. Heterogeneity of credit cycles due to country of the time series origin.

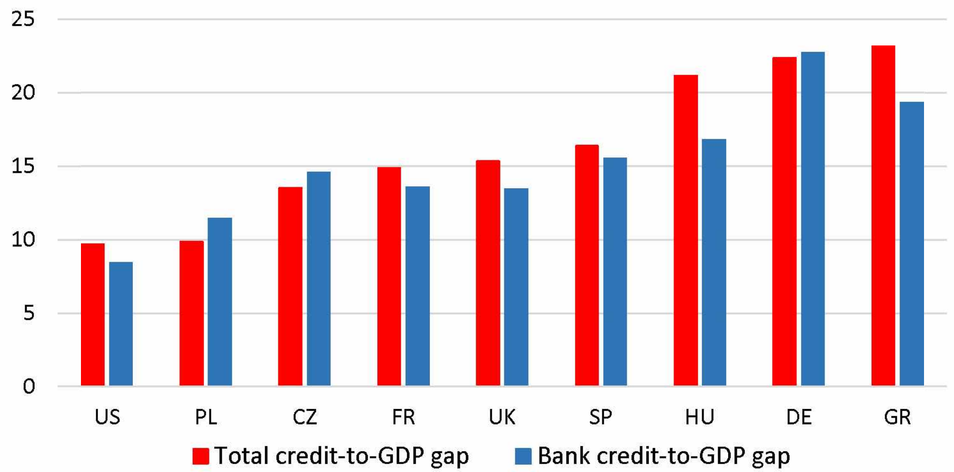
Finally, the prerequisite analysis of different credit cycle reference series for 9 selected countries shows substantial discrepancy between characteristics of these cycle in different economies, with US and Polish cycles being the shortest ones (approx. 10 quarters for full cycle), and German and Greek being almost two and half time longer.

In the substantial part of the empirical research we tried to select time series and find the models that were most useful for countercyclical buffer introduction (build-up) and release prediction for 9 analysed countries. The 6 top trivariate models (according to the AUROC criterion) used for build-up phase were presented in Table 3. Among them the first five were estimated with MMS-DL approach although their advantage on LR competitor was moderate.

Table 3. CCB introduction (build-up): top 6 trivariate models, all countries, quarterly data.

Model	AUROC	sdAUROC	Prob. TR for $\boldsymbol{\theta}$ = 0.7	TPR	FPR
MMSM-DL(2,2,4): Credit to households-to-GDP gap, Residential property prices to income gap Debt service ratio (YoY g.r.)	0.94	0.011	0.31	0.83	0.34
MMSM-DL(2,2,4): Bank credit (YoY g.r.) Residential property prices to income gap Debt service ratio (YoY g.r.)	0.93	0.011	0.26	0.85	0.33
MMSM-DL(2,2,8): Credit to households-to-GDP gap, Debt service ratio (YoY g.r.) GDP (YoY g.r.)	0.93	0.009	0,29	0.82	0.41
MMSM-DL(2,2,4): Credit to households-to-GDP gap, Residential property prices-to-income gap, Debt service ratio (YoY g.r.)	0.91	0.010	0,26	0,85	0,32
MMSM-DL(2,2,4): Credit to households-to-GDP gap, Share of wholesale financing (YoY g.r.), Current account-to-GDP ratio (YoY g.r.),	0.91	0.010	0,31	0,81	0,37
LR: Credit to households-to-GDP gap, Residential property prices-to-income gap GDP (YoY g.r.)	0.91	0.011	0,31	0,82	0,27

The most popular variables used to estimate the top most efficient models were selected from the group of private debt, banking sector and property prices data. However, statistical analysis of the whole population of estimated analytical structures indicated that the macroeconomic time-series (like GDP and current account-to-GDP ratio) are also significant leading measures of the financial cycles.



Graph 4. Financial cycles length (quarters) in the analyzed countries.

In the next step the estimated trivariate models were confronted with the naïve univariate models. Table 5 presents the characteristics of the top 10 such models.

Table 4. CCB introduction (build-up): inclusion of variables into models, top 10 variables with statistically significant coefficients, all countries, quarterly data.

Variable	MMSM-DL(2,2,4)	Models average AUROC	MMSM-DL(2,2,8)	Models average AUROC	LR	Models average AUROC
Credit to households-to-GDP gap	92.11%	0.86	90.79%	0.85	88,97%	0.78
Bank credit-to-GDP gap	90.34%	0.84	87.94%	0.85	91.24%	0.79
Residential property prices-to-income gap	87.63%	0.86	89.61%	0.84	90.13%	0.79
Total credit-to-GDP gap	80.58%	0.85	83.78%	0.82	88.68%	0.77
GDP (YoY g.r.)	77.91%	0.82	76.52%	0.82	82.52%	0.75
Debt service ratio (YoY g.r.)	73.24%	0.83	74.27%	0.84	71.64%	0.71
Bank credit (YoY g.r.)	60.11%	0.82	72.25%	0.81	63.25%	0.74
Current account-to-GDP ratio (YoY g.r.)	53.42%	0.82	61.15%	0.82	58.42%	0.72
Total credit (YoY g.r.)	47.16%	0.81	54.41%	0.82	53.97%	0.71
Equity prices (YoY g.r.)	40.33%	0.81	44.72%	0.80	43.24%	0.74

Table 5. CCB introduction (build-up): top 10 univariate models, all countries, quarterly data (own computations).

Variable	AUROC	sdAUROC	psAUROC	Prob. TR for $\boldsymbol{\theta}$ = 0.7	TPR	FPR
Credit to households-to-GDP gap	0.78	0.014	0.89	0.36	0.64	0.21
Total credit (YoY g.r.)	0.78	0.013	0.91	0.31	0.71	0.29
Total credit-to-GDP gap	0.77	0.014	0,84	0,27	0.81	0.31
Debt service ratio (YoY g.r.)	0.73	0.012	0.87	0,34	0,77	0,34
Bank credit-to-GDP gap	0.71	0.012	0.81	0,31	0,87	0,27
Residential property prices-to-income gap	0.71	0.011	0.90	0,29	0,83	0,29
Bank credit (YoY g.r.)	0.67	0.011	0.81	0,34	0,66	0,25
GDP (YoY g.r.)	0.63	0.010	0.88	0,31	0,83	0,31
Total credit gap	0,61	0.012	0.79	0,28	0,63	0,30
Debt service ratio gap	0,57	0.012	0.82	0,33	0,91	0,49

According to the AUROC criterion the trivariate models (estimated both with MMS-DL and LR approach) performed significantly better than their single variable competitor. For the purpose of countercyclical capital buffer operationalization, the better approach is to implement the composite indicator approach as it allows to eliminate false signals of the incoming crisis and forecast more accurately incoming periods of financial instability.

Table 5 presents 6 top most useful models (according to the AUROC criterion) for countercyclical buffer release prediction. Like in the case of analytical structures used for build-up phase forecasting the table was dominated by MMS-DL models. However, the most important time series were chosen from financial markets data macroeconomic sections of the database.

7. Conclusions

The results of research presented here support strongly the thesis that univariate indicators and indicators based on multivariate models are useful for forecasting financial crises and forecasting introduction and release of countercyclical capital buffer. Indicators estimated with multivariate approach are significantly better in forecasting financial crises and operationalizing countercyclical buffer introduction (build-up phase) than their univariate competitors (94% vs. 78% according to the AUROC criterion). Moreover, indicators constructed with nonlinear models (Multivariate Markov-Switching Models with Distributed Lags) are better (ca 3 p.p.) in forecasting financial crises/CCB introduction than benchmark Logistic Regression models.

Table 6. CCB release: top 6 trivariate models, all countries, monthly data.

Model	AUROC	sdAUROC	Prob. TR for $\boldsymbol{\theta}$ = 0.7	TPR	FPR
MMSM-DL(2,2,12): Interest rates spread (g.r.), Equity prices (g.r.), Share of wholesale financing (g.r.)	0.87	0.03	0.32	0.75	0.18
MMSM-DL(2,2,12): Interest rates spread (g.r.), Equity prices (g.r), Average bank CDS premia (g.r.),	0.84	0.04	0.35	0.77	0.33
LR: Interest rates spread (g.r.), Equity prices (g.r.), Average bank CDS premia (g.r.)	0.79	0.07	0,25	0.71	0.37
MMSM-DL(2,2,8): Interest rates spread (g.r.), Share of wholesale founding (g.r.), Real GDP (YoY g.r.)	0.75	0.07	0,21	0,74	0,34
LR: Interest rates spread (g.r.), Share of wholesale financing (g.r.), Real GDP (YoY g.r.)	0,75	0.05	0,31	0,78	0,37
MMSM-DL(2,2,12): Interest rates spread (g.r.) Share of wholesale financing (YoY g.r.), Total credit (YoY g.r.)	0.74	0.04	0,31	0,79	0,34

Generally, the time series dataset useful for forecasting CCB introduction is different from the dataset optimal for CCB release forecasting. The analysis of the variables used with the most efficient models for CCB introduction shows that the most useful measures are selected from private and public debt and property prices section (credit to households-to-GDP gap, dynamics of debt service ratio, residential property prices to income gap). They catch dynamics and tensions of credit action and tensions on residential real estate market. The financial variables (e.g. share of wholesale financing, interest rate spreads) are moderately useful in forecasting financial crisis/CCB introduction but are important for forecasting CCB release.

From the technical point of view it is important to mark that time series transformations (mainly cycle extraction methods) and selection of the variables used for analysis of credit action have significant implications on the gained results. Hence, the process of the composite indicators operationalizing for the purpose of supporting CCB introduction and release phase is the long-lasting and time-consuming procedure that needs to be tailored according to the characteristics of the financial cycle generated by local financial institutions and transmitted by financial markets.

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