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Article

The profitability and capital adequacy in central and eastern European countries in the light of the Basel III requirements

The Profitability and Capital Adequacy in Central and Eastern European Countries in the Light of the Basel III Requirements – a Forecast Approach

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Abstract

Previous studies have shown that the banking sector of the Central and Eastern European (CEE) countries performed better than other developed European sectors during the crisis, due to their sound capitalization and a high profitability before the crisis. That is why we consider that it is interesting to see how they will perform in terms of the profitability and capitalization ratios during 2016 – 2017 in the light of the new international capital adequacy regulations. We have used Combinatorial forecasting method and Artificial Neural Networks (ANN) forecasting method for the banking sectors of five Central and Eastern European countries, non-members of the Eurozone, in order to predict the further developments of capital adequacy ratio, return on assets (ROA) and net interest margin during 2016 – 2017. Our results show that the capital adequacy ratio will improve in all five analysed banking sectors. The bank net interest margin will increase in all five banking sectors (except in the Czech banking sector) and ROA will increase a lot in Hungary, but also in Bulgaria and Romania, while in Poland and in the Czech Republic it will slowly increase.

Keywords: *capital adequacy ratio, bank profitability ratios, Central and Eastern European banking sectors, ANN forecasting method, Combinatorial forecasting method*

JEL Classification: C45, C53, G21

Introduction

In the past decades, most countries in Central and Eastern Europe (CEE) have adopted structural reforms in view of increasing the size, stability and efficiency of financial systems. The banking systems in CEE, which had largely eschewed

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sub-prime loans and more exotic credit products, had been able to side-step the problems that befell their Western counterparts during the crisis. The main problem of the CEE banking sectors was represented by a high share of loans denominated in foreign currency (Hungary, Romania and, less exposed, Bulgaria). Even during the crisis, this share increased in Bulgaria, while in Hungary it decreased. Hungary and Romania had a large exposure to CHF currency that proved to be very volatile during the crisis. Anyway, it is worth to be mentioned that in Central European countries, the share of the long-term loans to total loans was much lower than in the Southern European countries (Radulescu, 2014).

Due to the economic growth in the CEE region, the banking sectors return to profit after the last crisis. A key challenge for European banks is related to the long period of low profitability in the sector. An important challenge is related to the difficulties in increasing revenues because of a low nominal growth and a low interest rate environment. Other profitability challenges in some countries are amplified by the large stock of non-performing assets (e.g. Bulgaria). This poses problem of banking profitability, not necessarily of banking solvency, because the European banking system is well capitalized according to the undertaken risks (Constâncio, 2016).

Previous studies have shown that the CEE banking sectors performed better than other developed European sectors during the crisis, due to their sound capitalization and high profitability before the crisis (Capraru and Ihnatov, 2014). That is why we consider that it is interesting to see how these CEE countries will perform in terms of the banking profitability and capitalization ratios during 2016 – 2017 in the light of the new capitalization regulations imposed by Basel III. Once the crisis is over, the banks claim the new requirements of Basel III will push their profits down. Some studies have shown that profitability ratios will decline against the levels recorded before the crisis period for the European banks, because of the implementation of Basel III (Harle et al., 2010). But banks can’t aim profitability no matter the risks undertaken. According to (Athanasoglou, Brissimis and Delis, 2008), a sound and profitable banking sector is better able to fight negative shocks and contribute to the stability of the financial system.

The aim of this study is to stress the correlation between the increase of the bank capitalization (requested by Basel III) and the profitability ratios of the selected CEE banking sectors and to draw some policy recommendations for the national monetary authorities in these countries. Our forecast is based on designing the best functions for forecasting the capitalization ratios, Return on Assets (ROA) or net interest margin in the selected CEE countries. From the forecast functions, we can stress the most important factors for determining the capitalization ratios or profitability ratios of the CEE banking systems. These factors determine the performance of each banking system. Some of them depend on the management of each bank and some of them depend on the regulations imposed by the national monetary authorities. Thus, we can elaborate some policy recommendations for each CEE banking system.

1. Literature Review

Basel III will greatly impact the European banking sector. New regulations request additional Tier 1 capital, short-term liquidity and long-term funding. It seems that those gaps will be greater in the European banking sector than in the US banking sector. Closing these gaps will have a substantial impact on profitability (Harle et al., 2010).

In Kosmidou, Tanna and Pasinouras (2005) and Demirgüç-Kunt and Huizinga (1999), the authors have used ROA and net interest margin as best proxy for banks profitability. In CEE region, the share of the interest revenues and interest costs is higher than in other European developed banking sectors, so the development of the net interest margin is highly relevant for the profitability of the banking systems in this area.

According to Krakah and Ameyaw (2010), ROA is an appropriate measure of bank profitability. In Rivard and Thomas (1997), it is argued that bank profitability is best measured by ROA in the sense that, ROA cannot be distorted by high equity multiplier.

Comparing to Return on Equity (ROE), the use of ROA takes into account the risks derived from the leverage and is the key bank profitability ratio (Athanasoglou, Brissimis and Delis, 2008). A possible limitation of ROA is the existence of the off-balance-sheet assets (not considered when ROA is measured), which represent an important source of profit for European banks.

Many studies (Demirgüç-Kunt and Huizinga, 1999; Mendes and Abreu, 2003; Goodard, Molyneux and Wilson, 2004; Pasiouras and Kosmidou, 2007) concluded that the most performing are the banks with high equity. They display lower financing costs. In Beltratti and Stulz (2012) it is emphasized that banks recorded better performance in the countries with strict capital adequacy requirements. But banks from countries with powerful supervision authorities recorded low market returns, as the shareholders were asked to raise new equity during the crisis period.

The equity level has a positive impact on the asset profitability, as long as it has the role of providing safety (Andries et al., 2016). In Capraru and Ihnatov (2014), the authors underlined that capital adequacy growth influenced the bank profitability (ROA and ROE and net interest margin). They noticed that banks with higher capital adequacy are more profitable for 5 CEE countries during 2004 – 2011 (Bulgaria, Hungary, Poland, Romania, Czech Republic). This effect is stronger for ROE than for ROA.

In Claeys and Vander Vennet (2008), the authors found out that capital adequacy impacts on the interest bank margin and supports stability and profitability of the banking systems in the EU accession countries. In Tomuleasa and Cocris (2014), there was found a significant positive impact of the capital adequacy rate on the net interest margin by analysing the biggest 20 financial groups in Europe operating at an international level during 2004 – 2012.

The results of Roman and Tomuleasa (2014) research show that bank profitability of most banks in the new EU member state (expressed by ROE) was significantly influenced by capital adequacy during 2003 – 2011 in the CEE countries. The capital adequacy has a positive impact on the profitability of Hungarian, Polish and Romanian banks. During the recent financial crisis, it can also be observed an inverse relationship between capital adequacy and banks profitability in Bulgaria and the Czech Republic.

In Petria, Capraru and Ihnatov (2015), the authors analyse the main determinants of banks' profitability in EU during 2004 – 2011. The capital adequacy ratio has not a statistically significant impact on ROE. The effect of the solvency on ROA is positive and statistically significant. Thus, there is evident a positive relationship between capital and profitability as it was demonstrated by some researches (Altunbas et al., 2007; Iannotta, Nocera and Sironi, 2007). On the other hand, there are some papers which came to the opposite results (Agoraki, Delis and Pasiouras, 2011).

However, there are some studies performed at the European level (not for the CEE region like the studies mentioned above), that have reached opposite results (Šútorová and Teplý, 2014). Based on their results of an analysis performed for 594 banks operating in the European Union in the 2006 – 2011 period, the higher capital requirements under the Basel III would cause a decrease in banks' profitability. So, these opposite results are in line with those of Harle et al. (2010) that stressed a decrease of ROE for the entire European banking system as a result of Basel III requirements. Cosimano and Hakura (2011) have emphasized that higher capital requirements of Basel III, by raising banks' marginal cost of funding, lead to higher lending rates. So, in the long-run, there will be a drop of credit growth which will negatively affect the banking profitability, but this drop will vary across the countries (more in European countries than in the USA).

The process of issuing financial forecasts in the banking system have become an increasingly complex task, especially after the 2008 – 2009 financial crisis which demonstrated that macroeconomic predictions can involve a larger degree of inaccuracy when the global economy is affected by large shocks (Fawcett et al., 2015). According to Khashei and Bijari (2010), artificial neural networks (ANNs) are one of the most accurate and widely used forecasting models that have enjoyed fruitful applications in forecasting social, economic, engineering, foreign exchange, stock problems.

The literature contains examples of using neural networks in financial forecasting, such as:

- Predicting bankruptcy, in Tsai and Wu (2008) the authors compared the performance of the single neural network model with the multiple neural network model over three datasets for the bankruptcy prediction and credit scoring problems and the results showed that the single neural network classifier is more suitable for the domain.
- A study Nazari and Alidadi (2013) focuses on the criteria in identifying the good and bad customers in Iran's banking sector.
- In Boyacioglu, Kara and Baykan (2009), four different neural network models are presented, like support vector machines and statistical methods to forecast bank failures;
- Another interesting paper refers to the forecasting of customer churn in Croatian banking services (Zoric, 2016); the forecasting reveals the loyal clients and focus on those who use less than three products, offering them other products according to their preferences.
- In Radulescu, Banica and Polychronidou (2015), the authors discussed the possibility to forecast the performance indicators of four Greek banks and their Romanian branches, based on artificial neural networks (ANN), starting from the balance sheet of these banks and their Romanian branches, during 2006 – 2012.

2. Methodology

Current forecasting methods and techniques cannot ensure the reliability of forecasts in banking sector, but they are able to generate models which best fit the requirements.

In order to obtain an accurate forecasting it is important to generate and evaluate several models based on a large input dataset of variables, give the appropriate weight to each variable, replace the missing values by interpolated values and finally, choose one of the models best fit for the forecast, with the highest degree of confidence.

Using GMDH Shell, we generated multiple forecasting models for each of the banking system indicators from an available set, and then we selected the final version by applying accuracy criteria and following the trend of the last three years. Then the optimal model was applied to the selected European countries involved in this study.

The computational modelling method, also called Group Method of Data Handling – GMDH, started from the discrete analogue Kolmogorov-Gabor polynomial (equation 1), performing the approximation of the relationship among the inputs and the outputs of complex systems (GMDH Shell, 2016; Radulescu, Banica and Zamfiroiu, 2015).

$$Y\left(x_1, x_2, \ldots, x_n\right) = a_0 + \sum_{i=1}^{n} a_i x_i + \sum_{i=1}^{n}\sum_{j=1}^{n} a_{ij} x_i x_j + \sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{k=1}^{n} a_{ijk} x_i x_j x_k \qquad (1)$$

where

$X(x_{1,} x_{2,\ldots,} x_n)$ – the input data vector,

$A(a_{1,} a_{2,\ldots,} a_n)$ – the vector of weights.

The GMDH algorithm, developed by Alexey G. Ivakhnenko (GMDH Shell, 2016) for one output is:

$$Y\left(x_1, x_2, \ldots, x_n\right) = a_0 + \sum_{i=1}^{m} a_i f_i \qquad (2)$$

where

f – elementary functions dependent on different sets of inputs,

a – coefficients,

m – the number of the base function components.

As the researchers of Geos Research Group specified (Geos Research Group, 2016), the core of all GMDH-type algorithms is "to apply a generator of gradually complicating models and select a set of models that show highest forecasting accuracy at previously unseen data". So, input data is separated into the learning (or training) subset and the validation or testing subset and an activation function is applied for generating the models.

Among the validation strategies offered by GMDH Shell software, we applied two of them, namely (GMDH Shell, 2016):

a) Training/testing – splits dataset into two parts, uses training part to find model coefficients and testing part to verify the generated model;

b) K-fold – splits dataset onto k parts, trains a model k-times using k – 1 parts, each time measuring model performance using the remaining part; residuals obtained from all testing parts are summarized in order to compare the model to other competing models.

Splitting ratio, as well as the number of K-folds, are modelling options and should be introduced empirically by the researcher.

There are two categories of risks in choosing the training subset:

- too few input variables that could not define the model or may be not representative;
- too many input variables which could prolong the processing time or even misrepresent the model.

If the model is too complex, the results can become less accurate.

According to GMDH Shell official site, there are two closely related learning algorithms (GMDH Shell, 2016), also called “core algorithms”:

- Combinatorial GMDH;
- GMDH-type neural networks.

Combinatorial GMDH is a polynomial function generated from a set of variables that is linear in the parameters. We applied this algorithm for a complexity limit of seven model parameters and we observed that forecasts take too much time and, in some cases, they did not have the required accuracy and the model does not comply with the previous trend. The efficiency of GMDH approach depends on the computational power of the machine and therefore it is recommended to use parallel processing (Koshulko and Koshulko, 2007).

GMDH-type neural networks modelling uses combinatorial algorithm for neuron connections. Economic and financial forecasting is a complex approach, because it is confronted with uncertainty, non-linearity and a wide range of external elements that influence the process (Maciel and Ballini, 2008).

Artificial Neural Network models generated with GMDH Shell are recommended for this class of systems. Unlike combinatorial GMDH, the neural networks algorithm works very fast due to several characteristics that recommend it (Radulescu and Banica, 2014):

- The capacity to approximate any continuous function with a high degree of accuracy;
- The usage of nonlinear methods, similarly with most of the real systems;
- The parallel-distributed processing of data.

The algorithm iteratively creates layers of neurons with two or more inputs. From a previous layer, the algorithm returns only a limited number of neurons, representing the input set for the new layer. Every neuron in the network applies a transfer function (usually has a quadratic or linear form). This process of generating new layers stops when a new layer does not improve the testing accuracy in comparison with the previous layer or if the number of layers has reached a certain defined limit (GMDH Shell, 2016).

To increase the efficiency of forecasting and avoid reaching large-size layers, the GMDH-neural network algorithm generates at K-layer only half of the number of neurons identified at the previous layer (GMDH Shell, 2016; Radulescu, Banica and Zamfiroiu, 2015):

$$N_k = 0.5 * N_{k-1} \tag{3}$$

To evaluate forecast accuracy as well as to compare among different models, GMDH Shell provides performance measures, such as: MAE, MSE and RMSE. Also, for each model, we obtained a table with values that depicts the original series and the forecast.

Mean absolute error (MAE) is the result of the absolute value of the difference between the estimated forecast (Y_t) and the actual value at the same time (F_t). It measures the average absolute deviation of forecasted values from original ones. This manner to calculate the errors does not suffer from the sign of values the effects of positive and negative errors do not cancel out (Saigal and Mehrotra, 2012).

$$MAE = \frac{1}{n}\sum_{t=1}^{n}\left|Y_t - F_t\right| \tag{4}$$

The mean squared error (MSE) represents the variability in forecast errors and it is a measure of average squared deviation of forecasted values (Radulescu and Banica, 2014):

$$MSE = \frac{1}{n}\sum_{t=1}^{n}(Y_t - F_t)^2 \tag{5}$$

As the opposite errors do not offset one another, MSE gives an overview of the error occurred during forecasting, but not about the direction of overall error.

The root mean square error (RMSE) measures the average magnitude of the error:

$$RMSE = \sqrt{MSE} \tag{6}$$

It is the square root of MSE and all its properties are transferred to RMSE.

For all the models generated in our study, the forecasting accuracy was estimated by using RMSE measure and the results demonstrated the performance, the accuracy for the computed values being less than 0.5.

3. Empirical Data and Analysis

In this paper, we used GMDH Shell 3.8.6 software to draw up the forecasts and two important classes of time series models: combinatorial and ANN (Artificial Neural Networks), considering their advantages and drawbacks (GMDH Shell, 2016).

We analysed the correctness of applying these models, taking into account the coefficients stability over time, nonlinearity, inclusion of fluctuations, and the ability of the macroeconomic variables to alter the model performance. Finally, we applied the combinatorial model to the series of banking systems of Poland, Bulgaria and the Czech Republic, and the ANN model to Hungary's and Romania's time series.

Based on the information published by The Global Financial Development Database (2016) for several Central and Eastern European countries (Romania, Bulgaria, Hungary, Poland and the Czech Republic), and using GMDH Shell 3.6.8 forecasting software, we analysed banking system indicators, in order to obtain a forecasting models for 2016 – 2017.

The Global Financial Development Database (2016) offers large amounts of data concerning financial institutions (banks, insurance companies), and financial markets. It also provides other indicators of of all countries' banking sector.

From the large input dataset provided by The Global Financial Development Database (2016) for each country, we evaluated several combinations and we selected a sample of seven variables for five Central and Eastern European Union countries, during 2002 – 2015. We used for our forecasting model: cost-to-income ratio, liquid assets to deposits and short-term funding ratio, provisions to non-performing loans, bank regulatory capital to risk-weight assets ratio, bank net interest margin, ROA and ROE.

The input dataset contains a few gaps, which are covered by interpolated values, but it is very fluctuating, especially in the case of Hungary and Romania.

In this paper, we have presented the short-term forecasting generated by GMDH for the following banking performance indicators for 2016 – 2017:

1. Bank regulatory capital to risk-weighted assets
2. Bank net interest margin
3. ROA (Return on Assets).

For the other four ratios used in our model we performed a forecast only for 2016, because these estimated values were necessary for forecasting the three main ratios in 2017.

A real problem in the forecasting domain is determining the dimension and the representativeness of the input sample required for building the model.

A model built upon an input dataset reduced in size should be able to improve the relationships between variables and should rely on the process of choosing the most representative set of data.

We used a set of historical data from 2002 to 2015 for each country, and the GMDH computing facility to interpolate unknown values. Overall, the evaluation period was relatively calm until 2008, but became more dynamic afterwards, when the global financial crisis started.

The relatively small number of observations – only 14, their incompleteness and also the fluctuations of the values, could be among the reasons for the inaccurate results obtained by using the GMDH combinatorial model for Romania and Hungary. Therefore, these two cases are modelled using GMDH neural networks, which allow the optimization of the parameter set at the input of each neuronal layer, while the accuracy increases.

The forecasting is based on an iterative algorithm that uses multiple layers of neurons. The *n*-th layer verifies the accuracy of the model for the input data, and provides the next layer ($n + 1$) with a limited number of representative neurons, which are the input set for this layer, and the process is iterated until the accuracy is reduced or the user specified limit is reached.

4. Results and Discussion

At the end of each table with data for a specific country and forecasts for 2016 – 2017, we have presented the determination functions for the bank regulatory capital, net interest margin and ROA in the CEE selected banking sectors. The determinants are presented in the descending order of their importance for the estimated variable, from the most important determinant to the least important one.

In Bulgaria, the bank regulatory capital is strongly determined by the bank net interest margin (Bulgaria, Romania and Hungary rely on interest revenues more than Poland and the Czech Republic), liquidity ratio and cost-to-income ratio. The bank net interest margin is strongly determined by the cost-to-income ratio, ROA, ROE and the bank regulatory capital. ROA is strongly determined by the cost-to-income ratio, the liquidity ratio, the bank regulatory capital and the provisions for non-performing loans (Table 1).

In Romania, the bank regulatory capital is strongly determined by the cost-to--income ratio, bank net interest margin and liquidity ratio. Both profitability ratios (especially ROA) are strongly determined by the bank regulatory capital, together with liquidity, provisions for non-performing loans or cost-to-income ratio (Table 2).

From the determination functions presented in Table 3, we can see that in Hungary, the bank regulatory capital is strongly determined by net interest margin and the liquidity ratio. Also, for determining ROA and net interest margin, the bank regulatory capital is one of the most important factors, together with liquidity ratio and provisions for non-performing loans ratio. Moreover, ROA is strongly determined both by regulatory capital and net interest margin.

T a b l e 1

Dataset and Forecasts for Bulgaria

Indicator name/Year/ Bulgaria	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016 Value/ RMSE**	**2017 Value/ RMSE**
Bank cost-to-income ratio (%)	60.6	59.1	56.8	53.3	50.5	45.9	46.9	47.5	48.2	50.5	52.5	54.1	37.8	35.1	34.3/ 0.14	
Liquid assets to deposits and short-term funding (%)	67.8	44.5	48.9	45.5	48.2	39.2	26.1	22.7	24.3	25.2	24.3	26.7	18.5	25.7	31.7/ 0.17	
Provisions to non- -performing loans (%)	59.6	50	138	131.4	109.9	100.4	77.1	58.2	61.4	59.5	63	65.6	49.4	55.83	59.5/ 0.0008	
Bank regulatory capital to risk-weighted assets (%)	*25.2*	*22*	*16.6*	*15.3*	*14.5*	*13.8*	*14.9*	*17*	*17.4*	*17.6*	*16.6*	*17*	*21.9*	*21.2*	21.2/ 0.0001	21.5/ 0.057
Bank net interest margin (%)	4.93	4.82	5.78	5.3	5.3	5.34	5.12	4.42	4.52	4.1	3.6	3.38	1.07	4.02	4.3/ 0.0004	4.4/ 0.11
ROA	*1.9*	*2.4*	*2.1*	*2.1*	*2.2*	*2.5*	*2.3*	*1.1*	*0.9*	*0.8*	*0.7*	*0.6*	*0.8*	*1*	2.1/ 0.016	1.9/ 0.005
ROE	14.4	22.7	20.6	22.1	24.4	25.4	21	9.3	6.7	6.1	5	5.7	7.2	7.4	13.4/ 0.12	

Note: ***Bank regulatory capital to risk-weighted assets*** – *f* (Bank net interest margin, Liquid assets to deposits and short-term funding, Bank cost to income ratio, Provisions to non-performing loans, ROA, ROE).
Bank net interest margin – *f* (Bank cost-to-income ratio, ROA, ROE, Bank regulatory capital to risk-weighted assets, Provisions to non-performing loans, Liquid assets to deposits and short-term funding).
ROA – *f* (Bank cost-to-income ratio, Liquid assets to deposits and short-term funding, Bank regulatory capital to risk-weighted assets, Provisions to non-performing loans, Bank net interest margin, ROE).

Source: Global Financial Development Database (2016); authors' calculations for 2016 – 2017.

T a b l e 2

Dataset and Forecasts for Romania

Indicator name/Year/ Romania	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016 Value/ RMSE**	**2017 Value/ RMSE**
Bank cost-to-income ratio (%)	62.9	69.5	57.6	66.2	68.3	63.4	49.0	45.1	45.9	54.6	55.3	55.9	47.2	49.5	50.14/ 0.0056	
Liquid assets to deposits and short-term funding (%)	65.1	47.3	51.3	50	57.7	43.3	32.6	30	16.6	13.9	12.7	14.1	17.1	37.2	40.81/ 0.44	
Provisions to non- -performing loans (%)		12.6	16.1	45.6	82	61.6	44.2	79.9	81.2	84.4	86.3	89.8	69.9	65.5	63.25/ 0.0002	
Bank regulatory capital to risk-weighted assets (%)	25	21.1	20.6	21.1	18.1	13.8	13.8	14.7	15	14.9	14.9	15.5	17.6	19.2	20.4/ 0.01	20.8/ 0.02
Bank net interest margin (%)	8.10	7.70	8.75	5.96	5.67	4.33	4.99	6.31	5.52	4.63	4.06	4.05	1.78	3.35	3.44/ 0.0001	3.82/ 0.02
ROA	2.6	2.2	2.4	1.9	1.5	1.3	2	0.5	–0.1	0.1	–0.6	0.45	–0.27	0.9	1.67/ 0.18	1.69/ 0.17
ROE	18.3	15.6	18.5	15.2	11.7	11.4	17.5	4	–2	0.7	–6	4.05	–2.67	8.77	15.9/ 0.0008	

Note: ***Bank regulatory capital to risk-weighted assets –*** *f* (Bank cost-to-income ratio, Bank net interest margin, Liquid assets to deposits and short-term funding, ROE, Provisions to non-performing loans, ROA).
Bank net interest margin – *f* (Liquid assets to deposits and short-term funding, Provisions to non-performing loans, Bank regulatory capital to risk-weighted assets , ROA, ROE, Bank cost-to-income ratio).
ROA – *f (*Bank regulatory capital to risk-weighted assets, Bank cost-to-income ratio, Liquid assets to deposits and short-term funding, Provisions to non-performing loans, Bank net interest margin, ROE).

Source: Global Financial Development Database (2016); authors' calculations for 2016 – 2017.

T a b l e 3

Dataset and Forecasts for Hungary

Indicator Name/Year/ Hungary	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016 Value/ RMSE**	**2017 Value/ RMSE**
Bank cost-to-income ratio (%)	64.7	60.3	55.1	54.2	53.6	69.4	71.4	50.7	54.7	55.2	72.6	75.6	117.8	68.9	70.2/ 0.0002	
Liquid assets to deposits and short-term funding (%)	44.8	40.2	33.1	33.8	33.7	28.7	28.1	30.2	26.2	28.3	27.2	29.7	47.8	21.5	26.03/ 0.038	
Provisions to non--performing loans (%)	50.8	47.3	83.5	65.1	57.1	64.8	43.6	32	39.1	45.8	48.6	51.7	59.4	60.01	50.1/ 0.0002	
Bank regulatory capital to risk-weighted assets (%)	13	11.8	12.4	11.6	11	10.4	12.3	13.9	13.9	13.8	16.3	17.4	16.9	16.9	17.35/ 0.052	17.26/ 0.002
Bank net interest margin (%)	5.21	4.5	5.60	5.03	5.18	4.39	3.77	3.68	3.99	3.34	3.38	3.44	2.08	4.48	4.52/ 0.09	4.56/ 0.02
ROA	1.5	1.5	2	2	1.8	1.8	0.2	0.1	0.05	–0.1	–0.4	0.47	–1.57	0.22	1.68/ 0.0001	1.66/ 0.04
ROE	20.2	19.3	25.3	24.7	24	22.9	13	12	3	–8	–3	5.1	–15.2	2.22	16.48/ 0.005	

Note: ***Bank regulatory capital to risk-weighted assets*** – *f* (Liquid assets to deposits and short-term funding, ROE, Bank net interest margin, Provisions to non-performing loans, ROA, Bank cost-to-income ratio).
Bank net interest margin – *f* (Provisions to non-performing loans, Bank regulatory capital to risk-weighted assets, Liquid assets to deposits and short-term funding, ROA, ROE, Bank cost-to-income ratio).
ROA – *f* (Bank regulatory capital to risk-weighted assets, Provisions to non-performing loans, Bank net interest margin, Liquid assets to deposits and short-term funding, ROE, Bank cost-to-income ratio).

Source: Global Financial Development Database (2016); authors' calculations for 2016 – 2017.

In Poland, the banking regulatory capital is less determined by the profitability ratios (ROA or net interest margin). The most important determinants for this indicator are liquidity ratio and cost-to-income ratio. The net interest margin is weakly determined by the regulatory capital, while ROA is strongly determined by the regulatory capital. The profitability ratios in Poland are strongly determined by the liquidity ratio and the bank cost-to-income ratio (Table 4).

In the Czech Republic, none of the analysed profitability ratios such as ROA and net interest margin are important for determining the bank regulatory capital. Only ROE influences the regulatory capital of the Czech banking system. ROA is strongly determined by the bank regulatory capital, together with cost-to-income ratio, bank net interest margin and liquidity ratio. Net interest margin is not directly and strongly determined by the regulatory capital, but by ROE and provisions to non-performing loans (Table 5).

Compared with the other CEE banking systems, Romania was the most affected by the crisis in terms of the bank net interest margin whereas Poland performed better, but not as well as Bulgaria or even Hungary (Table 1, Table 3 and Table 4). A comparison of profitability within the CEE region during the crisis reveals that the Czech Republic and Poland are the leaders in CEE region, while Hungary is among the countries with the lowest profitability. As a result of the debt crisis and the conversion of loans denominated in CHF, Hungarian banks recorded high negative profitability ratios.

The Czech Republic, Poland and Bulgaria had the highest ROE ratio before the crisis erupted. As far as ROA development is concerned, Bulgaria had the highest ratio before the crisis, but it lost its top position during the crisis. Poland started with the lowest ROA rate, but it ended the crisis period with a high ROA ratio, just like the Czech Republic. Hungary faced the greatest difficulties during the crisis period. The Hungarian banking sector faced losses for three years, just like the Romanian banking system did. The Romanian banking system displayed better ROE and ROA levels than the Hungarian banking system in 2008. The Romanian, Bulgarian and Hungarian banking systems recovered very hard, because of the negative pressures on the financial markets (even Poland and the Czech Republic felt those pressures during 2013 – 2014 and their profitability ratios also contracted, from already low levels) and a difficult economic environment during the first years after the crisis. The banking systems in Hungary and Romania faced losses again in 2012 and in 2014. Non-performing loans were high in Romania, Hungary and Bulgaria. Romania has a less concentrated banking market in the CEE region (only Poland and Bulgaria are ranking after Romania) and the lowest intermediation degree in this region (Radulescu, 2014; Radulescu and Tanascovici, 2012).

T a b l e 4

Dataset and forecasts for Poland

Indicator Name/Year/Poland	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016 Value/ RMSE**	**2017 Value/ RMSE**
Bank cost-to-income ratio (%)	80.8	87.4	64.3	59.6	58.4	58.4	55.3	53.8	52.9	52.5	52.3	54.6	50.2	52.9	53.36/ 0.13	
Liquid assets to deposits and short-term funding (%)	22.2	25.4	33.3	36.5	33.2	27.8	23.4	16.6	12.5	10.9	13.3	11.5	13.5	13.8	15.03/ 0.13	
Provisions to non--performing loans (%)	56.3	53.4	61.3	61.6	68.5	67.3	68.8	61.6	72.5	71.8	68.2	67.8	69.3	58.6	54.45/ 0.014	
Bank regulatory capital to risk-weighted assets (%)	13.8	13.8	15.4	14.6	13.2	12	11.2	13.3	13.9	13.1	14.8	15.7	14.7	16	16.85/ 0.06	17.13/ 0.005
Bank net interest margin (%)	3.84	3.65	5.57	4.30	4.35	3.65	3.28	3.1	3.24	3.07	3.45	2.89	2.43	2.95	3.23/ 0.03	3.36/ 0.03
ROA	0.5	0.5	1.4	1.6	1.7	1.8	1.5	0.8	1.1	1.3	1.3	1.1	1.1	0.8	0.91/ 0.01	0.95/ 0.004
ROE	5.5	5.4	17.1	21.9	21	25.6	20	10.5	12.4	15.1	14	12.1	12.3	9.1	9.85/ 0.1	

Note: ***Bank regulatory capital to risk-weighted assets*** – *f* (Bank cost-to-income ratio, Liquid assets to deposits and short-term funding, Bank net interest margin, Provisions to non-performing loans, ROA, ROE).
Bank net interest margin – *f* (Provisions to non-performing loans, Bank cost-to-income ratio, Liquid assets to deposits and short-term funding, Bank regulatory capital to risk-weighted assets, ROA, ROE).
ROA – *f* (Liquid assets to deposits and short-term funding, Bank regulatory capital to risk-weighted assets, Bank cost-to-income ratio, Bank net interest margin, ROE, Provisions to non-performing loans).

Source: Global Financial Development Database (2016); authors' calculations for 2016 – 2017.

T a b l e 5

Dataset and Forecasts for Czech Republic

Indicator Name/Year/ Czech Republic	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016 Value/ RMSE**	**2017 Value/ RMSE**
Bank cost-to-income ratio (%)	63.0	56.8	58.7	54.1	54.1	50.2	46.4	39.7	41.6	43.4	41.4	41.5	42.1	45.8	47.7/ 0.23	
Liquid assets to deposits and short-term funding (%)	67.5	59.8	39.8	45.7	38.3	39.9	30.1	28.8	28.6	24.7	23.6	27. 0	15.1	21	20.9/ 0.42	
Provisions to non- -performing loans (%)	77.5	76.7	71.2	64.5	53.6	60	57.4	49.7	47.9	48.8	49.2	51.6	47.7	59.9	62.1/ 0.41	
Bank regulatory capital to risk-weighted assets (%)	14.3	14.5	12.5	11.9	11.4	11.1	11.6	14	15.3	15	15.6	16.5	17	16.7	17.2/ 0.046	17.10/ 0.06
Bank net interest margin (%)	2.86	2.75	3.87	3.01	2.98	3.32	2.82	3.34	2.96	2.96	2.93	2.57	0.73	2.67	2.41/ 0.09	2.22/ 0.04
ROA	1.2	1.2	1.3	1.4	1.2	1.3	1.2	1.5	1.4	1.2	1.4	1.3	1.3	1.2	1.38/ 0.006	1.36/ 0.011
ROE	27.1	23.8	23.3	25.2	22.5	23.1	22	26	20.7	18.6	22	17.6	17.5	15.5	15.15/ 0.1	

Note: ***Bank regulatory capital to risk-weighted assets*** – *f* (Liquid assets to deposits and short-term funding, Bank cost-to-income ratio, ROE, Bank net interest margin, Provisions to non-performing loans, ROA).
Bank net interest margin – *f* (Provisions to non-performing loans, ROE, Bank cost-to-income ratio, Liquid assets to deposits and short-term funding, Bank regulatory capital to risk-weighted assets, ROA).
ROA – *f* (Bank cost-to-income ratio, Bank regulatory capital to risk-weighted assets, Bank net interest margin, Liquid assets to deposits and short-term funding, ROE, Provisions to non-performing loans).

Source: Global Financial Development Database (2016); authors' calculations for 2016 – 2017.

In 2015, Poland and the Czech Republic were considered high-growth markets, characterized by modest levels of financial intermediation, so the lending and asset growth can outpace GDP growth on a sustained basis in the near future. Hungary and Romania may be added to this group of countries. They regained their profits. Both banking markets displayed major improvements in the economic and banking sectors during 2014 – 2015 based on deleveraging and non-performing loans restructuring. In those Central European markets without traditional deleveraging needs (the Czech Republic, Poland) the trend of loan and deposit growth continued in 2014, with a slightly stronger deposit growth in comparison to loan growth (Raifeisen Bank, 2015).

Poland and the Czech Republic are the only CEE countries where the credit to the private sector increased during all the analysed years up to present (the increase was much stronger in Poland). Poland reached a level similar to Bulgaria in 2015, but in Bulgaria the domestic credit decreased during the last years, while in Poland we have a solid increase during the years. In the Czech Republic, this ratio was around 51% in 2015, following a solid increase during 2002 – 2015, too.

Banking markets with deleveraging needs (South Eastern European countries as well as Hungary) continued to show a significantly stronger growth in deposits than in loans.

The Czech Republic displayed a loan-to-deposit ratio of 82% in 2015, while in Poland this ratio decreased at 97% in 2015, after a long period of levels over 100%. The other countries displayed lower levels of this ratio. In Hungary, this ratio was 81% in 2015, in Bulgaria 75% and in Romania 69% (Raifeisen Bank, 2015).

The forecasted decrease of the Czech banks net interest margin is singular among CEE analysed countries. So, interest revenues will decrease for the Czech banks, while for the Polish banks will modestly increase. In the Czech banking systems, the focus will continue to be on the banking fees, not on interest revenues. For Hungarian, Bulgarian and Romanian banks, we forecast a significant increase of the net interest margin in the following years.

In the CEE region, ROA is expected to increase during 2016 – 2017, with the sharpest increase in Hungary. The lowest increase will be reached in Poland and the Czech Republic. In Romania and Bulgaria, ROA will double over the next two years.

The capital adequacy ratio will improve in all the analysed CEE countries. Bulgaria and Romania will face the strongest increase of their capital adequacy ratios (around 20%), while in Hungary, Romania and Bulgaria we can expect the strongest increase of the profitability ratios (Tables 1 – 5).

The liquidity in the Czech banking system is expected to increase, but it remains low just like in Hungary, while in Poland it is even lower than that. Romania ranks first in terms of banking liquidity (Tables 1 – 5).

In the CEE region, Bulgaria and Hungary are expected to be less affected in terms of banking profitability by the new tight regulation for the capital adequacy imposed by Basel III. These countries also display a descending trend of the cost-to-income ratio. In Bulgaria, this decrease was important and this factor is the most important one for the profitability ratios as we can see from the forecast functions we have discussed above. Romania ranks after them, with a higher capitalization ratio and a significant increase of ROA, but with a slow increase of cost-to-income ratio in the following years. Poland and the Czech Republic ranks on the last positions among the CEE analysed countries, both in terms of capitalization or profitability. In these last two countries, the cost efficiency ratio is expected to worsen, too. However, Bulgaria is still endangered by a high share of non-performing loans, which can affect the banking cost-efficiency and profitability (expressed as ROA) and Hungary still displays a very high cost-to-income ratio, although it has decreased significantly in the last years and it doesn't significantly influence the profitability ratios in the Hungarian banking sectors as we could see from the determination functions discussed above. So, even these two highest ranked CEE banking systems experience problems in some specific banking areas. A high share of non-performing loans and a high cost-income ratio could further endanger the profitability in Romania, Bulgaria and Hungary that rely mostly on the interest revenues (Tables 1 – 5).

In Poland and the Czech Republic, the banking profitability expressed by the net interest margin is not strongly determined by the regulatory capital, which can be explained by the fact that those two banking sectors don't rely on interest revenues as much as the banking sectors from Bulgaria, Hungary or Romania. Still, ROA is strongly determined by bank regulatory capital in Poland and the Czech Republic, while in Romania and Hungary, bank regulatory capital is the most important factor for determining ROA. The lowest impact of the regulatory capital on the banking profitability can be seen in Poland and the Czech Republic, while in Bulgaria this is an average impact among the CEE selected countries (Tables 1 – 5).

Another interesting result is the great importance of the liquidity ratio for determining bank regulatory capital or profitability ratios in all the selected CEE countries, because, for the first time, the new Basel III agreement imposes new regulations and constraints for the liquidity ratio. Liquidity ratio is not very significant for net interest margin only in Bulgaria and Czech Republic, while in Hungary and the Czech Republic is the most important factor for bank regulatory capital. In Romania or Poland, it is the most important factor for the profitability ratios (net interest margin, respectively ROA) (Tables 1 – 5).

The main differences in our forecasts belong to the estimated ROA values, but this ratio also displayed great differences during the entire analysed period between the CEE countries and even for the same country (especially in Romania and Hungary where the banking systems faced losses during the crisis and ROA became negative). According to the forecast functions, the main ratios impacting on ROA in these selected CEE countries are: banking regulatory capital, bank cost-to-income ratio and the provisions to non-performing loans. These above-mentioned ratios display different trends in the selected CEE countries. Thus, the forecasted ROA display different values in these selected CEE countries. Hungary and, even, Poland display a high bank cost-to-income ratio and some countries display a high share of the non-performing loans to the total loans (Bulgaria, Romania and Hungary). The regulatory capital is higher in Romania and Bulgaria against Hungary, Poland and the Czech Republic.

This relationship we have forecasted for the following years (until 2018 when the new Basel III should be fully implemented) between the capital adequacy ratio and the profitability ratios in the CEE region is supported by the findings of other previous studies performed for the CEE banking sectors (Capraru and Ihnatov, 2014; Beltratti and Stulz, 2012; Andries et al., 2016; Claeys and Vander Vennet, 2008; Petria, Capraru and Ihnatov, 2015). This means that a better supervision and some tight regulations for the banking capital and liquidity are positively correlated with the banking profitability, if the banks provide a good and adequate cost efficiency management and could reduce their non-performing loans. But this relationship is strong and positive only for several CEE countries (Bulgaria, Hungary and Romania), while in others, this relation is positive, but weak (Poland), or even negative if we consider the net interest margin (for the Czech Republic).

For the analysed CEE countries, on average, ROA will increase in the following years against 2015 data. So, the positive relation between the capitalization and profitability can be achieved only if the cost-to-income ratio displays a sharp descending trend. Otherwise, this relation is weak such as in Poland or in the Czech Republic. ROE will also increase for all the analysed CEE banking systems, despite the sound capitalization in those banking sectors. Our findings are opposite to the findings of other authors (Harle et al., 2010; Šútorová and Teplý, 2014; Cosimano and Hakura, 2011) that stated that Basel III will reduce the average profitability of the European banking system (expressed by ROE), but there are significant differences between the CEE banking sectors and the advanced European banking sectors. CEE banking sectors performed better than the advanced European banking sectors in terms of profitability and capitalization during the last crisis.

Our forecasts are supported by the data for 2016 and partial data for 2017 released by the European Banking Authority (2016 – 2017) for the analysed CEE countries, best forecasts being achieved for Poland and the Czech Republic. The maximum differences between our forecast and the data released by the European Banking Authority at the end of 2016 represent around 5 – 7% of the estimated figures, thus, according to any statistic test, this represents an accurate forecast. Poland reached a total banking capitalization ratio of 16.05% in 2016 against the level of 16.8% we forecasted for 2016. Romania reached a total banking capitalization ratio of 19.35% in 2016 against a level of 20.4% we forecasted. Bulgaria achieved a total banking capitalization ratio of 20% in 2016, while we predicted a ratio of 21.25%. Hungary reached a total banking capitalization ratio of 16.38%, while we forecast a ratio of 17.35% in 2016. In 2016, the Czech Republic reached a total banking capitalization ratio of 17.8% against the level of 17.17% we predicted. For ROA, the lowest differences between our forecast and the data released for 2016 by the European Banking Authority were reached in the Czech Republic (1.46% against our forecast of 1.38%) and in Poland (0.98% against our forecast of 0.91%). For the net interest margin, the lowest differences were reached for the Czech Republic (2.45% against our forecast of 2.41%) and in Romania (3.24% against our forecast of 3.44% in 2016). The trend we forecast is validated by the data released by the European Banking Authority in 2016 and 2017. This means that the forecasting functions are well elaborated and the main determinants for the banking profitability ratios of the CEE banking systems are well underlined.

Conclusions

If we consider both the capitalization (solidity) of the CEE banking sectors and their profitability (mainly expressed by the net interest margin, because it is the main source of profit in the CEE region), Bulgaria ranks first, followed by Hungary and Romania. On the 4th position it is Poland and the last position belongs to the Czech Republic. Bulgaria and Romania are better capitalized against their neighbours in the CEE region. The Romanian banking system was more severely hit by the recent financial crisis than the Bulgarian banking system in terms of profitability. The Romanian banking systems faced losses three years, just like Hungary. These two countries had a greater exposure to the loans denominated in foreign currency, especially to loans denominated in CHF that proved to be a very volatile exotic foreign currency during the crisis. In Bulgaria, due to its Currency Board, its exposure to the foreign exchange rate risk was much lower. Moreover, among the CEE analysed countries, Bulgaria is the only country that proceeded to important and long-lasting cost cut-offs. Hungary did the same, but the cuts-offs came from very high levels, so the current cost-to-income ratio is still high in Hungary, but on a sharp descending trend. The Polish and the Czech banking systems were less capitalized than the Bulgarian or the Romanian banking systems. Their profitability ratios were more stable than the ones of the other three countries in the region, but the levels displayed by the net interest margin were lower than in Bulgaria, Romania and Hungary. However, the level of the overall profitability ROA didn't displayed major differences among those five countries (except for the years when Romanian and Hungarian banking systems faced losses). Because of the losses, ROA fluctuated greatly from year to year, in Romania and Hungary. In the CEE region, bank net interest margin is significant for the banking profitability, because interest represents a great part of the total banking incomes and total banking costs.

The main indicator showing the banks' resilience in front of a potential crisis is the bank capital. The adequacy capital ratio has improved for the CEE banking sectors. New banking regulations include some requirements for liquidity as well as for the capital adequacy. Banks are required to have higher and larger quality buffers, including liquidity buffers. In terms of liquidity, Romania ranks first and Bulgaria comes on the second position. Hungary and the Czech Republic rank on the following positions and Poland displays the lowest liquidity ratio among the CEE analysed countries. But, what is worrying is the current profitability of the banks. The low level of interest rates is relevant for all the European countries. Net interest income is very important for the CEE banks revenues. In the long-run the funding costs can hit a lower limit and net interest margins will decline. Therefore, banks can focus on increasing their other revenues (from fees gained by releasing new products or attracting new clients, just like the Czech Republic did) or they can reduce their cost, especially where the cost-to-income ratio is high. Poland, Hungary and Bulgaria made important cost cut-offs during the last years. In Romania and Czech Republic these cuts were less significant. However, in the Czech Republic the cost-to-income ratio is the lowest in the CEE region, but the descending trend of this ratio is expected to reverse during 2016 – 2017, just like in Poland or in Romania. Hungary and even Romania performed very well in reducing their banking networks, so their cut-offs were important in the salary area, while in Poland and in the Czech Republic the salary expenses remained rather at the same level.

The new regulatory environment will put pressure on their profitability. Banks must adjust their business models by cutting costs and consolidating in a low-interest rate environment. For all the CEE analysed countries, the main indicator determining a positive relation between capitalization and banking profitability seems to be cost-to-income ratio. Some CEE countries could further improve their legal frameworks in order to deal with the non-performing loans (e.g. Bulgaria). Indeed, a strict regulation reduces banking opportunities to gain large profits, but only very well-capitalized banks could sustain and finance the economy with no fear of any other crisis that could erupt. If the cost-to-income ratio depends more on the management of each bank, the maximum level of the non-performing loans ratio can be regulated by the monetary authority, because this ratio is also very important for the relation between the banking capitalization and profitability in the CEE region according to our results.

The most important finding of this research is that all the analysed CEE countries will perform well as far as the banking profitability and capital adequacy are concerned (just like they performed during the crisis period) in the following years, but the main challenges are represented by their high share of the interest rate revenues of the total banking revenues (except for the Czech Republic), high cost-to-income loans to the total loans (Bulgaria, Romania and Hungary). These weak points could endanger the positive relationship we expect for the following years for the analysed CEE countries.

The macroeconomic situation and performance is inter-correlated with the state and performance of the banking sector, especially during the crisis period. We didn't consider the external factors of the banking sectors in this paper, although our analysis has also covered the crisis period when the macroeconomic environment became turbulent and significantly impacted on the banking capitalization and profitability. Thus, this represents a limitation of this study and a topic for further research.

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