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Efficiency dynamics of the Croatian banking industry: DEA investigation

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ABSTRACT

The paper deals with the efficiency dynamics of the Croatian banking industry, covering the period from 2006 to 2015. We have implemented the intermediation approach, using interest and non-interest expenses and revenues as the input and output variables, respectively. The variable return to scale (BCC) Data Envelopment Analysis (DEA) output-oriented model has been implemented, and we have estimated the crisis-driven efficiency trends, as well as the impact of the EU membership. We further estimated the efficiency effects of the relative market power/size, ownership structure, and origin of capital. The global crisis had detrimental effects since the overall efficiency score dropped by about 3%. On the contrary, Croatian banks have largely benefited from the EU membership, and the efficiency score after the EU association increased by about 45%. The market leaders are more efficient than the competitive fringe, which is in line with the efficiency structure hypothesis. In addition, the biggest banks are the most efficient ones, meaning that the scale efficiency hypothesis has also been upheld. Contrary to the agency theory hypothesis, state-owned banks are permanently more efficient than private banks. Finally, the results support the home-field advantage hypothesis exclusively for the pre-crisis period (2006–2009).

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1. Introduction

Over the last three decades, the global financial markets have undergone dramatic institutional transformations. They have been affected by liberalisation and financial globalisation on one hand, and a changing macroprudential regulation and supervisory role, on the other hand. In addition, the bank-based financial sectors of the former socialist countries, previously driven by central planning, lived through the disruptive financial meltdowns which required both restructuring and transition. The Croatian banking market was not isolated from these “tectonic” structural changes.

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After successful privatisation, the Croatian banking market became more competitive and internationalised. Official Croatian National Bank (CNB) data state that only about 6% of the market share was held by domestic banks in 2015. Also, the concentration indicators (CR5, HHI) suggest suboptimal competition (moderate concentration) of the banking market.

The dynamic and competitive environment, driven by ever-increasing market challenges, emphasises financial intermediation efficiency as an important performance, both for banks and the supervisory agencies. Namely, banks intend to increase their market share and profitability through efficiency, implicitly shaping the market structure (competition). Also, efficiency is an indicator of operational performances equally interesting for both the national and international regulatory bodies. By monitoring the efficiency dynamics, the supervisory authorities can react proactively to prevent bank failures or collusive behavior. This prudent activity is of utmost importance, bearing in mind that a significant efficiency drop of a systemic important bank could trigger extremely disruptive market trends and induced failures across the market. Also, increasing competition goes vis-à-vis with excessive risk-taking practices, which could result in liquidity crises, an undercapitalised banking industry, and systemic financial instability.

The paper aims to contribute to the existing literature that tackles efficiency dynamics in different banking structures, especially the literature that deals with post-transition banking markets (the young banking markets). More importantly, the main intention is to provide some empirical insight into the efficiency dynamics of the Croatian banking industry both at the sectoral and bank-group level. Accordingly, it is important to emphasise the several research questions this paper aims to tackle. First, it examines the crisis-driven impact on the efficiency trends of Croatian banks, together with the impact of EU membership. More importantly, we have challenged the scale efficiency and agency theory hypotheses, as well as the home-field advantage and efficiency structure hypotheses. It is worth noting that we will use the terms *economies of scale* and *scale efficiency* interchangeably, although some authors make a distinction between them.

Numerous country-based and region-based empirical studies have been published recently, and all of them rely on either the production or intermediation approach, using various parametric and non-parametric approaches (mainly SFA and DEA). We have chosen the intermediation approach, together with the variable return to scale (BCC) output-oriented DEA. The paper is structured as follows: the introductory section is followed by a literature outline focused on the methods, findings and possible methodological drawbacks; in the second part we have described our dataset and methodological framework (the DEA efficiency and super-efficiency models); the third part highlights the results and discussion, while the last section summarises the concluding remarks and policy implications.

2. Literature survey

There is a significant body of literature devoted to measuring the efficiency of banks, and the studies differ greatly regarding methodology, input and output variables, and

country/regional dispersion. To make the survey is more relevant from the perspective of the Croatian banks, we will focus on the empirical studies of the developing counties in Europe and Asia. For example, Nenovsky, Chobanov, Mihaylova, and Koleva (2008) have exploited DEA methodology (the operational and intermediation DEA approaches) to estimate the efficiency of Bulgarian banks, covering the period 1999–2006. Their results contrast the home-field advantage hypothesis as the foreign banks are more efficient than domestic banks, both the private and state-owned ones. Obviously, the privatisation of the state-owned banks has had beneficial effects in terms of operational efficiency. Also, there is the effect of scale economy, and large banks are more efficient than medium and small banks. (Nenovsky et al., 2008). The results generated from this approach are especially problematic, bearing in mind that some input variables (for example, fixed assets and the number of employees) are not always related to the output variables (loans and securities) in an operational sense.

In addition, Staub, Souza, and Tabak (2009) have used both the stochastic frontier approach (panel data analysis) and deterministic approach (DEA), aiming at measuring the technical and allocative efficiency of Brazilian banks in the period 2000–2007. The findings suggest that non-performing loans and market share are important efficiency determinants. The results also support the home field advantage hypothesis, since domestic banks are more cost-effective than foreign ones. Also, private banks are less efficient in comparison with state-owned banks, thus failing to uphold the agency theory hypothesis. By using both the stochastic and deterministic approaches, the analysis seems to be more reliable but the results are biased due to the nature of the NPL and equity (they are not fully controlled by banks).

Matthews, Xiao, and Xu (2009) have investigated the efficiency of the Chinese banks by using the DEA approach. Precisely, they measured cost-inefficiency and used a non-parametric bootstrapping method to decompose it into X-inefficiency and allocative inefficiency. Overall, the Chinese banks have upgraded their efficiency by reducing both X-inefficiency and allocative inefficiency, although state-owned banks were less successful in this process in comparison with joint-stock commercial banks. The results generated from the study are quite specific, but understanding could be deepened if they had challenged the scale efficiency hypothesis. In addition, it would be quite instructive to follow the efficiency trends of the Chinese banks during the pre-crisis and crisis years.

In addition, Andries and Cocris (2010) have compared the efficiency scores of the largest banks in Romania, the Czech Republic and Hungary in the period 2000–2006 by using the stochastic frontier approach and data envelopment analysis. The Romanian banks are the least efficient, although overall cost efficiency has increased dramatically over the years. This has been caused by the reduction of non-performing loans and administrative expenses (Andries & Cocris, 2010, A comparative analysis of the efficiency of Romanian Banks). The two-method approach minimises the potential error caused by the dataset distribution hypothesis sample used in the study. However, the sample is quite problematic because only the largest banks from different countries were selected, and they did not face the same market conditions.

In an extended research study, Castellanos and Garza-Garcia (2013) have examined the cost efficiency of banks in Mexico, covering the period 2002–2012. They found

evidence that crisis-driven factors have reduced the efficiency of Mexican banks, especially during the initial crisis years. Although their findings support the home-field advantage hypothesis in a sense (the local banks are more efficient), the results emphasise a kind of systematic efficiency of both the domestic and foreign banks. Finally, the Spanish banks are the efficiency leaders among the foreign banks, which also supports the home-field advantage hypothesis to an extent (Castellanos & Garza-Garcia, 2013). One critical point of this study is related to the scale efficiency hypothesis. Namely, the results do not shed light on scale economies, and it is also impossible to draw any conclusion regarding the market structure and efficiency structure hypotheses.

Another interesting study that tackles the Macedonian banking sector (Micajkova & Popovska, 2013) was aimed at measuring the technical, pure technical and scale efficiency of 15 Macedonian banks, covering the period 2008–2011. They used both the CCR and BCC models, with total deposits received and labor costs as the input variables, and loans to banks and customers and investments, as the output variables. The difference in scores suggests that scale efficiency is the main source of inefficiency. However, the study did not reveal other efficiency sources, such as ownership structure, economies of scale, or market dominance. Finally, this study does not address the impact of the global crisis.

In a comparative study, Jayaraman, Srinivasan, and Jeremic (2013) have employed the DBA and profit DEA to evaluate the efficiency of Indian banks, covering the period 2005–2012. They used deployed funds (performing loans and investments) as the output variables, and equity, borrowed funds (deposits and borrowings), work force (number of employees) and the number of branches as the input variables. Their findings are quite specific: out of 34 banks, seven banks are DBA efficient, 10 banks are DEA efficient and five are both DBA and DEA efficient. The results also revealed two important points: (a) there is no significant discrepancy in the rankings based upon the two approaches; (b) the results support scale efficiency. However, the results cannot be related to either the agency theory or home-field advantage hypotheses, and the input side of the model is over-specified. Furthermore, the global crisis is not considered an important determinant of bank performances.

In addition, Murat Ar and Kurtaran, (2013) estimated the efficiency of 13 Turkish banks in 2011, using an integrated AHP/DEA approach. They rejected the agency theory hypothesis since the state-owned banks are efficiency leaders. In addition, the foreign-owned banks are the least efficient, meaning that the results support the home-field advantage hypothesis. The most obvious disadvantage of this study is the static orientation, because the efficiency scores are only determined for one year, which could be highly influenced by random factors. In addition, it lacks scale efficiency analysis.

Another extensive study (Repkova & Paleckova, 2013) uses the Window DEA to determine the efficiency dynamics of the Czech banking sector. The study contrasts the CCR and BCC scores to reveal the scale efficiency, covering the period 2003–2012. The results have detected the return to scale as the main driving factor of inefficiency, since the CCR scores reached 70–78% and the BCC scores reached 84–89%. The study addresses neither crisis-driven effects nor the efficiency

differential between the group-level scores. Furthermore, the Window DEA is structurally built to measure the efficiency of internal DMUs that are productionally interdependent but controlled by the same higher-order managerial body.

In a more recent study, Fan (2016) investigated the efficiency trends of selected Chinese banks in the post-crisis years (2008–2014) by implementing the integrated DEA and super DEA models. Among the various detailed results, it is worth noting that the Chinese banks increased their efficiency after the crisis. Technical efficiency is mainly fueled by scale efficiency, while the latter is the main driving factor of the efficiency convergence among the banks. The agency theory hypothesis has been upheld, but state-owned banks have improved their efficiency dramatically since 2012. However, the comparison between the major bank groups sorted by size or origin of capital is missing, meaning that the main market hypotheses have not been addressed. Also, we do not know the market share of the banks that comprise the sample (60 banks sorted into three groups).

Finally, Andries and Ursu (2016) have implemented the multi-product translog specification to assess the EU banks' profit and cost efficiency in the period 2004–2010. Their findings argue in favor of a positive impact of the crisis, especially for the Eurozone banks. Specifically, the overall average efficiency score has increased by about 0.9% (cost efficiency) and 3.6% (profit efficiency). The most significant increase is recorded for the large banks (cost efficiency) and small banks (profit efficiency), while only the non-euro area banks slightly reduced their efficiency in the crisis years. As an extension of this research it would be quite interesting to see the efficiency trends for different banking groups in both the Eurozone and Non-Eurozone countries, and challenge the market structure hypotheses for the single EU banking market.

A closer look at the literature in the field did not reveal any comparable study that employs the data envelopment analysis to measure the efficiency of Croatian Banks, meaning that this study can be considered an important contribution to the existing literature. In addition, by varying samples/subsamples, this study provides a closer look at the efficiency trends of different banking groups, aimed at challenging several banking and market structure hypotheses. Furthermore, the results of the study can be used as a benchmark to compare efficiency trends of the EU banking structures. Finally, we have implemented both the DEA and super-efficiency DEA models, allowing the ranking of the relatively efficient banks.

3. Data and methodology

The aim of the study is to measure the efficiency of the DMUs using the intermediation approach, widely accepted in banking theory. As for the inputs and outputs structure, we have used interest and non-interest expenses as the input variables, and interest and non-interest revenues as the output variables. So, the multi-product approach has been implemented here, aimed at determining the relative efficiency scores of the decision-making units, as well as the super-efficiency of previously determined relative efficient ones.

The study deals with the DEA group of models used to determine the relative efficiency of many DMUs that use multiple inputs to produce multiple outputs. Many DEA models have been developed over time, starting from the constant return to scale (CCR) model, which has been further extended to the variable return to scale (BCC) model, then the additive and super-efficiency DEA models. DEA methodology is based on the Pareto optimality which states that a DMU is more efficient than the remaining ones if it is not possible to increase an output without decreasing another output or increasing inputs. More formally, an efficient DMU is located on the production possibility frontier, and the input and output slacks are zero. To determine the efficiency frontier, DEA uses available data for each DMU instead of using a pre-determined efficiency function. This is an obvious advantage of the DEA as a non-parametric methodology. For more analysis of the DEA models see Charnes, Cooper, and Rhodes (1978), Cooper, Seiford, and Tone (2007), and Wen (2015).

The paper employs both the BCC output-oriented and A-P super-efficiency models, using two inputs (interest and non-interest expenses) and two outputs (interest and non-interest revenues). According to Banker, Charnes, and Cooper (1984), Cooper et al. (2007), and Wen (2015), the models are presented in Table 1.

In these specifications, z_i and z_b are the input vectors, while y_i and y_b are output vectors of the selected and benchmark DMUs. Also, ω and γ are vectors of the input and output weights, respectively. By implementing the BCC, we have assumed the variable return to scale. It implies that the efficiency of a DMU is determined by the possibility of increasing output whilst keeping the amount of inputs fixed. So, the greater the output increase, the less efficient the DMU, i.e. a DMU is considered efficient if the relative efficiency score is 1 (100%). In addition, if the score is greater than 1 (100%), a DMU is considered inefficient, and this upward-sloping deviation from the cut-off point is a measure of inefficiency.

In comparison with the BCC model, the A-P super-efficiency model (Andersen & Petersen, 1993) can rank the relatively efficient DMUs. Namely, to compare a DMU with the remaining ones, the super-efficiency model does not use its own data as a reference point. Precisely, the super-efficiency score measures the distance of the evaluated DMU (that is relatively efficient) from the new efficient frontier (Jablonsky, 2016). So, it measures the input slack to keep the DMU within the reconstructed efficiency frontier. The model we have implemented is input-oriented, meaning that it determines the efficiency of a DMU by the possibility of decreasing inputs, keeping the outputs fixed. Any super-efficient DMU also has a score equal to 1 (100%), but the inefficient DMUs have a score below 1. Accordingly, there are downward sloping

Table 1. BCC and A-P models.

BCC output-oriented model	A-P super-efficiency model
$\left\{ \begin{array}{l} \underset{\omega, \gamma}{\text{Min}} \quad \varphi = \frac{\omega^T z_b + \alpha}{\gamma^T y_b} \\ \text{s.t.} \\ \omega^T z_j + \alpha \geq \gamma^T y_j, \quad j = 1, 2, 3, \dots, n \\ \omega \geq 0 \\ \gamma \geq 0 \end{array} \right.$	$\left\{ \begin{array}{l} \varphi = \underset{\text{s.t.}}{\text{Max}} \sum_{s=1}^n \gamma_s y_{sk} \\ \sum_{r=1}^m z_{rj} \omega_j - \sum_{s=1}^n y_{sj} \gamma_j \geq 0 \quad j = 1, 2, \dots, n, \quad j \neq k \\ \sum_{r=1}^m z_{rk} \omega_r = 1 \\ \omega_r \geq \varepsilon \quad r = 1, 2, \dots, p \\ \gamma_s \geq \varepsilon \quad s = 1, 2, \dots, s \\ \varepsilon > 0 \quad (\text{Non-Archimedean element}) \end{array} \right.$

Source: Derived according to Banker et al. (1984), Cooper et al. (2007), and Wen (2015).

efficiency deviations so that the farther the score from the efficiency frontier toward zero, the more inefficient the DMU.

The dataset consists of the bank-level data extracted from the official CNB reports, covering the period 2006–2015. To assess the crisis-driven efficiency trends, we have further divided the sample into two subsequent periods: (1) the pre-crisis (2006–2009); (2) the post-crisis (2010–2015). Furthermore, we have estimated the impact of the EU association on the efficiency trends. The overall efficiency score has been determined by using the full sample (all banks). To calculate the bank-group scores, we had extracted the individual scores from the full sample scores, grouped the banks with respect to different criteria, and then calculated the average scores for all the groups.

As for the group-level efficiency scores, we have additionally selected the banks according to their size/relative market power, ownership structure, and origin of capital. Specifically, to classify banks according to their size, we have used the criterion established by the Croatian National Bank (Croatian National Bank, 2006): the relative market share (%) calculated as a ratio of the bank asset to the total market asset. According to the CNB, the small banks have a relative market share below 1%, the medium banks within 1–5%, and the large banks above 5%. Also, both the ownership structure selection (state-owned and private banks), and the origin of capital classification (domestic and foreign banks) are based on the official data reported by the Croatian National Bank (CNB). By comparing different group-level scores, we have basically challenged the following postulates: (1) the scale efficiency and agency theory hypotheses; (2) the home-field advantage efficiency structure hypotheses.

4. Results and discussion

In this section we have presented the main efficiency trends both at the industry level and different group levels. To begin with, we will first consider the average efficiency scores calculated for the pre-crisis (2006–2009) and crisis periods (2010–2015) presented in the Appendix (see Table A1). Accordingly, the most efficient banks before the crisis were HVB Splitska Bank, Požeška Bank, and Zagrebačka Bank. By comparing the two periods, it is noticeable that the global crisis has reduced the efficiency of the Croatian banks by about 3%. This evidence mainly coincides with the results of the comparable studies, but it opposes the results for the EU banks (Andries & Ursu, 2016). The relatively efficient banks have a score equal to 100%, and they are considered the most efficient. This ranking should be treated cautiously, bearing in mind that some relatively efficient banks operated only for a couple of years during the observed periods. However, it is worth noting that some banks have kept their superior efficiency positions over the years (Zagrebačka Bank, Business Bank Zagreb).

As for the super-efficiency scores at the end of the periods, the efficiency winners have been presented in Table 2.

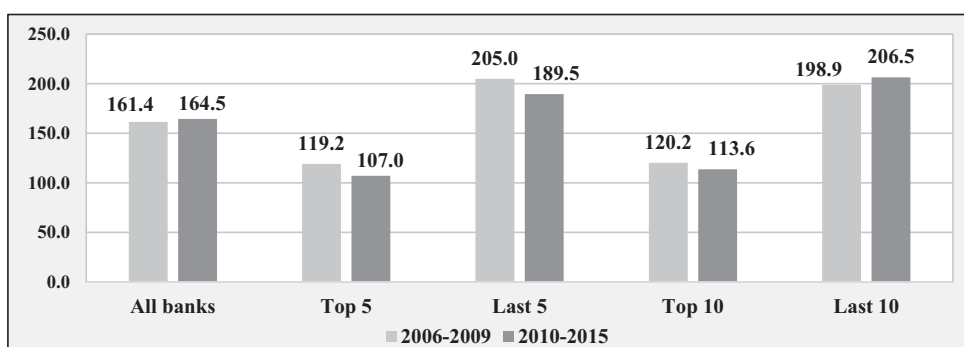
The super-efficiency banks are randomly distributed across different banking groups (see RS column), so that we have a small, private and domestic bank as an efficiency winner in the pre-crisis period. On the other hand, a large, private and

Table 2. Super-efficiency scores and ranks of the relatively efficient banks (%).

Bank/Scores/Rank	2009			Bank/Scores/Rank	2015		
	RES (%)	SES (%)	RS		RES (%)	SES (%)	RS
Sav. B. of Sm. Ent.	100.00	100.00	1	Erste&Steierm. Bank	100.00	96.35	1
Štedbank	100.00	85.38	2	OTP Bank Croatia	100.00	95.54	2
Karlovacka Bank	100.00	84.03	3	Primorska Bank	100.00	94.83	3
Erste&Steierm. Bank	100.00	83.98	4	Imex Bank	100.00	92.33	4
Soc-Gen-Splitska Bank	100.00	83.96	5	Croatian Post Bank	100.00	91.12	5
Obrtnička Saving Bank	100.00	81.52	6	Veneto Bank	100.00	90.68	6
Međumurska Bank	100.00	76.99	7	Bank Kovanica	100.00	88.14	7
BKS Bank	100.00	73.12	8	Cred. Bank Umag	100.00	86.23	8
Bank Kovanica	100.00	61.87	9	Soc-Gen. Spl. Bank	100.00	82.84	9
Zagrebačka Bank	100.00	51.58	10	Tesla Saving Bank	100.00	79.89	10
Average	100.00	78.24	-	Average	100.00	89.79	-

Note: RES – Relative Efficiency Score; SES – Super Efficiency Score; RS – Rank of a super-efficient bank.

Source: Authors' calculation based on the CNB official data.

**Figure 1.** The relatively-efficient scores for the market leaders and competitive fringe (%).

Source: Authors' calculation based on the CNB official data.

foreign bank takes the leading position during the crisis years. However, we have a reverse positioning at the bottom of this ranking: a large, private and foreign bank is at the bottom of the scale for the pre-crisis period. On the contrary, a small, state-owned and foreign bank, previously ranked as the most efficient, is the least super-efficient bank for the crisis period. If we consider the intra-period changes, Erste Bank and OTP Bank Croatia have improved their positions dramatically, while Štedbank and Karlovacka Bank have experienced an opposite trend.

To challenge the abovementioned banking and efficiency structure hypotheses, we further sorted the banks into different groups and calculated the average scores respectively. The results have been provided in the following figures.

Figure 1 shows the average efficiency scores for the market leaders and competitive fringe, as well as for all the market players (the year-by-year efficiency trends have been presented in Table A2, see Appendix). It is worth nothing that the results are related to the output-oriented model: an increased score implies a decrease in efficiency. Overall, the results are quite instructive for several reasons. Namely, the global crisis has diminished the efficiency of the Croatian banks, which is in line with the results of Castellanos and Garza-Garcia (2013), but in sharp contrast with the findings of Fan (2016), and Andries and Ursu (2016). A logical explanation of this is that

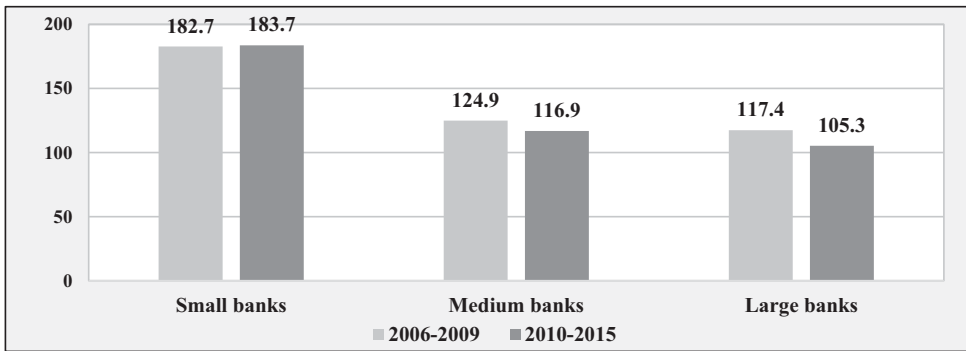


Figure 2. The average efficiency score of the small, medium, and large banks (%).

Source: Authors' calculation based on the CNB official data.

it has to do with the nature of the input-output model. Correspondingly, as the result of an external shock the Croatian banks have collected proportionally less revenue (the NPL has exploded during the crisis period), in comparison with slightly decreasing expenses. Consequently, the industry-level efficiency scores have dropped by about 3%. It is also assumed that banks had an asset/liability maturity gap prior to the crisis years, and the interest and non-interest revenues could not have been adjusted quickly without substantial costs. Thus, these dynamic reshufflings have resulted in increased inefficiency over the crisis years.

The results also showed a huge efficiency differential between the market leaders and competitive fringe. Namely, the market leaders exploit the scale economies effect and thereby the scale efficiency and efficiency structure hypotheses have been proved. Regarding scale efficiency, we can find the same results in Nenovsky et al. (2008). Specifically, the top ten, top five and bottom five banks improved their efficiency during the crisis, possibly as a result of necessary rationalisation on both the borrowing and lending sides. On the other hand, the last 10 banks recorded a decreasing efficiency trend (about 7.5%). It seems that the smallest banks have had a pronounced maturity gap, and the worst loan and investment portfolios, so that they ended up at the bottom of the efficiency ranking.

To make an additional challenge to the scale efficiency hypothesis, we have grouped the banks according to their size (their market share has been used as a criterion, which is in line with CNB standards). The results are presented in Figure 2, and it presents the size-specific average efficiency scores for Croatian banks for both periods (for annual efficiency trends see Appendix, Table A3). Medium and large banks have increased their efficiency dramatically, while small banks became even more inefficient during the crisis.

Apart from the maturity gap, an additional explanation could be that small banks had comparatively fewer options to reshuffle their balance sheets, and some inefficiency sufficed as the consequence of a weak market position. The downward efficiency trends can also be caused by less efficient risk management know-how, lack of cross-border support, or late/suboptimal countercyclical measures. Obviously, the biggest market players are the most efficient in both periods, and the results again support the scale efficiency (see Nenovsky et al., 2008) and efficiency structure

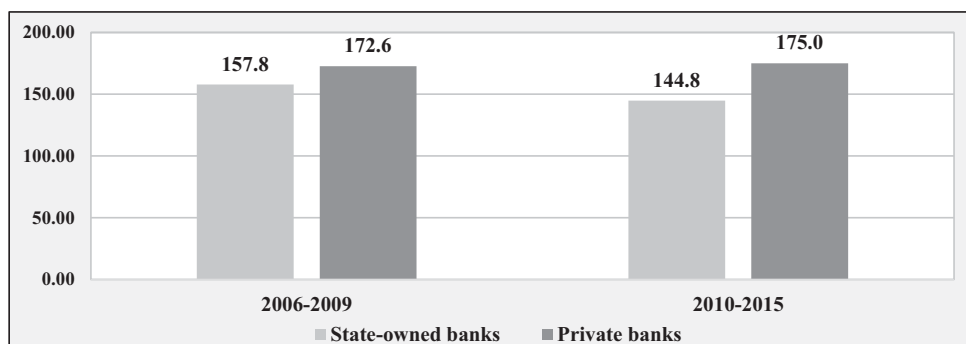


Figure 3. The average efficiency score of the state-owned and private banks (%).
Source: Authors' calculation based on the CNB official data.

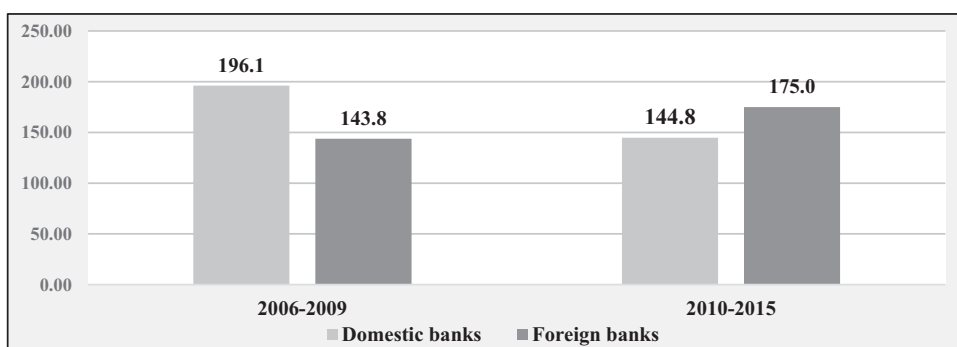


Figure 4. The average efficiency score of the domestic and foreign banks (%).
Source: Authors' calculation based on the CNB official data.

hypotheses. Consequently, the biggest banks acquire greater market share, shaping the market structure of the Croatian banking industry. The later results are very important, bearing in mind that the CNB acts in a supervisory authority, with one of its responsibilities to establish and maintain reasonable competition, as well as to protect customers in the banking market.

Figure 3 shows the ownership-specific efficiency scores in both periods (the annual efficiency changes have been presented in the Appendix, Table A4). These results are even more interesting, bearing in mind the common beliefs associated with the inefficiency of state ownership.

State-owned banks were more efficient than private ones in both periods. Thus, the agency theory hypothesis is strongly rejected, which coincides with the results of Staub et al. (2009) but opposes the findings of Fan (2016). Moreover, the state banks also improved their efficiency during the crisis years by 13%. Size-wise, the state banks are mainly medium and small, so that their efficiency improvements have not resulted from a dominant market position. Also, state-owned banks have been forced to improve their efficiency during the transition phase, and most of them were taken over by international strategic investors. Under increasingly competitive pressure, the remaining state banks have focused on operational efficiency to defend their market positions. However, it is important to note that we have here just a couple of state

banks, and that variations in the average scores could be caused by the sample structure.

On the other hand, private banks, although some of them are market leaders, are moderately efficient, and the global crisis even lowered their average efficiency score. Accordingly, the cross-border business relations (the international exposure) of the Croatian banks, which are in fact branches of the foreign banking groups, are indisputably the main cause of these adverse efficiency trends.

Figure 4 shows the average efficiency scores for the banks grouped according to capital origin (the annual efficiency movements are presented in the Appendix, Table A5). Here we have the most obvious irreversible efficiency movements: (a) the relatively inefficient domestic banks in the first period improved their efficiency score remarkably during the crisis time (by about 52%); (b) initially far more efficient foreign banks lowered their efficiency score during the crisis. Consequently, we can reject the home-field advantage hypothesis for the first period, which coincides with the results of Nenovsky et al. (2008). On the contrary, we fail to reject the hypothesis for the crisis period and we can find the same evidence in some recent studies (Staub et al., 2009; Castellanos & Garza-Garcia, 2013; Murat Ar & Kurtaran, 2013). Obviously, the foreign banks are far more vulnerable to the adverse shocks due to maturity mismatch, international exposure, poor risk management in the pre-crisis period, and ineffective/inappropriate business model reconfiguration. Specifically, a sharp decline in efficiency in 2010 was initiated by the inappropriately rebalanced liabilities and sharply decreasing/worsening productive asset so that the income fall was not fully offset by the expenses cut.

It is also important to analyse the efficiency dynamics of the Croatian banking industry relative to the EU association (July 2013). To recognise the main trends, we have used the annual efficiency changes (see Appendix, Table A1 through Table A5). Bearing in mind that the output-oriented model has been implemented here, the lower the score the more efficient the bank (bank group). Accordingly, the Croatian banking industry has increased its efficiency since EU association. Specifically, the average overall score before the EU membership was 176.98%, while the score after EU association was 131.76%.

The beneficial effects of EU membership can be explained by the risk premium before and after EU association. Namely, the Croatian economy (and its banking sector) is considered less risky after the association, meaning that cross-border borrowings became less expensive. Namely, the risk decline is now reflected through lower interest rates for the intra-bank borrowings (the transactions between the bank holdings abroad and their representatives in Croatia), and the Croatian banks have become more efficient. In addition, the non-interest expenses for the international transactions with EU counties have been adjusted as Croatia became an EU member. On the other hand, the real sector expectations are positively impacted by this move and the Croatian companies have become more risk-loving. Consequently, the real sector was more willing to invest and take additional banking loans. This asymmetric risk perception has led to greater interest and non-interest revenues and smaller interest and non-interest expenses, causing an upward sloping efficiency trend following EU membership.

Although the banking industry has improved its efficiency, these benefits are not equally shared across the bank groups. For example, small and large banks improved their efficiency after EU membership, in comparison with the medium banks whose efficiency scores deteriorated slightly. The key market players were able to manage the increasing pressure from the single EU market successfully, which is predominantly reflected in increased revenues. In addition, the small banks serving particularly closed market niches were not exposed to such a sharp competitive pressure. Consequently, their revenues remained stable, and the cost cutting resulted in increased operative efficiency. All other bank groups (see Appendix, [Table A2](#) through [A5](#)) also increased their efficiency dramatically after 2013 (for example, the private banks for 58%, state-owned banks for 44.8%). Finally, the medium banks recorded a minor efficiency decline in 2015 (about 1.8%), which was caused by a significant efficiency drop of the SBER Bank (by about 33%).

5. Concluding remarks

The paper aims to estimate the efficiency trends of the Croatian banking industry, covering the period 2006–2015. We have implemented the variable return to scale (BCC) output-oriented DEA model to determine the relative efficient scores, together with the super-efficiency DEA model to rank the relatively efficient banks. Within the intermediation approach we have selected the interest and non-interest expenses on one hand, and interest and non-interest revenues on the other hand, as the input and output variables, respectively. The initial sample is further collapsed into the pre-crisis (2006–2009) and post-crisis (2010–2015) periods to address the crisis-driven efficiency movements. The impact of the EU membership is also assessed by comparing the scores before and after EU association. It is worth of noting that these results should be treated cautiously because the period before the EU association overlaps the period of adverse crisis effects, so that it is impossible to isolate the pure effects. To challenge the banking and market hypotheses, the Croatian banks have additionally been grouped according to the relative market power (small, medium, large, market leaders, and competitive fringe), ownership structure (state-owned and private banks), and origin of capital (domestic and foreign banks).

Overall, the results are quite instructive, so that at least two important conclusions can be drawn: (1) the crisis has had detrimental effects on the Croatian banking industry, and the overall efficiency score has declined by about 3%; (2) the banking industry has largely benefited from EU membership, bearing in mind that the overall efficiency score has increased by about 45%. The first statement regarding the crisis effects is to some extent in line with other empirical findings (for example, Castellanos & Garza-Garcia, 2013) but is also in sharp contrast with some recent studies (Fan, 2016; Andries & Ursu, 2016). It seems that the Croatian banks could not optimise their operational efficiency and mitigate the adverse effects of the crisis, due to such a hostile business environment and balance sheet maturity gaps.

The group-specific results are particularly interesting. Namely, the market leaders are far more efficient than competitive fringe, and there is a significant positive efficiency differential between the large, medium and small banks. Correspondingly, we

can draw at least two important conclusions: (1) the Croatian banks exploit economies of scale, implying that the scale efficiency hypothesis has been proved; (2) the banking market is predominantly shaped by the leading banks, meaning that we have also proved the efficiency structure hypothesis. The scale efficiency effect is an expected result due to similar findings of others (for example, Nenovsky et al., 2008), while the results regarding the efficiency structure hypothesis have not been identified by any previous research. Moreover, medium and large banks have increased their efficiency in the post-crisis years, implying that they are more flexible to rapid market changes caused by adverse external shocks. The efficiency differentials between different banking groups are mainly caused by a balance sheet maturity mismatch, coupled with a dominant market position, and financial and operational advantages that are largely exploited by the market leaders. Finally, both small and large banks benefited from EU association, while medium banks have recorded more or less the same average efficiency score as before the EU membership. Specifically, large banks have improved their efficiency score by about 8%. However, small banks have benefited the most (they improved their average efficiency score by about 45%), probably due to isolated market niches (not significantly affected by the increased competition) coupled with increased operative efficiency.

The results regarding the ownership-specific efficiency trends are quite counterintuitive. Namely, state-owned banks were more efficient than the private ones in both periods. Furthermore, the crisis-driven factors have influenced only private banks adversely, while state banks additionally improved their efficiency performances over the crisis years. Consequently, the agency theory hypothesis is strongly rejected, and these results coincide with the results of Staub et al. (2009), while opposing the findings of Fan (2016). The main reasons for these reverse movements are related not only to the extensive international exposure of the private banks, but also to the appropriate maturity setting and operational flexibility of the state banks inherited from the transitional phase. In addition, the state banks are not the market leaders, and efficiency trends are not guided by relative market dominance. On the other hand, a vast minority of the Croatian banks are state-owned (for example, two out of 25 banks in 2015), meaning that efficiency movements are also largely affected by the sample structure. As for EU membership effects, both bank groups largely benefited, but the private ones have obtained significantly larger efficiency gains (58% compared to 44.8%).

Our findings regarding the home-field advantage hypothesis are mixed, dependent upon the observed timeframe: (1) initially more efficient foreign banks have experienced a significant efficiency drop over the crisis years; (2) initially inferior domestic banks have increased their efficiency during the crisis. Accordingly, the home-field advantage hypothesis has been rejected for the pre-crisis period (similar to Nenovsky et al., 2008), and accepted for the latter period. The later result matches Staub et al. (2009), and Castellanos and Garza-Garcia (2013). These reversible movements are mainly caused by the proportionally larger international exposure, together with inappropriate risk management of the foreign banks prior to the global crisis. In addition, the balance sheet structure of the domestic banks proved to be more resilient to adverse external shocks. Finally, the foreign banks benefited more from the EU

membership than the domestic ones (58% compared to 48%), but both bank groups have rapidly increased their efficiency. This result is expected because the Croatian banking industry was strongly internationalised before EU association, so that the foreign banks have experienced a kind of competitive advantage when entered the single EU market.

The main implications of the findings are at least twofold, both at the bank level and industry level. Namely, private ownership is not a decisive efficiency determinant, and economies of scale are largely exploited by the most efficient banks. Consequently, Croatian banks should implement the scale efficiency approach and improve their overall efficiency through mergers and acquisitions. At the industry level, the results are quite intuitive for the regulatory bodies in Croatia. Namely, to prevent possible bank failures and internally generated financial crises, the regulatory authorities could monitor efficiency trends as a part of the prudent supervisory measures against the most inefficient banks. To prevent the banking market from becoming over-competitive, regulatory agencies should closely monitor the efficiency movements of the market leaders. It is a critical point, keeping in mind that the over-competitive environment forces market players to implement an excessive risk-taking practice, making banks prone to liquidity crises and failures.

Disclosure statement

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APPENDIX

Table A1. Efficiency scores and corresponding ranks of banks in Croatia.

Bank name/Average score/Rank	Average 2006–2009	Rank 2006–2009	Bank name/Average score/Rank	Average 2010–2015	Rank 2010–2015
A Saving Bank of Small Enterp.*	100.00%	1	A Saving Bank of Small Enterp.*	100.00%	1
Gospodarsko-Kreditna Bank*	100.00%	1	Credo Bank*	100.00%	1
HVB Splitska Bank	100.00%	1	Privredna Bank Zagreb	100.00%	1
Požeška Bank	100.00%	1	Zagrebačka Bank	100.00%	1
Zagrebačka Bank	100.00%	1	Erste&Steiermarkische Bank	105.00%	2
Banca Sonic *	100.29%	2	Voklsbank	105.77%	3
Hypo-Aple-Adria-Bank	106.01%	3	Tesla Saving Bank	106.12%	4
Podravska Bank	108.12%	4	Štedbank	113.20%	5
Međumurska Bank	110.78%	5	Međumurska Bank**	113.62%	6
Kvarner Bank	111.12%	6	Istarska Credit Bank Umag	114.77%	7
Štedbank	114.36%	7	Societe-Generale-Splitska Bank	114.81%	8
Slavonska Bank	118.89%	8	OTP Bank Croatia	114.96%	9
Societe-Generale-Splitska Bank	119.83%	9	Croatian Post Bank	114.98%	10
Privredna Bank Zagreb	120.58%	10	Raiffeisenbank Austria	117.37%	11
Croatian Post Bank	121.67%	11	Hypo-Aple-Adria-Bank	120.45%	12
Voklsbank	123.56%	12	Imex Bank	127.99%	13
Raiffeisenbank Austria	126.26%	13	Bank Brod**	128.42%	14
Erste&Steiermarkische Bank	135.09%	14	Veneto Bank	136.58%	15
Banco Popolare Croatia	136.09%	15	Partner bank	136.69%	16
Istarska Credit Bank Umag	136.62%	16	Sberbank**	137.86%	17
OTP Bank Croatia	140.21%	17	Banco Popolare Croatia	142.29%	18
Veneto Bank	145.86%	18	Vaba Bank Varaždin	143.83%	19
Centar Bank	158.94%	19	Bank Splitsko-Dalmatinska	147.51%	20
Bank Splitsko-Dalmatinska	161.70%	20	Jadranska Bank	153.26%	21
Slatinska Bank	169.73%	21	Slatinska Bank	156.04%	22
Obrtnička Saving Bank**	180.06%	22	Centar Bank	160.42%	23
Vaba Bank Varaždin	180.95%	23	BKS Bank	163.75%	24
Jadranska Bank	183.33%	24	Croatia Bank	167.18%	25
Imex Bank	192.87%	25	Karlovacka Bank	173.87%	26
Karlovacka Bank	196.95%	26	Credit Bank Zagreb	176.80%	27
Croatia Bank	200.78%	27	Bank Kovanica	177.51%	28
BKS Bank**	209.43%	28	Samoborska Bank	181.26%	29
Partner Bank	216.36%	29	Nava Bank	216.59%	30
Bank Brod	221.56%	30	Primorska Bank	303.68%	31
Nava Bank	225.95%	31	Podravska Bank	501.52%	32
Credo Bank	241.74%	32	Kentbank	648.21%	33
Credit Bank Zagreb	269.91%	33	Banca Sonic	BNO	BNO
Samoborska Bank	271.97%	34	Gospodarsko-Kreditna Bank	BNO	BNO
Bank Kovanica	298.41%	35	Kvarner Bank	BNO	BNO
Primorska Bank	301.10%	36	Obrtnička Štedna Bank	BNO	BNO
Kentbank	BNO	BNO	Požeška Bank	BNO	BNO
Sberbank	BNO	BNO	Slavonska Bank	BNO	BNO
Tesla Saving Bank	BNO	BNO	HVB Splitska Bank	BNO	BNO
Average score	161.43%		Average score	164.51%	

Source: Authors' calculations based on the CNB official reports.

*Banks which operated for a single year during the analysed period; **Banks which operated for just two years during the analysed period.

Table A2. Efficiency scores for the market leaders and competitive fringe (%).

Pre-crisis period							
Bank group/Year			2006	2007	2008	2009	Average
All banks			175.48	140.06	181.35	148.84	161.43
Top 5			110.36	128.32	135.15	102.75	119.15
Bottom 5			189.82	134.33	272.8	222.87	204.96
Top 10			109.96	126.12	135.56	109.32	120.24
Bottom 10			170.65	169.72	261.03	194.04	198.86
Post-crisis period							
Bank group/Year	2010	2011	2012	2013	2014	2015	Average
All banks	269.88	120.15	201.6	142.07	137.1	116.11	164.48
Top 5	100.00	107.42	109.89	108.24	100.00	116.60	107.03
Bottom 5	387.23	140.95	184.39	178.06	127.06	118.98	189.45
Top 10	119.11	105.73	113.2	118.07	105.46	120.26	113.64
Bottom 10	291.09	130.63	370.17	169.74	150.55	126.64	206.47

Source: Authors' calculation based on the CNB official data.

Table A3. Efficiency scores: small vs medium vs large banks (%).

Pre-crisis period							
Bank group/Year			2006	2007	2008	2009	Average
Small			202.77	146.13	221.7	160.29	182.72
Medium			111.96	122.84	144.95	119.86	124.9
Large			108.64	128.31	129.3	103.43	117.42
Post-crisis period							
Bank group/Year	2010	2011	2012	2013	2014	2015	Average
Small	326.85	125.77	245.72	149.67	139.3	114.76	183.68
Medium	124.29	104.52	108.13	124.03	113.42	126.71	116.85
Large	114.77	106.19	108.24	101.25	102.05	115.07	105.31

Source: Authors' calculation based on the CNB official data.

Table A4. Efficiency scores: state-owned vs private banks (%).

Pre-crisis period							
Bank group/Year			2006	2007	2008	2009	Average
State-owned banks			198.89	140.97	143.33	148.04	157.81
Private banks			174.01	140.01	214.68	161.71	172.6
Post-crisis period							
Bank group/Year	2010	2011	2012	2013	2014	2015	Average
State-owned banks	234.7	111.39	100.00	104.86	116.43	106.00	127.23
Private banks	272.15	121.01	217.13	137.71	128.51	117.33	165.64

Source: Authors' calculation based on the CNB official data.

Table A5. Domestic vs foreign banks (%).

Pre-crisis period							
Bank group/Year			2006	2007	2008	2009	Average
Domestic banks			220.23	153.46	256.61	154.14	196.11
Foreign banks			130.72	130.19	169.47	144.66	143.76
Post-crisis period							
Bank group/Year	2010	2011	2012	2013	2014	2015	Average
Domestic banks	200.93	128.91	144.78	148.2	126.71	119.25	144.8
Foreign banks	320.68	114.08	249.87	123.58	127.54	114.09	174.97

Source: Authors' calculation based on the CNB official data.