CHARLES UNIVERSITY
Faculty of Social Sciences

UNIVERSITY COLLEGE LONDON
School of Slavonic and East European Studies

Determinants of Commercial Bank Efficiency in 11 CEE Countries: An External Two-stage Bootstrap DEA Approach

Master's Thesis

Author of the Thesis: YEFENG SUN

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Supervisor: Prof. Marek Vokoun; Dr. Svetlana Makarova

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Reference

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Abstract

This study estimates the determinants of bank efficiency for 11 Central and Eastern European (CEE) countries from 2013 to 2021. The output-orientated BCC and SBM efficiency score using the Data Envelopment Analysis (DEA) method are calculated in the first step. Following the approach developed by Simar and Wilson (2007), the second step of this study includes the estimation of the Double Bootstrap Truncated Regression (DBTR) and the testing of the separability hypothesis about various efficiency determinants. The results show that the relationship between bank size and bank efficiency is positively significant in the linear model while this relationship is a U-shape between the bank size and the pure technical efficiency in the non-linear model. Moreover, the equity ratio, the deposit ratio and the market concentration ratio significantly affect the bank efficiency positively, while the loan/asset ratio, loan loss reserve to asset ratio as well as income diversification significantly impact the bank efficiency negatively.

Keywords: Two-Stage DEA; Double Bootstrap Truncated Regression; CEE; Bank Efficiency

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Introduction

This thesis aims to find out the determinants of bank efficiency for 11 Central and Eastern European (CEE) countries from the year of 2013 to the year of 2021. The results show that bank size, equity ratio, deposit ratio and market concentration ratio have positively significant relationships with bank efficiency. However, loan-asset ratio, loan loss reserve to asset ratio and income diversification significantly affect the bank efficiency negatively. Data Envelopment Analysis (DEA) comprises a non-parametric mathematical linear programming method. It can be used to compare a set of homogeneous Decision Making Units (DMUs) with the same inputs and outputs combinations. DEA can recognise the most productive and efficient DMUs, identify the levels and sources of inefficiency and identify the actions about how to make inefficient organisations become effective (Stavárek and Řepková 2013; Henriques et al., 2020). As the most common parametric approach, the biggest drawback of Stochastic Frontier Analysis (SFA) is that the SFA model should be defined precisely. Conversely, the DEA technique is a nonparametric approach which quantifies efficiency into a specific number without prior standardization (Svitalkova, 2014). Therefore, the DEA method is simpler and more appropriate for the ranking of bank efficiency (Holod and Lewis 2011).

To assess the banks' performance, ROI (Return on investment), ROA (Return on asset) and ROE (Return on equity) have been commonly used as financial indicators in the past. However, the financial performance seems unsatisfied since the performance of an organisation has more than one dimension (Lewin and Minton, 1986). Therefore, satisfactory financial performance in ROA or ROE does not mean that the organisation is excellent (Chakravarthy, 1986). Thus, another business performance assessment method should be designed to quantify the multidimensional performance of organisations. Moreover, there is a lag in financial indicators compared to efficiency indicators during the financial crisis. Jurcevic and Zaja (2013) compared the efficiency and the financial performance of Croatian Banks and insurance companies using the sample from 2005 to 2010 in Croatia. The results showed that efficiency scores captured by DEA achieved the lowest values in the banking sector in 2008 but already indicated obvious low scores in 2007. However, the lowest ROE and ROA were observed in 2009. It shows that the DEA method can sign the crisis earlier than financial indicators. Therefore, DEA is quite a useful technique to solve these issues above. To examine the efficiency under the DEA framework, managers and policymakers will know how far inputs can be decreased or how far output can be increased without wasting or absorbing other resources also with fewer lags (Zhu, 2000).

This thesis focuses on the bank-specific, industry-specific, and macro determinants of the efficiency of banks in 11 Central and Eastern European countries. This paper contributes to the CEE literature in several ways. The majority of the studies for CEE banks use the one-stage simple DEA approach. The problem is that the simple approach cannot control the external environment and with lower explanatory effect compared with parameter estimation. Therefore, this article follows the Bootstrap approach adopted by Simar and Wilson (2007). Since the efficiency score is limited to (0,1), traditional OLS regression is biased and censored methods such as Tobit and Truncated regression technique should be used. Besides, due to the score separability, the Truncated-based Bootstrap approach will provide a less biased estimator. The literature indicates that most papers focus on the period before 2017. Moreover, most literature focuses on one specific country in CEE. In that case, this research is a cross-country analysis focusing on 11 CEE countries inside the EU, including Visegrád four countries (Czech Republic, Slovakia, Hungary, Poland), three Baltic countries (Estonia, Latvia, Lithuania) and four Balkan countries (Bulgaria, Croatia, Romania, Slovenia) during a period until 2021. Using factor analysis, we construct explanatory indicators based on individual measures of bank-specific variables, such as capital adequacy, asset quality, earnings, and liquidity, commonly known as CAMEL or Basel variables. Compared with other studies, this paper incorporates undesirable output, which is non-performing loans, making the analysis more complete and closer to reality. Many studies do not show the decomposition of the banks' operating income and operating expenses clearly. However, this paper decomposes them into interest part, fee part and other parts mainly including the investment and trading (income). Although the sum of all parts remains the same, however, the decomposition affects the efficiency score obviously.

The remainder of the paper is organized as follows. Section two reviews the relevant literature on the efficiency of the banking sector. Specifically, the classification and development of DEA in the banking sector will be reviewed first. Then, the literature on DEA analysis in CEE countries will be reviewed. After that, the literature about the determinants of bank efficiency will be analysed. Section three explains the methodology used to calculate the efficiency score and how the variables are regressed, as well as the descriptive statistics. Moreover, the variable list and the model specification equation are also presented in this part. In Section Four, the efficiency scores and empirical regression results with robust test and heterogeneity analysis are presented followed by a discussion. Finally, section five provides limitations and concluding remarks.

1. Literature review

The introduction part above answers why the efficiency analysis in banks is essential compared with the traditional parameter estimation methods and discussed why the traditional financial indicator is not enough in assessing the overall performance of an entity. Large number of studies focus on the banking sector in the field of DEA analysis. The DEA analysis in the banking sector is the most extensively researched of all business sectors (Paradi and Zhu, 2013). In this part, the literature review of the DEA analysis in the banking sector will be conducted in three levels. First, this paper reviewed the development of DEA analysis in the banking sector. After that, the literature on DEA analysis in CEE countries and bank efficiency determinants will be reviewed. After going through the literature review, the reader will have a clear understanding of the position of this paper, which is an external two-stage output-orientated DEA model in the Banking sector focusing on 11 CEE countries.

Data Envelopment Analysis (DEA) is one of the most well-established methods to analyse the organisation's efficiency due to the development of operational research approaches (Wu, Yang, & Liang, 2006). Compared with the parametric method, DEA has a number of unique advantages. First, it is obvious that no prior information is required when applying this model. Moreover, the production frontier creation depends on observation solely while no specifications are needed in DEA. Different from the traditional approaches, DEA can not only deal with inputs and outputs in varying units (Svitalkova, 2014) but is also useful when facing a multi-stage manufacturing cycle (Schaffnit, Rosen, & Paradi, 1997). DEA is possible to examine every DMU independently by comparing with other DMUs (Řepková, 2014). Therefore, the DUM that is less efficient than the benchmark can be recognised (Aggelopoulos & Georgopoulos, 2017). There are a number of reviews regarding the DEA approach. However, Paradi and Zhu (2013) and Henriques et al. (2020) specialized in the banking sector, while the latter focused only on bank efficiency with a two-stage technique, which is a topic that became popular (Emrouznejad and Yang, 2018). After the brief introduction of the characteristics of the DEA, the following paragraphs focus on the development and determinants of the DEA for banks.

1.1 Two stage DEA research method in the banking sector

In the beginning, the traditional simplest DEA model was used in the banking sector. However, the obvious drawback of the simple DEA analysis is that it treats the production procedure as a black box. That is to say, there is no clear procedure showing how the input combinations are converted into output combinations during the operation procedure for DUMs (Färe & Grosskopf, 2000). Furthermore, the suggestions provided by the simple DEA are always ignored by management since the simple DEA fails to consider the external environmental variables that cannot be controlled by managers (Paradi, Rouatt and Zhu, 2011). For instance, people can simply argue that efficient banks perform well only because they operate in an advantageous environment. Thus, a simple DEA score is biased although consistent (Jebali, Essid, and Khraief, 2017). For these reasons, the two-stage DEA approach becoming popular within DEA research. Regarding the two-stage DEA, it comprises two varieties, internal two-stage DEA and external two-stage DEA (Henriques et al., 2020).

1.1.1 Internal two-stage DEA

The internal two-stage DEA model decomposes the production process into more than one substage. The decomposition of the simple DEA model, also known as the network DEA model was first initiated by Färe and Grosskopf (1996). However, it evaluates the two stages separately, later scholars use multiplication (Kao and Hwang, 2008) or addition (Chen et al., 2009) to integrate two phases together, while the latter can be applied in both VRS and CRS models. (Chen et al., 2010) refined this model by introducing the concept of shared inputs for both the first and the second stages, while some scholars considered situations when there are additional inputs applied to stage two only (Li et al., 2012).

Under the theory of the network DEA in the banking industry, the first stage's outputs can be treated as the second stage's inputs (Chen, Liang and Zhu, 2009). Therefore, it is possible to analyse the profit efficiency in the first stage and measure the banks' marketability efficiency in the second stage (Shih-Fang and Wen-Min, 2006). Under a similar logic, Wanke and Barros (2014) used the network DEA method to measure banks' cost efficiency in the first stage by using the scale of branches and personnel as inputs while using management and staff expenditures as outputs. In the second stage, to measure the productive efficiency, the management and staff expenditures are treated as inputs while equity and permanent assets are outputs in this network DEA model. Similarly, Wang et al. (2014) utilised the network DEA method to examine the efficiency of the Chinese banking sector via 16 commercial banks. To analyse the deposit-producing process at the initial stage, fixed assets and the staff number were used as inputs while the bank deposit quantity was used as an intermediate variable. To evaluate the profit-earning process in the subsequent phase, various sources of income, as well as non-performing loans (as undesirable output), were used as outputs (Milenković et al., 2022). Moreover, the use of the internal two-stage DEA model enables the combination of both the production and the intermediation approaches. Therefore, researchers do not require the judgment regarding whether the deposit should be treated as inputs or outputs, or should bank keep a higher level of deposit (under the production approach) or lower level of deposit (under the intermediation approach) to be efficient (Holod and Lewis, 2011).

1.1.2 External two-stage DEA

Differently from the internal DEA approach, the two-stage external DEA approach applies a different technique during the second phase separate from the operation process. The simple one-stage DEA approach fails to incorporate the external environment variables into the analysis. External factors, however, impact the outcomes of the simple DEA model. Therefore, the improvement suggestions from the simple DEA model are often rejected by management (Paradi, Rouatt and Zhu, 2011). To solve this problem, external regression methods can be combined into the second step. That is to say, the DEA score from the initial stage becomes the explained variable while the external variables are the explanatory variables (Henriques et al., 2020).

Paleckova (2019) used the traditional OLS regression in the second stage to find out the determinants of the cost efficiency of Slovak and Czech banks. Similarly, (Sufian, 2010) used the external two-stage DEA model to examine the efficiency of Malaysian banks. They calculated and decomposed the technical efficiency (TE) of the Malaysian banking sector in the first stage, subsequently, they analysed the efficiency changes before and after the period of mergers and acquisitions. In the subsequent phase, Sufian (2010) used the Tobit regression technique to find out the determinants of various Malaysian banking efficiencies. Under a similar regression approach but applied to the central bank, Dar, Ahn and Dar (2021) found that the export level impacts the central bank's efficiency significantly. Using an external two-stage DEA model, Barth and Staat (2005) focused on the efficiency of branches for a bank in Germany. Using the Bootstrap regression technique in the second stage with branch characteristics, customer potential and competition level as explanatory variables. The result reveals that eight inefficient bank branches under the simple model were proved to be inefficient under the two-stage approach (Milenković et al., 2022), which indicates the necessity of conducting external regression for DEA analysis.

1.1.3 Approaches of DEA in the banking sector

The inputs and outputs specifications in the banking sector could be categorized into three approaches: production approach, intermediation approach and profit approach. Each approach represents one main dimension of the banking activity. Benston (1965) proposed the production approach which is always applied to the efficiency evaluation of the bank branches. This approach mainly assesses the basic activity of a bank which is a customer service provider

(Berger and Humphrey, 1997), which is also called the service-oriented approach. The implementation of the DEA analysis is well suited for management when making decisions about the bank branches' sustainability (Milenković et al., 2022). In most cases, this approach involves using the inputs of labour, capital and other resources while various banking products and services will always be considered as outputs.

Highlighting the primary financial intermediary role of the bank. Sealey and Lindley (1977) proposed the intermediation approach of the DEA model specification. Under the intermediate approach, banks try to optimize their resource allocation to increase efficiency. Specifically, the key funding source for banks is customer deposits, and banks try to use them to make as many loans or other earning assets as possible. In other words, the intermediation approach measures how efficiently the bank transforms the deposit sources into earning assets or loan placements (Milenković et al., 2022).

Like other organisations, banks also operate for profits. Drake, Hall, and Simper (2006) proposed the profit approach. Under the profit approach, banks are the generators of profit factors, including interest income, fee and commission income, investment income, trading income and other incomes, which are converted by various inputs, such as interest expenses, fee expense, operating expenses as well as loan losses (Aggelopoulos & Georgopoulos, 2017). It is well-suited for capturing the strategic response diversity for banks when facing rapid changes in environments with fierce competition (Fethi and Pasiouras, 2010).

These three approaches are complementing, which can be used separately or jointly based on different research purposes. The inter-bank level production approach is suitable for branch analysis within a specific bank. Oppositely, the intermediation approach and the profit-oriented approaches are suited for a country-level or cross-country bank efficiency comparison (Henriques et al., 2020; Cikovic, Smoljic and Lozic, 2021; Milenković et al., 2022). In many cases, the classification of the approaches is not very clear, different approaches are always combined even in the simple one-stage or the first stage of the external two-stage DEA approach. Thus, the input variables and output variable specifications are highly dependent on how researchers frame the DEA variables.

In summary, the DEA technique has been introduced to assess bank efficiency for many years. Over the decades, to overcome the black-box problem, the internal and external two-stage DEA approaches were introduced while the internal one decomposes the processes and the external one controls the external environments and finds out the efficiency determinants. The production approach, intermediate approach and profit approach are commonly used in the banking sector under the DEA framework. Drawing on the fundamental DEA model, internal (network) and external two-stage DEA with regression of environment variables become popular in banking sector analysis.

1.2 Literature of DEA in CEE banking sectors

1.2.1 Simple DEA in the CEE banking sector

As discussed before, the DEA model can be used solely without the combination of parametric regression and many scholars conducted country-level DEA analysis. Focusing on the Croatian banking sector, Jemric and Vujcic (2002) analysed its efficiency from 1995 to 2000 using a simple one-stage DEA model. They made both the CRS and VRS assumptions under both the profit and the intermediation approaches. Under the profit approach, various sources of cost and expenditures such as interest cost, commission, labour cost (gross wage) and capital cost (amortization and office cost) were used as inputs, which are converted to various incomes as outputs. Meanwhile, under the intermediation approach, asset scale, personnel scale, as well as deposit scale, were selected as inputs, while the loan placement and the bond holding scale were selected as outputs. Without the combination of regression methods in the second stage. The authors found that newly established, foreigner-controlled and smaller banks tend to perform better generally. However, the exception is that bigger banks display higher efficiency under the VRS assumption.

Focusing on the Czech banking sector between 2003 and 2012, Řepková (2014) measured the efficiency of 11 commercial banks under the intermediation approach using the dynamic window DEA technique. Using the personnel and deposit scale as inputs, while using net interest income and loan placement as outputs. The results suggested that the smaller banks tend to be more efficient in Czech, which is probably due to the diseconomies of scale and the excess deposits suffered by the banks with larger sizes.

Under a similar technique, Grmanová and Ivanová (2018) focused on the Slovak banking sector between 2009 and 2013. Using customer and institution deposits as well as administrative expenditures as inputs while using loan placement and non-interest revenue as outputs. The results indicated that the three largest banks show the highest efficiency tend to be more efficient than other banks in Slovak.

Utilising the profit approach, Davidovic, Uzelac and Zelenovic (2019) analysed the bank efficiency changes in Croatia via a simple DEA approach using the sample from 2006 to 2015. Using various sources of expenses (interest and non-interest) and using total income as the inputs and output, respectively. They found that larger banks, state-controlled banks, and market leaders show higher efficiency. Furthermore, the EU accession benefits the efficiency but the Croatian banking efficiency is harmed by the global financial crisis.

Utilising both intermediation and profit approaches but still targeting on Croatia. Učkar and Petrović (2021) measured the bank efficiency through the one-stage DEA technique with the sample from 2014 to 2019. Furthermore, ROE and ROA are also used for comparing the difference between financial performance and efficiency scores. Using the assets, personnel, and deposit levels (intermediation approach), interest, non-interest cost, and operating expenditures (profit approach) as inputs and using security holding, loan placement (intermediation approach), various kinds of incomes (profit approach) as outputs. Without the external regression, they found that bigger banks own both better efficiency and more favourable financial performance generally, although some small banks also operate efficiently. However, the efficiency advantage of middle-sized banks is unclear. Moreover, since the creation of big banks that are generally efficient due to financial institution consolidation, the banking sector become more efficient over the last six years.

Using the simple one-stage DEA technique methodology and still focusing on Croatia, Čiković and Cvetkoska (2022) analysed the bank efficiency from 2009 to 2019. Using interest operating expenditures as inputs while using the corresponding incomes as outputs. They found that the highest efficiency occurred in 2009 with the number of 0.96 and the lowest efficiency score occurred in 2017 with the number of 0.9. The average efficiency is 0.92 between the year of 2009 and the year of 2019.

Apart from the literature in the V4 group and Balkan countries, there are also many papers related to the bank efficiency of Baltic countries. Titko, Stankevičienė and Lāce (2014) analysed the banking efficiency of Latvia. Under both the profit and the intermediation approaches, the VRS input-orientation DEA model was used. Regarding the variable specification, the inputs were selected from deposit level, capital level, and various sources of expenses while the outputs were selected from security holding, loan placement as well as various kinds of revenues. As a result, fourteen different combinations of inputs and outputs were constructed for this research. The result showed that the loans and deposits were not the critical outputs and inputs to assess the Latvian banking sectors.

Similarly, using the simple one-stage DEA model but focusing on Latvia, Novickytė and Droždz (2018) measured the commercial bank efficiency within a low interest rate environment. Using the deposit scale and personnel expenditure as inputs while using pre-tax profit, operating profit as well as net interest income as outputs. Under the intermediation, profit and production approaches with different variable combinations, five different models were formulated. The results indicated that larger foreign subsidiaries show higher efficiency compared with local smaller banks and bank subsidiaries of Nordic banks tend to be more efficient than banks with local ownership.

1.2.2 Multi-country study using simple DEA in the CEE banking sector

The literature above shows how the simple DEA framework is used to analyse bank efficiency for one country. However, the sample of single-country analysis is restricted, thus, apart from the single-country analysis, the simple one-stage DEA model can also be applied to cross-sectional analysis in CEE countries to overcome the data limitation and make the country-level efficiency comparison possible. Multi-country analysis assumes a shared cross-region production frontier, that is to say, banks operating in different nations will be analysed in the same efficiency frontier. It is so-called the multi-country, single-year (MCSY) frontier or the multi-country, multi-year (MCMY) frontier with the panel data (Pancurová and Lyócsa, 2013).

Utilising the one-stage simple DEA method, Popovici (2014) examined the efficiency of banking sectors in Estonia, Latvia and Lithuania using the sample from 2007 to 2011 over the global financial crisis under an intermediation approach with the Malmquist index. Using deposit scale and administrative expenditures as inputs while using investment holding, loan placement and other revenues as outputs. Popovici (2014) found that the bank efficiency in the

Baltic three countries improved from 2010 to 2011 because of better cost and deposit management.

Making the cross-sectional analysis using the one-stage simple DEA technique, Titko and Jureviciene (2014) aimed to compare the banking sector efficiency of Latvia and Lithuania utilising the VRS setting under the input-orientated assumption. The choice of variables is based on the intermediation (input: deposits; outputs: loans, investment) and production approaches (inputs: interest expenses staff costs; outputs: deposits, loans). Titko and Jureviciene (2014) found that there was inconsistency between the efficiency scores and the financial indicators for banks. Besides, banks with larger sizes display higher efficiency.

Similarly, using the one-stage DEA technique, Svitalkova (2014) compared the efficiency of the banking industries of six countries, including V4 groups, Slovenia and Austria from 2004 to 2011 to find what makes the banks less efficient. The difference compared to other models is that the undesirable output-loan loss provision was incorporated. The findings indicated that the banks are inefficient because of the shortage of loan supply and an extensive amount of loan loss provisions, which also explains why the existence of the loan loss provision affects the results of the model. Svitalkova (2014) argued that the higher level of loan loss provision is also linked to liquidity problems and default loans during the financial crisis.

Still focusing on the V4 group, Palečková (2016) examined the commercial bank efficiency in the Czech, Hungary, Poland and Slovakia with the sample between 2009 and 2013 utilising the one-stage simple DEA approach. Using asset scale, personnel scale and deposit level as inputs while using net interest income and loan placement as outputs within the intermediation approach. Palečková (2016) found that average efficiency decreased from 2010 to 2012 probably because of the global financial crisis, followed by a recovery in 2013. Palečková (2016) found that Czech and Hungary own more efficient banking sectors. Moreover, the finding indicated that small banks demonstrated higher efficiency in the CRS assumption but medium-sized banks tend to be more efficient under the VRS assumption.

1.2.3 Two-stage DEA in the CEE banking sector

However, the simple DEA model cannot control the external factor, therefore, external regression such as OLS, Tobit and Bootstrap methods are considered to control the external factor and to make estimations. Under the intermediation approach, Havrylchyk (2006) measured the bank efficiency in Poland from the year of 1997 to the year of 2001 using two-stage external DEA. Using the asset scale, personnel scale and deposit level as input variables, while using bonding holding, loan placement and off-balance sheet items as output variables. Using the traditional Tobit regression approach, the findings indicated that greenfield banks demonstrate greater efficiency compared to takeover banks, domestic private banks, as well as state banks. Moreover, loan loss provisions ratio and loan-to-assets ratio showed a negative relationship with bank efficiency while the variance of ROA showed a positive relationship with bank efficiency. Different from other studies, this paper did not find a significant relationship between bank size, bank capitalisation and bank efficiency.

Similarly, the external two-stage DEA framework can be used to conduct cross-country research rather than focusing only on one country. Grigorian and Manole (2006) examined bank efficiency in 11 CEE and 6 CIS countries from the year of 1995 to the year of 1998 under the MCMY frontier. The models are defined with three different sets of inputs and two different sets of outputs. The result of Tobit regression revealed that bank consolidation, bank restructuring, foreign controlling ownership and higher capitalisation benefit the bank efficiency. However, the effect of prudent tightening on bank efficiency varies depending on various prudent regulations.

Utilising DEA techniques with an intermediation approach, Andries (2011) measured the efficiency and efficiency determinants of CEE banks in Bulgaria, Czech Republic, Poland, Romania, Slovakia, Slovenia, and Hungary from the years 2004 to 2008. Using deposit level, asset scale and administrative expenditure as inputs while using investment holding, loan placement and other income as outputs. Utilising the traditional OLS regression technique in the second stage, the finding indicated that the general bank efficiency improved in CEE countries from 2004 to 2008. The efficiency increase can be explained by the introduction of foreign banks, the EU accession, and the legislative reforms.

Utilising external two-stage DEA methods with an intermediation approach, Paleckova (2019) estimated the banking sector efficiency determinants in the Czech and Slovak from 2005 to 2015. Using deposit level, asset level as well as staff scale as inputs, while using loan placement as output. Under OLS regression in the second stage, the results indicated that larger banks, less liquid banks and banks with low net interest margins tend to be more efficient. In terms of macroeconomic determinants, Paleckova (2019) suggested that lower inflation and higher GDP growth rates benefit the cost efficiency of banks.

Early researches utilise traditional OLS, GMM, GLS and Tobit regressions techniques in the second stage. However, the DEA scores are not the result of the censoring process but they are fractional data (McDonald, 2009). For this reason, the predicted values are constrained to the unit interval by the conditional mean of the fractional response. Simar and Wilson (2007, 2011) claimed that the efficiency scores follow the truncated distribution, therefore, they hold the belief that a truncated regression is the appropriate technique to capture the unbiased estimators in the second-stage estimators. Additionally, the traditional regression techniques do not consider the correlations among efficiency scores, the bootstrap regression methods proposed by Simar and Wilson (2007), however, considered the dependent structure of efficiency scores and it was well-accepted by the researchers afterwards (Pancurová and Lyócsa, 2013).

Similarly, using the external two-stage DEA, Chronopoulos, Girardone and Nankervis (2011) researched the efficiency of 8 CEEC and 2 other EU countries from 2001 to 2007 with the intermediation approach. Asset scale, personal scale and deposit level were used as inputs. Meanwhile, scales of various earning assets were used as outputs. In the second stage, using the truncated regressions with the bootstrapped standard recommended by Simar and Wilson (2007), they found that larger banks, diversified banks as well as less capitalised banks demonstrated higher efficiency. However, the relationship between foreign controlling ownership and bank efficiency was not proved to be significant.

Using an external two-stage DEA model, (Chortareas, Girardone and Ventouri, 2012) investigates the bank efficiency and efficiency determinants of banking sectors for 22 EU countries (including 8 CEE countries) over 2000–2008. Using asset scale, deposit level and personnel expenditures as inputs, while using loan placement, other earning assets and fee income as outputs. Under the truncated bootstrap regression in the second stage, they found that foreign-owned banks tend to be more efficient. Moreover, enhancing official supervisory powers, and tightening capital restrictions enhance bank efficiencies. However, interventionist regulations like private business monitoring and limiting banking activities are associated with lower bank efficiency. These relationships are more significant in countries with better institutions.

Utilising the external two-stage DEA method with an intermediation approach, Pancurová and Lyócsa (2013) measured efficiency and efficiency determinants of banking sectors using the data of 11 Central and Eastern European (CEE) countries over the period from 2005 to 2008. Using total deposits and total costs as inputs while using various kinds of earning assets as outputs under the bootstrap regression technique. The regression results indicated that bigger and well-capitalised banks demonstrated both higher cost efficiency and higher revenue efficiency. Interestingly, more loan placement significantly impacts revenue efficiency positively but affects cost efficiency negatively. Conversely, foreign banks were related to lower revenue efficiency and higher cost efficiency.

The previous literature can be analysed in three levels. First, from the perspective of the sample selection, some focused on a single country while some made cross-country level efficiency analyses, such as the sample from V4 countries (Svitalkova, 2014; Palečková, 2016; Paleckova, 2019), Baltic-3 countries (Popovici, 2014; Jureviciene, 2014), CEE countries (Andries, 2011; Pancurová and Lyócsa (2013), EU countries (Chortareas, Girardone and Ventouri, 2012; Chronopoulos, Girardone and Nankervis, 2011), as well as the CIS countries (Grigorian and Manole, 2006). Regarding the cross-country analyses, V4 countries are studied frequently, but the most focus is on the year before 2016 and the same problems with the Baltic-3 countries. Although there are extensive studies focused on Croatia (Jemric and Vujcic, 2002; Davidovic, Uzelac and Zelenovic, 2019; Učkar and Petrović, 2021; Croatia, Čiković and Cvetkoska, 2022) even in recent years, few studies targeted on single country analysis in Romania, Bulgaria, Slovenia, and focused on the cross-national efficiency analysis in the Balkan region in CEE. Second, from the perspective of the specifications of inputs and outputs selections. Most literature selected production and intermediation approaches while few selected the pure profit approach. Moreover, few literatures consider the existence of undesirable outputs. Regarding the DEA techniques, the two-stage approach become popular and the truncated regression method in stage two has become a consensus although there are not many CEE-level two-stage DEA Bootstrapping analyses in recent years.

1.3 Determinants of Bank Efficiency

In the previous paragraphs, the development of the DEA approach in the Banking sector and the DEA literature focusing on CEECs were reviewed. From this paragraph, the research about the bank efficiency determinants will be reviewed. This thesis is different since the CAMEL framework is incorporated.

1.3.1 Theories about the CAMEL framework

The CAMEL model focuses on banking system parameters by assessing performance in a bank's financial statements. It is well suited for evaluating bank performance and forecasting bank failures (Salhuteru & Wattimena, 2015; Trung, 2021). The CAMEL model is an internationally well-accepted performance appraisal framework for banking sectors (Kumar & Bindu, 2022), which was proposed by the Bank of International Settlements (BIS) in 1988. Incorporating Capital Adequacy, Asset Quality, Management, Earnings, and Liquidity dimensions, this model is extremely useful when making consistent evaluations regarding the banks' financial health for both on-site and off-site investigations (Saif, Saha and Md, 2017; Nizar et al., 2023). The CAMEL model is popular in bank investigations, facilitating appropriate supervisory response and addressing the supervisory concern to mitigate the negative impacts on banks from an unfavourable market environment (Dang, 2011; Saif, Saha and Md, 2017). This framework remains effective although incorporates a wide range of market information on banks (Barker and Holdsworth, 1993). Therefore, the CAMEL framework is not only possible to recognise the advantages and drawbacks of the overall bank performance internally, but also critical for the regulators and investors as a benchmark to assess bank health (Kamaruddin & Mohd, 2013). Specifically, it is shown that the CAMLE-based bank-specific variables are considered early indicators of future banking stability variations (Louzis, Vouldis and Metaxas, 2012; Nizar et al., 2023).

Many literatures utilise the CAMEL framework to find out the bank efficiency determinants globally under the two-stage DEA framework. In Asia, Gulati and Kumar (2017) used Network DEA (NDEA) to investigate the efficiency determinants of Indian Banks. Employing the CAMEL framework, the loan-to-deposit ratio (L), non-interest income proportion (E), non-performing assets ratio (A), administrative cost ratio (M), bank size and ownership type (private or not) were used as explanatory variables. The results of the external bootstrap estimation revealed that the bank size, loan-to-deposit ratio, and non-interest income ratio positively impact the bank efficiency significantly; the administrative cost ratio has a significant negative effect on the bank efficiency while the bank size and ownership type do not have a significant relationship with the bank efficiency in India.

Focusing on Southeast Asia, Sufian (2016) examined the efficiency of Malaysian banks using the DEA approach during the period 1999-2008. In the second stage, Sufian (2016) found out bank technical efficiency determinants followed both the OLS and Bootstrap estimation approach proposed by Simar and Wilson (2007). Regarding the explanatory variables, loan loss provision ratio (A), bank capitalisation ratio (C), non-interest expenditure ratio (M), non-interest revenue ratio (E), loan placement ratio (A/L) and bank size were used as bank-specific explanatory variables while CPI, GDP and H-H index were used as macro and industry explanatory variables. Dummies for foreign ownership, publicly listed and government links were also considered. The regression in the second stage revealed that ln non-interest income ratio, equity ratio, bank size and market concentration have significant and positive relationships with efficiency.

Kamarudin et al. (2017) investigated the efficiency determinants of 29 Islamic banks in Malaysia, Indonesia and Brunei using the DEA approach with the combination of the

Malmquist index. In the second stage, the OLS method with the CAMEL framework is used. As for the explanatory variables, loan loss provisions ratio (A), bank capitalisation level (C), loan placement ratio (A/L), non-interest expenses ratio (M) and bank size were selected, besides, GDP, CPI and financial crisis dummy were also included. The OLS regression indicates that loans over the bank's assets (negative), non-interest expenses (positive) and the global financial crisis (positive) affect bank efficiency significantly.

In the Middle East, Shawtari, Ariff and Abdul Razak (2015) investigated the efficiency of the banking industry in Yemen employing the window DEA approach using the sample from 1996 to 2011. The OLS regression approach with the CAMEL framework was used similarly in the second stage. Equity ratio (C), loan loss provision ratio (A), total loan (total finance) (A) and non-interest income (non-finance income) (E) were selected as explanatory variables. Besides, Islamic bank dummy, GDP, CPI, H-H index and bank size were also considered. The results of OLS regression revealed that loan loss provision ratio and ln total loan (total finance) have a positive relationship with efficiency.

In Africa, Alhassan and Tetteh (2017) found out the determinants of Banks in Ghana from 2003-2011 using a two-stage DEA approach, followed by bootstrap estimation. Using the CAMEL framework, Loan loss provisions (A), leverage (C), loan over total asset (L), bank size and market concentration as explanatory variables. The results in the second stage indicated that there is a curve-linear relationship between bank size and efficiency. Besides, the leverage and loan loss provisions have a significant negative relationship with efficiency.

In Europe, utilising the DEA approach, Havrylchyk (2006) evaluated the efficiency of the banks in Poland from 1997 through 2001. In the second stage when finding out the efficiency determinants, governance and countries variables were considered while CAMEL framework was used to select the bank-specific determinants. To be more specific, equity ratio

(C), loan loss provisions ratio (A), loan placement ratio (A/L), bank size and growth of assets were selected as independent variables. The results of Tobit regression indicated that loan loss provision ratio and loan placement ratio have a significant negative relationship with efficiency.

Employing a sample of 10 countries in the European Union over 2001–2007, Chronopoulos, Girardone and Nankervis (2011) investigated the determinates of cost and profit efficiency of banks for a sample of 10 EU countries using the DEA approach. Bank-specific, industry-specific and macro determinants were regressed as explanatory variables in the second stage. Income diversification (E), equity ratio (C), loan placement ratio (A/L), and loans to deposits ratio (L) were included as CAMEL variables. In addition, bank size, H-H index, CPI, GDP growth rate and the EU dummy were also included. The results showed that income diversification level, bank size, loans-to-deposit ratio and foreign ownership have a significant positive impact on efficiency. In contrast, bank capitalisation, loan placement ratio and the EU accession have significant negative effects on efficiency.

Pancurová and Lyócsa (2013) examined the efficiency and its determinants for banking sectors from 11 CEEC countries from 2005 to 2008. In the second stage, Bootstrap estimation was used to find out the bank-specific and macro determinants of CEE banks. Specifically, equity ratio (C), loan-asset ratio (A/L), ROAE (E), bank size, CPI, GDP growth rate and dummies of foreign control, country and year were selected. The results of Bootstrap estimation revealed that bank size, bank capitalisation, loans-asset ratio, and ROAE have significant positive effects on revenue efficiency. Conversely, foreign ownership has a significant negative effect on revenue efficiency.

Aggelopoulos and Georgopoulos (2017) analysed the efficiency of the banking sector in Greece from 2006 to 2016. In the second stage, Bootstrap estimation was used to find out the determinants. Using the loan to Deposit (L), fee income to pre-provision income (E), control by ROCE, size and location. The results indicated that loan to Deposit balances have a significant positive impact on bank efficiency while income diversification has a significant negative impact on bank efficiency in Greece.

Using the sample from 2007 to 2014 in European countries, Fernandes, Stasinakis and Bardarova (2018) analysed the bank efficiency and efficiency determinants. In the second stage, equity ratio (C), loan placement ratio over assets (L/A), interest margin (E), loan loss provisions ratio (A) and bank size were used as explanatory variables. The results showed that the loan placement ratio and loan loss provisions ratio negatively affect bank efficiency, whereas bank capitalisation and interest margin positively impact bank efficiency.

Paleckova (2019) estimated determinants of the cost efficiency of the banking sectors in Czech and Slovak from 2005 to 2015 using the two-stage DEA approach. Employing the CAMEL model, the ratio of equity ratio (C), loan-asset ratio (A/L), loan-deposit ratio (L), loan loss provision ratio (A), bank size, GDP per capita and inflation were selected as explanatory variables. The results of the OLS regression indicated that GDP per capita, loan-deposit ratio and bank size have a significant positive relationship with efficiency, whereas the CPI has a significant and negative relationship with efficiency.

The literature on the CAMEL application shows that it is well-accepted in many regions when assessing bank efficiency as an explanatory variable in stage two of the DEA approach. Regarding the independent variables' selection for the regression equation, the studies above imply that bank size and CAMEL are always selected as bank-specific variables. Meanwhile, the industry-specific variables such as concentration level and macro economies variables such as GDP and CPI will also incorporated.

1.3.2 Hypothesis development

This study adopts a similar variable specification method as the literature above. The dependent variables contain six bank-specific variables, one industry-specific variable as well as two macroeconomic variables.

1.3.2.1 Bank-specific variables

Bank size

Bank size is commonly regarded as a key factor in assessing bank efficiency (Alhassan and Tetteh, 2017; Kamarudin et al., 2017; Paleckova, 2019). Similar to previous literature, the natural logarithm of Total Assets (TA) serves as the proxy of bank size, which is also incorporated in the regression equation to examine how the bank size influences efficiency. Prior literature about banking efficiency indicated that there is no agreement concerning the influence of size on efficiency (Aggelopoulos and Georgopoulos, 2017). Specifically, some scholars (Pancurová and Lyócsa, 2013; Sufian, 2016; Kamarudin et al., 2017, Fernandes, Stasinakis and Bardarova, 2018 and Paleckova, 2019) discovered a positive relationship between bank size and efficiency. (Goddard, Molyneux and Wilson, 2004) argued that banks with larger sizes may profit from scale economies, resulting in reduced costs and increased profits. In contrast, banks with smaller sizes face the problem of scale diseconomies which result in higher costs and lower performance. (Sufian & Noor, 2009; Ismailetal.,2013; Guidi, 2022). Compared with smaller banks, banks with larger size banks can use advanced technology and they can expand more off-balance sheet activities (Reddy and Nirmala, 2013; Alhassan and Tetteh, 2017). Moreover, larger banks gather and process information relatively cheaply (Staub, da Silva e Souza and Tabak, 2010; Fernandes, Stasinakis and Bardarova, 2018). Under the DEA framework, bank size may impact the bank's performance positively through two possible channels. Firstly, banks with larger sizes pay less for inputs because of stronger market power. Secondly, the scale of return increases with the increase in bank size, specifically, ratios of output (such as service volume) to input (such as risk management and risk) will be higher under the larger bank size (Kamarudin et al., 2017).

Conversely, Isık – Hassan, 2002; Chen, Skully and Brown, 2005 and Shawtari, Ariff and Abdul Razak, 2015) identified a negative and significant relationship between bank size and bank efficiency. Focusing on the banking sector in the Czech, Řepková (2013) discovered that small and medium banks demonstrated higher efficiency than larger banks. The probable explanation is that banks may face the problem of bureaucratic structure when they are big enough, which will decrease their efficiencies. In other words, extremely large banks may face the problem of scale diseconomies (Guidi, 2022). Sufian and Habibullah (2010) suggested that the problem of resource misallocation results in lower efficiency even if under the advantage of economies of scale for larger banks (Alhassan and Tetteh, 2017).

Eichengreen and Gibson (2001) suggested a bell-shaped non-linear relationship between bank size and performance. Specifically, bank performance improves before a certain size and then performance declines. Therefore, banks with small sizes can approach scale economies and increase efficiency if expanding scale. Nevertheless, huge banks need to downsize to be efficient if their scale economies are exhausted. Based on the specification above, the hypothesises of the bank size are:

H1a: the relationship between bank size and bank efficiency is positively significant;

H1b: there is a U-shaped or bell-shaped relationship between bank size and bank efficiency.

Bank capitalisation

The ratio of Equity to Total Assets (ETA) is used as the proxy of capitalisation level.

There is also no agreement regarding the direction of the relationship between bank capitalisation and bank efficiency. Pancurová and Lyócsa (2013), Sufian (2016) and Alhassan and Tetteh (2017) discovered a positive relationship between the equity ratio and bank efficiency. Based on previous literature, several theories can be used to explain this positive relationship. Firstly, higher bank capital reduces the agency problems between the owners and managers. The reason is that owners tend to monitor the managers tighter when they account for more shares of banks, resulting in higher cost efficiency because of higher cost discipline (Mester, 1996; Eisenbeis, Ferrier and Kwan, 1999). Moreover, Carvallo and Kasman (2005) suggested that banks with higher capitalisation levels earn higher profits, thus, more earnings are retained as capital under the revenue efficiency model. Additionally, it is assumed that well-capitalised banks have better protection, therefore, they engage in more rewarding investments with higher risk (Pancurová and Lyócsa, 2013).

In contrast, according to Shawtari, Ariff and Abdul Razak (2015) and Kamarudin et al. (2017), the bank capitalization level had a significant negative effect on efficiency in the banking sector. Goddard, Molyneux and Wilson (2004) argued that overcapitalised banks always operate too cautiously, which will ignore profitable opportunities (Guidi, 2022). Moreover, Sufian (2009) suggested that banks with low efficiency may be involved in riskier investments and operations. Therefore, they need to keep a higher capital level because of the regulatory pressures and safety considerations. It differs from the moral hazard theory, which proposes that managements are motivated to monitor bank efficiency under a higher equity ratio (Tecles and Tabak, 2010; Shawtari, Ariff and Abdul Razak, 2015). Therefore, the hypothesis about the capitalisation in this study will be:

H2: the relationship between equity/asset ratio to bank efficiency is positively significant.

Loan/total assets

Following similar studies (Berger and Mester, 1997; Havrylchyk, 2006; Alhassan and Tetteh, 2017; Kamarudin et al., 2017; Fernandes, Stasinakis and Bardarova, 2018), The LCTA ratio is also incorporated into the regression model to assess the bank efficiency. The LCTA ratio is calculated as loan to customer divided by total assets. It is the proxy for both liquidity (L) and asset quality (A). The reason is that higher LCTA sometimes means excessive loan placement with higher risk while it shows lower liquidity since the loan assets are less liquid.

From the perspective of loan placement, Shawtari, Ariff and Abdul Razak (2015) suggested that higher loan placement will result in higher bank efficiency. Interest income from loans is the main revenue source of banks, which positively affects the bank performance while efficient operation is assumed to be associated with stronger market power (Sufian, 2009). Sufian (2009) suggested that efficient banks operate with lower production costs as well as increased market power due to the well-managed operation. Based on the same logic, Isik and Hassan (2003) also suggested the reason why the LCTA influences bank efficiency positively is that efficient banks have a cost advantage and can provide more reasonable loan terms, which is helpful to lend more and capture more market share. Moreover, from the perspective of liquidity, Havrylchyk (2006) and Brissimis, Delis and Papanikolaou, (2008) found that less liquid banks tend to be more efficient since they hold fewer liquid assets in the asset portfolio. Therefore, less liquid banks have more capacity to lend and invest, which improves the outputs of banks under the logic of the DEA model. However, holding fewer liquid assets implies a higher liquidity risk exposure, which threatens the stability of banks. Thus, banks need to keep a balance between risks and efficiency (Paleckova, 2019).

In contrast, some studies found a negative relationship between LCTA and bank efficiency. Pancurová and Lyócsa (2013) argued that this negative relationship may be because extensive loan placement may indicate that banks have poor credit management while holding high-risk loans. Furthermore, Naceur and Ghazouani (2007) suggest that a higher proportion of loan placement in the balance sheet implies higher cost monitoring and screening costs because loans are considered to be associated with higher operating costs compared with other types of assets for banks (Fernandes, Stasinakis and Bardarova, 2018). Therefore, the hypothesis is:

H3: the relationship between customer loan /total assets to bank efficiency is negatively significant.

Loan loss reserve to asset ratio

The ratio of Loan Loss Reserve to Total Assets (LLRA) ratio is also incorporated in the regression model to assess how credit risk affects bank efficiency. There are always two methods to calculate the loan loss reserve level. One is the loan loss reserve divided by the total loans granted. The other one is the loan loss reserve divided by total assets. The latter calculation method is chosen since this study considers a wider perspective on the overall risk level rather than just focusing on loans. Besides, the non-performing loan in the DEA approach already reveals the bank's loan risks as undesirable output. Therefore, this study uses the total assets as the denominator here to avoid repetition and also to have a broader view of bank credit risk.

Sufian and Kamarudin (2015) suggested that banks with higher risk exposure will demonstrate lower efficiency since the non-performing loans will bring about loan loss which lowers the banks' performance. Therefore, banks tend to tighten their risk appetite by stronger monitoring of high-risk loans and tightening the screening process (Fernandes, Stasinakis and Bardarova, 2018). It aligns with previous research by Barr et al. (2002), who argued that banks with higher risk appetites generally perform worse than competitors (Kamarudin et al., 2017). Similarly, Havrylchyk (2006) also agreed that a significant negative relationship between the loan loss provisions/loans and bank efficiency since more monitoring costs and loan repayment enforcing costs are created by problem loans. Banks with high credit risk should pay more attention to managing the credit risk of failing to recognise and write off impaired assets (Sufian and Habibullah, 2010). Therefore, it is expected that the bank efficiency will be negatively influenced by the loan loss reserve ratio (LLRA) since the deterioration of a bank's investment portfolio will lead to increased provisions and investment losses and the profit will be lowered. Therefore, the hypothesis is:

H4: the relationship between loan loss reserve/total assets to bank efficiency is negatively significant.

Income diversification

The non-interest income/operating revenue ratio of banks is utilised to assess the degree of diversification of the bank's revenue sources and the level of reliance on non-interest income. A higher ratio usually indicates that banks have a more diversified source of income, relying not only on traditional interest income (such as loan interest and deposit interest), but also on various non-interest income (such as handling fees, commissions, transaction income, investment income, etc.). This helps to reduce the risk of income fluctuations. Thus, expanding income channels and enhancing overall profitability. Especially in situations where interest rate environments change or credit markets fluctuate significantly, non-interest income can provide a certain buffer effect. It reflects the operational efficiency and cost management ability of banks, as many non-interest incomes do not rely on significant capital investment and are relatively more efficient. Vallascas, Crespi, and Hagendorff (2012) argued that banks benefit from income diversification since the banks' income sources are not bound to a narrow activity (Vallascas, Crespi, and Hagendorff, 2012).

Conversely, Stiroh (2004a, b) suggested that bank diversification results in worse risk-adjusted bank performance. Non-interest income activities provide little risk diversification benefits, which increase the bank risks. Laeven and Levine (2007) explained the diversification discount from the perspective of agency theory. To be more specific, banks with diversified activities have severe agency problems. Therefore, diversified banks are outperformed by banks that only focus on specific activities. Thus, the hypothesis is:

H5: the relationship between income diversification to bank efficiency is negatively significant.

Deposit to total asset ratio

The customer deposit-to-total asset ratio of banks is used to measure the structure and stability of their funding sources. It represents how much of the bank funds are covered by public deposits (Mwangi, Muturi and Ombuki, 2015). A higher ratio usually indicates that the bank has a stable source of funding, as customer deposits are generally viewed as a relatively stable source of funding than other forms of financing (such as wholesale funding markets). Usually, the interest cost of customer deposits is lower than that of wholesale financing or other lending methods. Thus, an increased deposit ratio helps to lower the fund costs for banks and improve profit efficiency (Helms, 2006). A higher deposit ratio may reflect customers' trust and confidence in the bank, which positively influences the bank's reputation and market image. Banks rely on customer deposits instead of high-risk wholesale financing, which can reduce financing risks caused by market fluctuations and enhance their risk management capabilities. Thus, the hypothesis is:

H6: the relationship between customer deposit/assets ratio to bank efficiency is positively significant.

1.3.2.2 Industry-specific variable

Market concentration ratio

This study employs Herfindahl-Hirschman Index (HHI) to control the impact of market concentration on banks' efficiency in the industry level. The HH index equals the proportion of total commercial banking assets that the three largest commercial banks hold. A number of literature found a negative and significant relationship between the HHI and banks' efficiency, which challenges the structure–conduct–performance (SCP) hypothesis (Liu and Wilson, 2010; Saka, Aboagye and Gemegah, 2012; Batten and Vo, 2019). Researchers suggest that a highly concentrated market may result in lower bank efficiency because of the absence of competition. (Lieu, Yeh and Chiu, 2005; Pancurová and Lyócsa, 2013; Alhassan and Tetteh, 2017).

In contrast, the SCP hypothesis assumes that the higher market concentration level helps to enhance efficiency. The SCP hypothesis suggested that banks operating in a highly concentrated market are expected to perform better because of the collusion. (Molyneux, Altunbas, & Gardener, 1996; Sufian, 2016). Specifically, the bigger a firm's market share, the stronger market power it has to set prices for its products or services, thus earning greater profits, which enhances the efficiency under the profit approach (Guidi, 2022). Pasiourasa and Kosmidou (2007) also drew the same conclusion. They argue that even if a highly concentrated market reduces bank efficiency via less market discipline, however, concentration improves the company's performance through collusive investment and pricing policies due to weaker competition (Shawtari, Ariff and Abdul Razak, 2015). Therefore, the hypothesis is:

H7: the relationship between market concentration to bank efficiency is positively significant.

1.3.2.3 Macroeconomic control variables

Regarding the macro controls, this study used inflation rate (CPI) and (GDPP) to control the macroeconomic environment's impact on bank efficiency. Specifically, the GDPP is incorporated to evaluate the impact of economic growth on bank efficiency. A number of literature (Shawtari, Ariff and Abdul Razak, 2015; Paleckova, 2019; Fernandes, Stasinakis and Bardarova, 2018) showed that economic growth has a significant and positive effect on bank efficiency since banks tend to lend more during economic expansion. Thus, more profit is generated and the efficiency is improved under the profit approach. Shawtari, Ariff and Abdul Razak (2015) suggested that stronger economic conditions benefit the improvement of bank performance since the demand for banks will be increased during the economic expansion, resulting in increased wealth. Conversely, lower financial services demand is always accompanied by higher default of loans, resulting in decreased national output. However, Sufian (2016) argued that a healthier economic environment enhances the business climate and reduces barriers to newcomers to the banking sector, which intensifies the competition. As a consequence, it dampens the bank's efficiency (Liu & Wilson, 2010).

Apart from the indicator that captures the macroeconomic growth, the inflation rate is also incorporated into the analysis. It is suggested that how the inflation rate affects bank performance based on whether banks can forecast future movements in prices (Guidi, 2022). If that is the case, the inflation rate increase will lead to bank efficiency improvements. Conversely, Pancurová and Lyócsa, (2013) and Paleckova (2019) argued that economic growth has a negative effect on efficiency because inflation hinders creditor institutions. Since macro factors are just used as controls, their coefficients and significance levels are not the main focus. Thus, a hypothesis about macro variables will not be made.

1.4 Summary of the literature review

To sum up, this study reviews the DEA model in the banking sector initially. To overcome the black box problem of the simple model, the semi-parametric approach with an external regression became popular in the banking sector. Moreover, the literature indicates that most papers used the sample from 2006 to 2016, and few two-stage DEA approach researches focused on the CEE level in recent years. Regarding the inputs and outputs selection, most precious studies utilised the production and intermediation approach, while few used a pure profit approach. The review of the efficiency determinants reveals that variable selection attributes to the framework include bank-specific (CAMEL), industry-specific (H-H), and macro-specific variables globally. Therefore, this study employs the two-stage approach with the bootstrap regression technique focusing on 11 CEE countries until the year 2021. This study follows a profit approach rather than the common production and intermediation approaches, while the undesirable output will also be incorporated. As the dependent variable in stage two, the efficiency score will be regressed by well-selected six bank-specific (CAMEL), one industry-specific (H-H), and two macro-specific variables.

2. Data and methodology

2.1 Data sources

The sample of this thesis contains 80 commercial banks in 11 Central and Eastern European countries, including the Czech Republic, Hungary, Poland, Slovakia, Slovenia, Croatia, Bulgaria, Romania, Estonia, Latvia and Lithuania. The bank-specific CAMEL data is selected from BankFocus, while the industrial and macro controls are selected from the World Bank Databank. The data starts from 2013 and ends in 2021 for several reasons. First, the bank concentration H-H index available ends in 2021. Second, since the DEA calculation relies on highly-balanced data, the data started in 2013 to avoid too much data missing. To be more specific, the data missing for one year will result in the removal of the whole observations of the specific DMU to keep the balanced panel. Therefore, panel data is strongly balanced in this study.

2.2 Variables and descriptive statistics

The variables list is divided into three parts. Efficiency and biased corrected efficiency scores under CRS and VRS assumptions are used as the dependent variables. Radial BCC and CCR efficiency scores are calculated by the radial measure of technical efficiency, the Debreu-Farrell measure (teradial command) in STATA 18. Some Basel or CAMEL (Capital adequacy, Asset quality, Management, Earning and Liquidity) variables are included as bank-specific variables. In terms of controls, industry-specific and macro variables are introduced. Comparing the asset scale of the largest three banks with the whole, the H-H indicator is commonly used to represent the concentration of the banking sector within a country while CPI and GDP per capita growth are used to control the macro-economic environment.

Table 1 Variable list

Variable list		
Variable name	**Explanation**	**Data source**
Inputs		
IE	Interest expense	BankFocus
FE	Fee and commission expense	BankFocus
TOE	Total operating expenses, such as salaries, depreciation/ amortisation and marketing expenses	BankFocus
Outputs		
II	Interest income	BankFocus
FI	Fee and commission income	BankFocus

NIFI	Income that is not attributed to interest, fee and commission, but always related to trading and investment	BankFocus
Undesirable output		
NPLC	Non-performing loans to customers	BankFocus
Dependent Variable		
EFF	Efficiency score of banks ranging from (0,1)	STATA
Bank-specific CAMEL independent variables		
lnTA	Total assets - the proxy of bank size	BankFocus
TAS	The square term of lnTA	BankFocus
ETA	Equity/Total assets - the proxy of Capital Adequacy	BankFocus
LCTA	Loan to customer/Total assets – the proxy of both Asset Quality and Liquidity	BankFocus
LLRA	Loan loss reserve/Total assets – the proxy of Asset Quality	BankFocus
NIIOR	Non-interest income/Operating revenue – the proxy of Earning Capacity	BankFocus
DTA	Deposit/Total assets – the proxy of Liquidity	BankFocus
Industry-specific variable		
HH	Assets of three largest commercial banks as a share of total commercial banking assets (Herfindahl-Hirschman Index)	The World Bank
Macroeconomic Variables		
GDPP	The growth rate of GDP per capita	The World Bank
CPI	The annual inflation rate	The World Bank

Based on reviews of the literature, it is hypothesized that CEE banks' efficiency will be positively impacted by the bank size, ETA, DTA, and H-H, while the CEE banks' efficiency will be negatively impacted by the LCTA, LLRA and NIIOR. Tables 2 and 3 show the descriptive statistics of variables including inputs and outputs, Tables 4 and 5 show the changes in the variable's means over the nine years while Table 6 shows the correlation matrix.

Table 2 Descriptive statistics of variables - 1

Stats	FI	II	NIFI	TOE	FE	IE	NPLC
N	720	720	720	720	720	720	720
SD	190000	510000	73888	330000	42961	140000	620000
p10	3088	9896	1292	8850	640.7	1875	17075
p25	8703	23534	3832	21440	1955	6046	40910
p50	38818	110000	17618	62596	10529	21156	150000
Mean	110000	310000	47469	200000	25943	72966	400000
p75	140000	330000	63182	270000	29003	73051	490000
p90	270000	880000	130000	510000	58868	210000	1000000
Unit	000 (EUR)						

Table 3 Descriptive statistics of variables - 2

Stats	lnTA	ETA	LCTA	LLRA	NIIOR	DTA	HH	CPI	GDPP
N	720	720	720	720	720	720	720	720	720
SD	1.61	3.90	16.20	3.73	14.21	11.52	13.24	1.65	3.84
p10	12.54	6.10	39.14	0.73	21.81	63.17	47.83	-0.53	-1.51
p25	13.70	8.59	53.46	1.40	29.43	70.42	54.92	0.14	2.08
p50	15.16	10.50	63.29	2.81	36.28	77.05	62.33	1.50	3.74
Mean	14.98	10.74	61.21	4.01	37.91	75.91	62.78	1.53	3.21
p75	16.17	12.88	72.60	5.51	44.74	83.84	66.84	2.78	4.80
p90	17.07	15.36	78.15	9.03	55.81	88.58	87.32	3.72	6.50
Unit	%								

Table 4 Descriptive statistics of variables - 3

Year	FI	II	NIFI	TOE	FE	IE	NPLC
2013	98825	326062	41174	169258	21890	124205	518974
2014	99374	303554	44603	177960	21749	95373	502687
2015	100794	285370	48393	187802	21647	79677	459376
2016	99938	273690	57521	186480	22284	62488	389711
2017	110820	287007	51011	199592	25154	55172	365658
2018	117683	312493	45728	208357	27509	60807	346828
2019	128709	357584	50594	232392	30478	77720	337685
2020	123549	309908	40502	219831	29284	54075	334744
2021	140061	312246	47695	226090	33491	47175	308770
Mean	113306	307546	47469	200863	25943	72966	396048
Unit	000 (EUR)						

Table 5 Descriptive statistics of variables - 4

Year	lnTA	ETA	LCTA	LLRA	NIIOR	DTA	HH	CPI	GDPP
2013	14.74	10.83	65.05	5.46	38.28	72.08	58.00	1.71	0.83
2014	14.77	10.77	63.51	5.46	38.31	74.10	59.60	0.06	2.74
2015	14.83	10.77	62.23	4.87	38.45	75.26	66.43	-0.34	3.90
2016	14.88	10.80	61.02	4.13	40.09	76.36	60.46	-0.35	3.20
2017	14.98	11.03	60.36	3.64	38.26	76.15	61.06	2.06	5.09
2018	15.06	10.97	61.12	3.63	37.56	77.14	62.91	2.47	4.54
2019	15.11	10.82	61.83	3.18	37.19	77.78	64.37	2.43	3.72
2020	15.18	10.55	58.86	3.05	35.75	77.26	65.54	1.79	-4.06
2021	15.27	10.11	56.95	2.65	37.27	77.07	66.65	3.91	8.92
Mean	14.98	10.74	61.21	4.01	37.91	75.91	62.78	1.53	3.21
Unit	%								

Table 6 Correlation matrix

Variables	lnTA	ETA	LCTA	LLRA	NIIOR	DTA	HH	CPI	GDPP
lnTA	1.00								
ETA	0.14	1.00							
LCTA	0.23	0.24	1.00						
LLRA	-0.24	0.05	0.39	1.00					
NIIOR	-0.13	-0.13	-0.56	-0.19	1.00				
DTA	-0.19	-0.13	-0.08	0.02	0.01	1.00			
HH	-0.23	0.05	-0.14	-0.23	0.13	-0.01	1.00		
CPI	0.16	-0.04	-0.12	-0.22	-0.01	-0.01	0.07	1.00	
GDPP	0.01	0.02	-0.03	-0.03	0.04	0.05	0.04	0.21	1.00

There are 720 observations including 80 banks for 9 years. The capitalisation is around 10.74% on average. The highest equity/total assets ratio occurred in 2017 with a ratio of 11.03%, but decreased obviously in 2020 and 2021, probably because of the covid. The mean of the loan/total assets is 61.21% over the years, but this ratio is lower than 60% after 2020 (58.86% in 2020 and 56.95% in 2021). The loan loss reserves/total assets ratio decreased over the years, from 5.46% in 2013 to 2.65% in 2021. The DTA increased steadily over the years, from 72.08% in 2013 to 77.07% in 2021, while the NIIOR fluctuated with an average of 37.91%. Over the nine years, the industry concentration of banks increased continuously, from

58.00% in 2013 to 66.65% in 2021, even during the COVID period in 2020 and 2021. The increase in concentration is probably due to the restructuring and consolidation in the banking sector. At the macro level, CPI stayed at a low level from 2014 to 2016, and the inflation kept at around 2% afterwards. The CPI decreased to 1.79% in 2020 while the increased sharply in 2021 to 3.91%, which indicates the recovery the consumption. GDP per capita increase rate fluctuated over the nine years, with a decrease in 2020 (-4.06%), followed by a recovery in the next year (8.92%). The correlation matrix indicates that most expenses and income are highly correlated, which aligns with the logic of DEA that the use of resources is highly consistent with output goals. However, the correlation between the independent variables is not obvious.

2.3 Methodology

This section specifies the methodologies to obtain the bank efficiency score and the regression method to find out the bank efficiency determinants. Firstly, this paragraph introduces the BCC, SBM and Malmquist index models to measure the bank efficiency and its change. After that, the Bootstrapped Truncated Regression will be discussed, followed by the regression model specifications.

2.3.1 DEA in the first stage

The methodology of DEA is about the model selection, the orientation direction and the assumption of the scale efficiency changes. However, there is no agreement about variable selection approaches, orientation directions, as well as the regression method in the second step (Henriques et al., 2020). Basic DEA models can be classified into radial, additive, and slack-based models (Paradi, Sherman and Tam, 2018).

CRS and VRS

Based on Farrell's seminal paper "The Measurement of Productive Efficiency" (Farrell 1957), the first DEA model so-called CCR model was proposed by Charnes, Cooper, and Rhodes (1978). Six years later, with the VRS assumption, the BCC model was proposed by Banker, Charnes, and Cooper (1984). These two popular models are radial DEA models named by the initials of their authors (Novickytė and Droždz, 2018; Cikovic, Smoljic and Lozic, 2021).

Under radial models such as CCR and BCC, the efficiency score is calculated according to what degree of all inputs can be decreased and to what extent outputs should be expanded to be efficient while the changes are proportionate. The Slack-Based Measures (SBM) proposed by Tone (2001) is a non-radial DEA model. Unlike radial models, the SBM model does not assume the proportional changes of inputs and outputs to achieve efficiency. The non-radial models, however, focus on slacks (Tone, 2017), that is to say, they focus on the specific amount of input decrease and output increase required for DUMs to be efficient (Palečková, 2016). Specifically, the calculation of the former two radial efficiency scores depends on the distance to the efficient frontier while the latter is based on the slackness. Based on these models, Tone and Tsutsui (2010) developed the EBM approach which focuses on both radical and non-radical adjustments.

The only difference between the CCR and BCC models is the return-to-scale assumptions. Specifically, the CCR model holds the constant-return-to-scale (CRS) assumption, the BCC model, however, assumes variable-return-to-scale (VRS) activities (Skuflic, Rabar and Skrinjaric, 2013). Therefore, the CCR model is a special type of BCC model when CRS is assumed. In other words, the constant-return-to-scale (CRS) assumption in the CCR model assumes a proportional output increase based on inputs. Thus, the CCR model is ineffective in many cases. That is why the BCC model was introduced, which is an improvement of the early

CCR model. Under the BCC model, the output changes are not affected by the input changes proportionally (Cikovic, Smoljic and Lozic, 2021). The efficiency score of the CCR model is called technical efficiency while the efficiency score of the BCC model is called pure technical efficiency, as the equation is shown below:

Technical efficiency (TE)=Pure technical efficiency (PTE) x Scale efficiency (SE)

Under the VRS assumption, the BCC model measures the pure technical efficiency (PTE), without the incorporation of the scale efficiency. Under the CRS assumption, the efficient DMUs remain efficient under all scales, while the efficient DMUs may become inefficient under the VRS assumption. In other words, the earlier CCR (CRS) model is only fitting when every DMU operates at a scale that is optimal (Mishra et al., 2024). In the banking industry, the constant returns to scale (CRS) model can be used only when banks operate efficiently in scale (George Assaf, Barros and Matousek, 2011), which is not possible in reality. Therefore, most recent studies utilize the VRS to estimate efficiency (Fethi and Pasiouras, 2010). However, it does not mean that the VRS model is superior to the CRS model since different things are measured. Specifically, the CCR (CRS) model captures the overall efficiency or technical efficiency (TE), which includes the scale efficiency. The BCC (VRS) model, however, captures pure technical efficiency (PTE), which focuses on administrative capacity solely. Thus, PTE and TE are the same when ignoring the effect scale (dis)economies (Henriques et al., 2020). However, some studies prefer CRS but not VRS, indicating that the application of the VRS assumption should be cautious (Soteriou and Zenios, 1999). Due to the lack of consensus, many theses report both PTE under the VRS assumption and TE under the CRS assumption (Casu and Molyneux, 2003; Fethi and Pasiouras, 2010). According to similar logic, the technical efficiency in the SBM model can also be decomposed with different return-to-scale assumptions.

Dynamic DEA-Malmquist index

The CCR and BCC are designed to present the efficiency score but do not show the magnitude of efficiency change over time. To solve this problem, some dynamic DEA models were introduced to capture the efficiency change over time (Palečková, 2016). Specifically, Färe and Grosskopf (1997) first proposed the application of the Malmquist index in DEA analysis. It is an innovative method to capture the performance of DUMs over the periods. The Malmquist index can be decomposed into Technological Change (TC) and Efficiency Change (EC), while Efficiency Change (EC) can still be decomposed into Pure Technical Efficiency Change (PTEC) and Scale Efficiency Change (SEC). Different from the static DEA, the Technological Change (TC) is unique in Malmquist measurement since it measures the change of frontier over time. Specifically, TC measures whether the technology progressed or regressed. It measures the innovations of the industry as a whole or the changes in the environment in which the DMUs operate, which is a change in the production conditions.

Inputs and outputs specification

When selecting the inputs and outputs variables of the profits approach, a full understanding of the bank's profit composition is essential. This paper focuses on the regular business of banks, therefore, the income and expense of banks' main business are the main focus. In other words, the non-operating parts of profit will not be included in the analysis. Banks have three main income sources, including interest income, fee and commission income as well as investment and trading parts from the financial markets. The operating income of banks includes net interest income, net fee and commission income and other incomes not attributed to the interest and fee parts. The calculation of the other incomes equals operating income plus interest expense minus interest income plus fee and commission expense minus fee and commission income. Different from the operating income, the operating expense does not include the interest expense and fee expense. The operation of banks mainly includes the personnel, administrative and depreciation/amortization expenses.

Early studies often utilize production and intermediation approaches to capture the efficiency of banks (Fernandes, Stasinakis and Bardarova, 2018). However, these two approaches do not focus on the function of banks as financial channels and transaction processing service providers (Berger and Humphrey, 1997). The profit consideration is also significant for banks since profit maximization is also one of the most important targets for banks, similar to other organisations (Sahoo et al., 2014) Therefore, this thesis chooses to utilize the profit approach DEA method. The profit approach uses various expenses and incomes as inputs and outputs. To examine the change in efficiency for Greek bank branches, Aggelopoulos and Georgopoulos (2017) utilize loan provisions and operating expenditures as inputs, meanwhile, they use fees and other revenues as outputs. Similarly, analysing the efficiency impact of Chinese banks' earning asset diversification. Du, Worthington and Zelenyuk (2018) use various sources of expenditures (interest and non-interest) as inputs while they use total net incomes as outputs. Focusing on PIIGS countries, when evaluating the efficiency of banks in Europe, Fernandes, Stasinakis and Bardarova (2018) selected interest expenses and operating expenditures as inputs while they selected total revenue as output.

Therefore, the expenses and incomes are selected as inputs and outputs like much prior literature. In terms of the inputs, operating expenses include various administrative expenditures such as PPE depreciation/Amortisation, personnel expenditure and marketing expenses. Interest expenses represent the cost of bank funds, which mainly means the interest paid to depositors. Additionally, fee expense represents the cost incurred for providing the transaction service to the customer or the commission cost paid to the third party. Correspondingly, the total income is selected as output. To measure the efficiency more accurately, the total income is divided into three categories: interest income, fee and commission income, as well as non-interest and fee operating income. The latter mainly contain the investment and trading outcomes of banks.

Traditional simple CCR and BCC model fails to consider the undesirable outputs. In practice, however, it is important to decrease the undesirable output to optimise the efficiency of the DMU. In this study, the undesirable output - non-performing loan is introduced, which is seen as the by-product of banks. Since the non-performing loan is what needs to be minimized and to simplify the calculation, it is simply treated as inputs when formulating the efficiency score in the traditional BCC model. However, there is a specific position for the undesirable output in the SBM model.

Input and output orientations

The orientation relates to the idea of moving the inefficient DUMs towards the frontier to make them efficient. To be efficient, it is possible to cut the abundant inputs devoted or extend the deficit in outputs produced (Novickytė and Droždz, 2018). The input orientation and the output orientation are two potential orientations of DEA models. Specifically, the input orientation targets decreasing the input level as far as possible but remaining the output level unchanged at the same time. On the contrary, the output orientation emphasises maximizing the output amounts while keeping the input level constant (Skuflic, Rabar and Skrinjaric, 2013; Cikovic, Smoljic and Lozic, 2021). In addition, under the SBM and EBM non-oriented model, it is also possible to minimize the inputs while maximizing the outputs simultaneously.

There is no agreement about how to choose the orientation of the DEA model (Cook, Tone and Zhu, 2014), therefore, professional judgment is needed when choosing the orientation direction. In this study, the output-oriented DEA is used. The efficiency scores mean the possible proportional increases in the output level to become efficient when keeping the inputs constant (in this study, all score is translated to the scale between 0 and 1, if a score is close to 1, it means less output increase potential). Based theories on the 'social control' of banks (Ataullah, Cockerill and Le, 2004; Fernandes, Stasinakis and Bardarova, 2018) postulate that banks are output-oriented naturally since the management has greater flexibility in managing the outputs than inputs for banks, particularly within nations experiencing stricter economic and financial conditions (LaPlante and Paradi, 2015). Furthermore, many banks aim to expand to capture more customers and market shares, therefore, reducing the inputs for contraction is not desirable and possible. Thus, output orientation is suggested for these reasons in this study.

The number of inputs and outputs is another consideration when capturing the efficiency under the DEA model. The widely accepted 'rule of thumb' indicates that the number of DMUs must exceed three times of the sum number of inputs and outputs. If this quantitative relationship cannot be satisfied, a big proportion of DMUs will become efficient, which will result in efficiency discrimination because of the low degrees of freedom (Cooper, Seiford and Tone, 2007). In this study, three inputs, three outputs and one undesirable output are selected to measure the efficiency. Since there are 80 DUMs, it is obvious that the 'rule of thumb' is met in this thesis.

The formula of the output BCC model is to max score subject to four conditions: $\sum_{i=1}^{n} \lambda X \leq X_i$ (1), $\sum_{i=1}^{n} \lambda Y \geq \text{score} \cdot Y_i$ (2), $\lambda \geq 0$ (3), $\sum \lambda = 1$ (4), i=1, 2, 3…..n DMU. X represent the inputs while Y represents the outputs for individual banks. The score_i represent the efficiency score of the bank i. Banks are efficient if the score equals one, while a higher than one efficiency score means banks do not operate efficiently. The formula (4) is a restriction of the variable scale efficiency. Thus, the CCR model combines formula (1) to (3), while the BCC model combines formula (1) to (4). The SBM formulas follow a similar linear programming method but incorporate the slacks. Since the BCC (CCR) is the main focus of this study, the

SBM calculation procedure will be discussed here. There are 720 observations in this study, therefore, the linear programming procedure will be repeated 720 times, specifically, once for each line of observation (Fernandes, Stasinakis and Bardarova, 2018). Early Simar and Wilson (2007) focused on output-oriented DEA and the efficiency score is bounded to (1， infinite), however, later Simarwilson command of Badunenko and Tauchmann (2019) in Stata suits for the efficiency both for (0,1) and (1, infinite). For comparison purposes, the invert of the efficiency scores and bias-corrected efficiency scores are used to make the score bound to (0,1), and these inverted scores are presented in the first stage as well as used as the dependent variable in the second stage.

2.3.2 Bootstrap in the second step

A number of banking efficiency studies utilise the so-called two-stage approach. The efficiency scores estimated in the first stage become the dependent variable of the second stage, which is regressed on external explanatory variables (Sun and Chang, 2011; Fernandes, Stasinakis and Bardarova, 2018). The traditional ordinary least-squares (OLS), Tobit, Truncated and Bootstrap regression techniques can be found in the literature (Henriques et al., 2020). After reviewing hundreds of DEA articles employing the external regression method, Simar and Wilson (2007) found that early studies just used the traditional OLS regression technique or mostly used the censored regression (Tobit and truncated) to deal with the natural boundary of the efficiency score (0, 1 or 1, +∞).

The DEA approach has an inherent separability issue, specifically, the distribution of the DEA score is close to 1. Therefore, traditional regression approaches are inappropriate to regress the efficiency score in the second stage. To solve this problem, Simar and Wilson (2007) designed a bootstrap truncated regression technique to solve this problem (Henriques et al., 2020; Badunenko and Tauchmann, 2019). To explain in detail, since the efficiency score is limited to unit intervals (0-1), the Tobit censored regression technique was used to estimate the coefficients. Different from OLS estimation, the Tobit model can get consistent coefficient estimates when facing bounded dependent variables (Grigorian and Manole, 2006). Although the Tobit-like regression is popular and looks reasonable, the estimators of the traditional model have bias. The reason is that the conventional two-stage technique treats efficiency scores as independent observations which is inappropriate, and may result in a biased inference because of the serial correction problem. In fact, the DEA scores are estimated from a sample of data.

Moreover, the sample bias exists if efficient DMUs are omitted which results in the underestimation of distance from the DEA. Also, boundary inefficiency problems exist under the traditional OLS method. Therefore, the truncated bootstrap technique was introduced, which solves the problems above while providing a bias-corrected efficiency score. The bootstrapping approach overcomes the structural weakness of bias affected by sample size (Staat, 2002; Simar and Wilson, 2007; Aggelopoulos and Georgopoulos, 2017; Badunenko and Tauchmann, 2019). For the reasons above, the bootstrap DEA procedure proposed by Simar and Wilson (2007) is used to regress the dependent variable-efficiency scores while generating the unbiased estimators and it used a truncated rather than the Tobit-based regression model.

There are two algorithms of the Simar and Wilson approach. The detailed mathematical processes were well explained by Badunenko and Tauchmann (2019) in their paper about the simarwilson command in Stata. Simply speaking, the estimation approach is based on equation $score_i = X_i beta + e_i$ (5) ,while algorithm #1 does not estimate the biased corrected efficiency score or the biased corrected efficiency scores are externally calculated. In the second step, only the inefficient efficiency score will be kept and a truncated regression will be used to estimate the score, coefficient beta and its variance σ. In the third stage, a truncated distributed artificial error e will be used to formulate the artificial efficiency score for each DUM. After that, a maximum likelihood truncated bootstrap will be used for the equation (5), to get the bootstrapped estimates beta and confidence interval. In this study, the third stage is repeated 2000 times to get the set of bootstrap estimates. The DBTR technique in Algorithm #2 is based on Algorithm #1 but with a biased corrected score generation process before the third stage of Algorithm #1. In this study, 1000 times is used to generate the biased-corrected efficiency score. Since this bootstrap truncated model suits for efficiency score from the radial model and initially for the CCR and BCC model (Badunenko and Tauchmann, 2019), this study will not regress the SBM efficiency score and MPI index from the first stage, but only the CCR/BCC score.

2.4 The Regression Model specification

In the second stage, this paper uses the bootstrap truncated regression technique to find out the CAMEL-based determinants of bank efficiency.

$$\mathrm{EFF} = \alpha_i + \beta_1 \mathrm{lnTA} + \beta_2 \mathrm{ETA} + \beta_3 \mathrm{LCTA} + \beta_4 \mathrm{LLRA} + \beta_5 \mathrm{NIIOR} + \beta_6 \mathrm{DTA} + \beta_7 \mathrm{HH} + \beta_8 \mathrm{GDPP} + \beta_9 \mathrm{CPI} + \varepsilon \ldots\ldots(1)$$

$$\mathrm{EFF} = \alpha_i + \beta_1 \mathrm{lnTA} + \beta_2 \mathrm{TAS} + \beta_3 \mathrm{ETA} + \beta_4 \mathrm{LCTA} + \beta_5 \mathrm{LLRA} + \beta_6 \mathrm{NIIOR} + \beta_7 \mathrm{DTA} + \beta_8 \mathrm{HH} + \beta_9 \mathrm{GDPP} + \beta_{10} \mathrm{CPI} + \varepsilon \ldots\ldots(2)$$

The CAMEL model includes five dimensions: Capital Adequacy, Asset Quality, Management Efficiency, Earning capacity as well as Liquidity. The Equity to Total Asset (ETA) ratio is the proxy for capital adequacy (C). The higher the ratio means the bank is more capitalised. The loan loss reserve/total asset (LLRA) is the proxy for the asset quality (A), the higher the ratio, the higher the reserve for the projected risk of the investment portfolio of banks.

There is no proxy for management efficiency (M) since the whole thesis focuses on bank efficiency. The non-interest income/Operating revenue (NIIOR) is the proxy of earning (E), the higher ratio indicates that bank income earning is less dependent on the traditional loan placement, but probably from intermediatory income and investment. The deposit/total asset ratio (DTA) is the proxy for liquidity (L) since the customer deposit is the stable fund source for banks. The loan/total asset ratio (LCTA) is the proxy for both liquidity (L) and asset quality (A). The reason is that higher LCTA sometimes means excessive loan placement with higher risk while it shows lower liquidity since the loan assets are less liquid. lnTA is the proxy of bank size, which is not classified into any of the five dimensions, while the addition of the square term of total assets (TAS) is used to capture the non-linear relationship between the bank size and efficiency. Apart from the bank-specific independent variables, further industry variables such as market concentration and macroeconomic explanatory variables such as rate of Inflation (CPI) and real GDP growth Rate Per Capita (GDPP) are incorporated to control the effect of the industrial and macro environment of commercial banks. Moreover, the year dummy is incorporated to control the time effect, while 'ε' represents the error term that is not captured by the variables in the specified model.

To sum up, this study employs output-orientated DEA models under the profit approach. In the first stage, the BCC, SBM and Malmqusit index will be calculated while only the BCC (biased corrected) efficiency scores will be regressed by the bootstrapping method in stage two.

3. Empirical regression results

3.1 Introduction of the results

Based on the precious literature, (Novickytė and Droždz, 2018) found that 36% of the DEA studies utilize the variable returns to scale (VRS) assumption, 26% of the DEA studies utilize the constant returns to scale (CRS) assumption, while 40% of papers utilize both the VRS and CRS assumptions. To better compare the bank efficiency in CEE countries, this thesis uses both the annual frontier and the pooled frontier setups, however, the annual frontier setup is the main focus. Besides, the SBM pooled frontier and the BCC pooled frontier efficiency scores are included as robust. The BCC bias-corrected efficiency scores of the pooled frontier setup are shown in Table 7, the BCC efficiency scores of the pooled frontier setup are shown in Table 8, the SBM efficiency scores of the pooled frontier setup are shown in Table 9, while the BCC efficiency scores of the annual frontier setup are shown in Table 10. Table 11 and Table 12 show the current and global technical change using the Malmquist index.

3.2 Results and robust of the first stage DEA efficiency scores

3.2.1 Basic BCC biased corrected model

The calculation of efficiency score was calculated by teradial command in STATA 18 (for BCC) and Dearun V 3.2.0.3 (for SBM and Malmquist index). There are arguments about the orientation as discussed in the methodology part. However, in this study, output orientation is assumed in the BCC method since banks focus more on expansion rather than contracting inputs. In this study, both the BCC and SBM DEA methods are used since BCC (and CCR under CRS assumption) focus on radical improvement while the SBM focuses on non-radical adjustments. Since the original BCC formula does not integrate the undesirable outputs into the formula, therefore, this study treats it as an input for calculation. SBM technique, however, leaves a space for undesirable outputs in the formula. Therefore, this study presents both BCC and SBM efficiency scores with both CRS and VRS assumptions. To make the results of different years comparable and to identify the group characteristics, the global frontier is incorporated. Since the efficiency score is just a kind of ranking but not the absolute value, only the current year's efficiency is not comparable over the years. Global frontier solved this problem by treating all DMUs and all times as a cross-sectional to form a frontier for the whole.

Table 7 Biased corrected BCC efficiency score - global

TE								
Global	**V4**	**B3**	**B4**	**Ecomer**	**Lcomer**	**Listed**	**Unlisted**	**Total**
2013	0.7174	0.7335	0.6646	0.7148	0.6682	0.7096	0.6945	**0.6991**
2014	0.7159	0.7532	0.6747	0.7217	0.6751	0.7172	0.7012	**0.7060**
2015	0.6877	0.7420	0.6405	0.6955	0.6446	0.6911	0.6729	**0.6783**
2016	0.6948	0.7557	0.6570	0.7035	0.6644	0.6970	0.6874	**0.6903**
2017	0.7097	0.7301	0.6507	0.7082	0.6533	0.7047	0.6832	**0.6896**
2018	0.7274	0.7536	0.6539	0.7294	0.6499	0.7098	0.6995	**0.7026**
2019	0.7304	0.7043	0.6484	0.7210	0.6382	0.7071	0.6870	**0.6930**
2020	0.6889	0.6885	0.6533	0.6891	0.6463	0.6900	0.6680	**0.6746**
2021	0.7444	0.7210	0.6784	0.7334	0.6756	0.7398	0.7028	**0.7139**
Total	0.7129	0.7313	0.6580	0.7130	0.6573	0.7074	0.6885	**0.6942**
PTE								
Global	V4	B3	B4	Ecomer	Lcomer	Listed	Unlisted	**Total**
2013	0.8020	0.7573	0.7077	0.7762	0.7176	0.8060	0.7352	**0.7564**
2014	0.8025	0.7826	0.7214	0.7865	0.7275	0.8207	0.7434	**0.7666**
2015	0.7870	0.7936	0.6977	0.7745	0.7091	0.8052	0.7298	**0.7525**
2016	0.8020	0.8079	0.7170	0.7886	0.7307	0.8104	0.7513	**0.7690**
2017	0.8226	0.7732	0.7101	0.7937	0.7205	0.8175	0.7482	**0.7690**
2018	0.8341	0.8088	0.7254	0.8151	0.7294	0.8198	0.7718	**0.7862**
2019	0.8385	0.7577	0.7346	0.8086	0.7321	0.8300	0.7625	**0.7828**
2020	0.7957	0.7387	0.7455	0.7748	0.7477	0.8087	0.7472	**0.7657**
2021	0.8405	0.7910	0.7613	0.8191	0.7630	0.8365	0.7846	**0.8002**
Total	0.8139	0.7790	0.7245	0.7930	0.7309	0.8172	0.7527	**0.7720**
SE								
Global	**V4**	**B3**	**B4**	**Ecomer**	**Lcomer**	**Listed**	**Unlisted**	**Total**
2013	0.8973	0.9584	0.9429	0.9217	0.9352	0.8846	0.9441	**0.9262**
2014	0.8940	0.9531	0.9373	0.9174	0.9301	0.8773	0.9407	**0.9217**
2015	0.8760	0.9313	0.9228	0.9000	0.9130	0.8617	0.9227	**0.9044**
2016	0.8681	0.9309	0.9192	0.8926	0.9131	0.8624	0.9154	**0.8995**
2017	0.8645	0.9403	0.9191	0.8944	0.9098	0.8643	0.9147	**0.8996**
2018	0.8730	0.9288	0.9040	0.8958	0.8938	0.8689	0.9064	**0.8951**
2019	0.8733	0.9295	0.8864	0.8944	0.8767	0.8544	0.9030	**0.8884**
2020	0.8711	0.9275	0.8769	0.8925	0.8651	0.8570	0.8946	**0.8833**
2021	0.8892	0.9079	0.8918	0.8973	0.8862	0.8871	0.8963	**0.8935**
Total	0.8785	0.9342	0.9112	0.9007	0.9025	0.8686	0.9153	**0.9013**

Table 8 BCC efficiency score - global

TE								
Global	**V4**	**B3**	**B4**	**Ecomer**	**Lcomer**	**Listed**	**Unlisted**	**Total**
2013	0.7887	0.8306	0.7307	0.7901	0.7390	0.7756	0.7716	**0.7728**
2014	0.7816	0.8437	0.7392	0.7925	0.7422	0.7733	0.7764	**0.7755**
2015	0.7497	0.8282	0.7061	0.7626	0.7134	0.7549	0.7422	**0.7460**
2016	0.7619	0.8581	0.7181	0.7787	0.7268	0.7503	0.7659	**0.7612**
2017	0.7808	0.8336	0.7107	0.7856	0.7155	0.7597	0.7629	**0.7620**
2018	0.7947	0.8441	0.7130	0.8016	0.7100	0.7618	0.7745	**0.7707**
2019	0.7991	0.7882	0.7080	0.7928	0.6979	0.7605	0.7609	**0.7608**
2020	0.7513	0.7611	0.7196	0.7539	0.7137	0.7441	0.7387	**0.7403**
2021	0.8215	0.8099	0.7476	0.8139	0.7428	0.8072	0.7825	**0.7899**
Total	0.7810	0.8220	0.7214	0.7857	0.7224	0.7653	0.7640	**0.7644**
PTE								
Global	**V4**	**B3**	**B4**	**Ecomer**	**Lcomer**	**Listed**	**Unlisted**	**Total**
2013	0.8793	0.8618	0.7818	0.8573	0.7978	0.8760	0.8206	**0.8372**
2014	0.8654	0.8808	0.7872	0.8572	0.7968	0.8795	0.8185	**0.8368**
2015	0.8437	0.8809	0.7654	0.8381	0.7811	0.8674	0.7981	**0.8189**
2016	0.8628	0.9062	0.7796	0.8582	0.7957	0.8650	0.8252	**0.8371**
2017	0.8894	0.8724	0.7744	0.8671	0.7879	0.8745	0.8258	**0.8404**
2018	0.8988	0.8982	0.7856	0.8850	0.7915	0.8722	0.8454	**0.8534**
2019	0.9101	0.8382	0.7996	0.8807	0.7995	0.8878	0.8386	**0.8533**
2020	0.8620	0.8095	0.8204	0.8415	0.8256	0.8695	0.8219	**0.8362**
2021	0.9217	0.8750	0.8649	0.9004	0.8720	0.9213	0.8777	**0.8908**
Total	0.8814	0.8692	0.7954	0.8651	0.8053	0.8792	0.8302	**0.8449**
SE								
Global	**V4**	**B3**	**B4**	**Ecomer**	**Lcomer**	**Listed**	**Unlisted**	**Total**
2013	0.9000	0.9600	0.9407	0.9240	0.9322	0.8885	0.9432	**0.9268**
2014	0.9038	0.9532	0.9411	0.9245	0.9330	0.8827	0.9465	**0.9273**
2015	0.8897	0.9366	0.9273	0.9108	0.9172	0.8722	0.9304	**0.9129**
2016	0.8832	0.9404	0.9246	0.9062	0.9166	0.8684	0.9274	**0.9097**
2017	0.8791	0.9515	0.9209	0.9074	0.9107	0.8708	0.9246	**0.9085**
2018	0.8845	0.9376	0.9099	0.9063	0.8992	0.8751	0.9163	**0.9039**
2019	0.8804	0.9371	0.8903	0.9019	0.8793	0.8590	0.9094	**0.8943**
2020	0.8776	0.9310	0.8806	0.8983	0.8682	0.8610	0.8998	**0.8882**
2021	0.8938	0.9202	0.8744	0.9045	0.8635	0.8793	0.8956	**0.8907**
Total	0.8880	0.9409	0.9122	0.9093	0.9022	0.8730	0.9215	**0.9069**

Using the interest expense, fee expense, and operating expense as the inputs while using the interest income, fee income, and other income as the outputs while using non-performing loans as undesirable outputs. Table 7,8,9,10 shows the efficiency score of 80 CEE banks over the nine years. Among the 9 years, the lowest technical efficiency occurred in 2020, with an average score of 0.7644 in the BCC global BCC model and 0.6942 in the BCC bias-corrected model. In contrast, the highest efficiency occurred in 2021, with an average score of 0.7899 and 0.7139 for BCC and BCC-biased corrected models, respectively. The total efficiency revealed a decreasing trend, from 0.6991 in 2013 to 0.6746 in 2020 but the efficiency score recovered from 0.6746 in 2020 to 0.7139 in 2021 under the BCC biased corrected model. The trend of BCC and SBM is consistent, the efficiency scores are obviously different in the different model because of their different calculation method. BCC score is based on the distance from the efficient frontier, whereas the SBM score is based on the slacks, and BCC bias-corrected scores are robust under the Bootstrap technique. Similar to the trend of technology efficiency, the biased corrected BCC pure technology efficiency increased from 0.7564 to 0.7828 in 2019, but decreased to 0.7657 in 2020, ending with 0.8002 in 2021. Regarding the scale economy, it also shows a decreasing trend from 2013 to 2020, followed by a recovery in 2021. The scale economy decreased from 0.9262 to 0.8833 from 2013 to 2020 with a recovery to 0.8935 in 2021 for the BCC biased corrected efficiency score (the BCC efficiency score is 0.9268, 0.8832 and 0.8907 for 2013, 2020 and 2021, respectively). And similar trends also can be seen in the SBM model (except for the SE in 2021). Therefore, the conclusion is that technology efficiency, pure technology efficiency and scale efficiency generally show a decreasing trend until 2020, followed by a slight recovery in 2021.

In this study, the dataset includes three regions, V4, Baltic-3 and Balkan-4 countries. Among these three groups, the Baltic three and V4 countries indicate higher technical efficiency over the nine years, with average biased corrected scores of 0.7313 (0.8220 in the BCC model) and 0.7129 (0.7810 in the BCC model), respectively. By contrast, the four countries in the Balkan indicate the lowest technology efficiency over the nine years, with an average efficiency score of 0.6580 (0.7214 in the BCC model).

In terms of the pure technology efficiency, the efficiency scores are 0.8139, 0.7790 and 0.7245 for V4 group, Baltic-3 and Balkan-4 countries respectively under bias corrected BCC (0.8814, 0.8692 and 0.7954 under non-biased corrected BCC with the same trend), and the scale efficiency scores are 0.8785, 0.9342 and 0.9112 for V4 group, Baltic-3 and Balkan-4 countries respectively under biased-corrected BCC (0.8880, 0.9409 and 0.9122 under non-biased corrected BCC). The Baltic banks achieved the highest overall efficiency due to the higher scale efficiency. The V4 countries rank second in overall efficiency because of the lowest scale efficiency. However, the V4 banks perform the best in pure technical efficiency. The Balkan-4 banks ranked the least overall efficiency due to the lowest pure technical efficiency.

When dividing the countries into EU earlycomers and latecomers. Similarly, for EU earlycomers, the lowest biased corrected efficiency score occurred in 2020 with scores of 0.6891, 0.7748 and 0.8925 for TE, PTE and SE, respectively. For EU latecomers, the lowest technical efficiency occurred in 2019 with a score of 0.6382, the lowest pure technical efficiency occurred in 2015 with a score of 0.7091, while the lowest scale efficiency occurred in 2020 with a score of 0.8651. It shows that the external environment such as the covid is not the only trigger of the efficiency decline for EU latecomers.

In general, under the biased corrected model, there is no obvious difference between earlycomers and latecomers regarding scale efficiency (0.9007 for earlycomers and 0.9025 for latecomers). However, the technical efficiency (0.7130 and 0.6573 for early comers and late comers respectively) and the pure technical efficiency (0.7930 and 0.7309) of early comers are higher than the late comers obviously. It shows that the technical efficiency of latecomers is lower than earlycomers because of the difference in PTE but not SE. B4 and EU latecomers have a high degree of overlap except for Slovenia. Here are three possible explanations for the higher PTE for earlycomers. Firstly, the EU earlycomers have more operating experience and they are familiar with the EU policies. This advantage makes them more efficient in managing resources and implementing policies. Secondly, the EU earlycomer always has more advanced economic and financial systems, as well as more developed infrastructure. In contrast, the EU latecomers still developing these infrastructures and systems. Moreover, the EU earlycomres usually have more advantages in market openness and integration because of the earlier participation. Specifically, the single market policy helps them to improve the administrative efficiency of commercial banks. In other words, the EU earlycomers can better utilize larger markets and more consistent regulatory environments. These factors, when combined, may lead to early EU member states exhibiting higher PTE in DEA analysis compared to those that later joined.

The average biased corrected PTE for listed (publicly traded) and unlisted banks are 0.8172 and 0.7527, respectively (0.8792 and 0.8302 in the BCC model, respectively), whereas the average SE for listed and unlisted banks are 0.8686 and 0.9153 respectively. It indicates that listed banks have an advantage in PTE but have a disadvantage in SE. The possible explanation for the higher PTE is that listed banks own more technology capacities. Moreover, they have more talents to maintain high operating efficiencies. The technology capacities and higher operating efficiency can be shown in more advanced IT systems and more professional staff training. Furthermore, since the listed bank can always make cross-border operations. Therefore, the credit and investment risks can be well-diversified risk and the downturn of a single market segmentation will not affect the whole performance of the listed banks. This helps listed banks to decrease the undesirable output-non-performing loans as well as the loan loss provisions as costs. Additionally, listed banks tend to have stronger bargaining powers and reputations in the market, thus, it is easier for listed banks to get high-quality customers with low default risk.

On the contrary, the lower scale economy for listed banks is probable because of the bigger size since listed banks show a decreasing return of scale in the scale economy dimension. Here are several possible explanations. First, larger banks tend to have subsidies and branches. Thus, the communication and decision-making channels are extremely long with time lags. The bigger scale may bring about scale efficiency. However, the marginal benefits will be decreased if the banks do not have enough managerial capabilities. Moreover, due to the cross-border operation of bigger banks, their compliance costs will be high since they should comply with the regulations of all nations although the cross-border operation brings broader customers for banks. Thus, larger banks should always maximise the pure administrative efficiency advantages but optimise their scale to operate at an efficient level for both PTE and SE.

3.2.2 Robust and heterogeneity analysis

The BCC and BCC bias-corrected efficiency scores are almost the same. There are big differences between the scores of BCC and SBM since the BCC is a radial model while the SBM is a non-radial model. However, they share similar trends. Specifically, the pure efficiency scores of the V4 and B3 countries are higher than Balkan 4 countries, while the B3 countries own the highest scale efficiency. Furthermore, the pure efficiency score of EU early comers is higher than the EU late comers while the scale efficiency between these two groups is almost the same (0.8349 and 0.8399). Similar to the BCC model, the listed banks have more pure technology efficiency (0.7466 for listed and 0.6435 unlisted), but the unlisted banks have higher scale efficiency (0.7609 for listed and 0.8690 for unlisted).

Table 9 SBM efficiency score - global

TE

Global	V4	B3	B4	Ecomer	Lcomer	Listed	Unlisted	Total
2013	0.5633	0.7423	0.4701	0.5756	0.5216	0.5865	0.5449	**0.5574**
2014	0.5667	0.6803	0.5193	0.5797	0.5439	0.5781	0.5632	**0.5676**
2015	0.4916	0.6655	0.4737	0.5239	0.4972	0.5819	0.4861	**0.5149**
2016	0.5666	0.7566	0.5451	0.6086	0.5572	0.5930	0.5905	**0.5912**
2017	0.5741	0.6992	0.4780	0.5841	0.5056	0.5726	0.5512	**0.5576**
2018	0.5527	0.6838	0.5001	0.5846	0.4957	0.5175	0.5705	**0.5546**
2019	0.5601	0.6371	0.5113	0.5806	0.5019	0.5297	0.5645	**0.5540**
2020	0.4954	0.5959	0.4625	0.5140	0.4720	0.4779	0.5092	**0.4998**
2021	0.5595	0.6720	0.5296	0.5870	0.5285	0.5421	0.5780	**0.5672**
Total	0.5478	0.6814	0.4988	0.5709	0.5137	0.5532	0.5509	**0.5516**
PTE								
Global	**V4**	**B3**	**B4**	**Ecomer**	**Lcomer**	**Listed**	**Unlisted**	**Total**
2013	0.7423	0.7800	0.5503	0.7012	0.6149	0.7708	0.6298	**0.6721**
2014	0.6932	0.7630	0.5826	0.6834	0.6176	0.7559	0.6206	**0.6612**
2015	0.6286	0.7727	0.5366	0.6412	0.5696	0.7366	0.5658	**0.6170**
2016	0.6790	0.8192	0.6042	0.6975	0.6267	0.7384	0.6459	**0.6736**
2017	0.7051	0.7677	0.5636	0.6874	0.6047	0.7291	0.6296	**0.6595**
2018	0.7258	0.7827	0.5840	0.7232	0.5922	0.6986	0.6706	**0.6790**
2019	0.7611	0.7200	0.6196	0.7321	0.6291	0.7322	0.6823	**0.6973**
2020	0.6778	0.7004	0.5784	0.6608	0.6051	0.7177	0.6096	**0.6420**
2021	0.8196	0.7520	0.7200	0.7774	0.7493	0.8402	0.7370	**0.7680**
Total	0.7147	0.7620	0.5933	0.7005	0.6233	0.7466	0.6435	**0.6744**
SE								
Global	**V4**	**B3**	**B4**	**Ecomer**	**Lcomer**	**Listed**	**Unlisted**	**Total**
2013	0.7963	0.9492	0.8787	0.8520	0.8639	0.7879	0.8852	**0.8560**
2014	0.8311	0.8929	0.8971	0.8617	0.8812	0.7893	0.9022	**0.8683**
2015	0.8139	0.8673	0.8883	0.8425	0.8736	0.7994	0.8760	**0.8530**
2016	0.8499	0.9171	0.9049	0.8809	0.8891	0.8151	0.9130	**0.8837**
2017	0.8303	0.9059	0.8666	0.8633	0.8478	0.7991	0.8834	**0.8581**
2018	0.7741	0.8837	0.8580	0.8217	0.8369	0.7482	0.8606	**0.8269**
2019	0.7482	0.8891	0.8426	0.8077	0.8164	0.7384	0.8416	**0.8106**
2020	0.7533	0.8575	0.8203	0.7981	0.7988	0.6922	0.8438	**0.7983**
2021	0.7161	0.8971	0.7822	0.7858	0.7514	0.6787	0.8151	**0.7742**
Total	0.7904	0.8955	0.8599	0.8349	0.8399	0.7609	0.8690	**0.8366**

The current BCC model formulates the efficient frontier for each year, or the multi-country and single-year (MCSY) frontier. It helps to compare the efficiency ranking of DUMs within the same year, but not well-suited for cross-year comparisons. Indicating similar trends with the global BCC and SBM models, the Balkan 4 countries have the lowest efficiency in both pure technology efficiency (0.9525 for V4, 0.9581 for B3 and 0.8886 for B4) and scale efficiency (0.9327 for V4, 0.9573 for B3 and 0.9202 for B4). Additionally, for the pure technical efficiency score, the EU earlycomers (0.9423) are higher than EU late comers (0.8997) while the listed banks (0.9465) are higher than unlisted banks (0.9200).

Table 10 BCC efficiency score - current

TE								
Current	**V4**	**B3**	**B4**	**Ecomer**	**Lcomer**	**Listed**	**Unlisted**	**Total**
2013	0.8861	0.9222	0.8112	0.8847	0.8189	0.8859	0.8524	**0.8624**
2014	0.8814	0.9205	0.8211	0.8832	0.8267	0.8817	0.8566	**0.8641**
2015	0.8942	0.9231	0.7974	0.8856	0.8113	0.8763	0.8538	**0.8605**
2016	0.8748	0.9267	0.8080	0.8775	0.8173	0.8386	0.8651	**0.8572**
2017	0.8825	0.9026	0.7916	0.8764	0.7972	0.8404	0.8536	**0.8497**
2018	0.8899	0.9652	0.7947	0.9078	0.7811	0.8445	0.8738	**0.8650**
2019	0.8832	0.8888	0.8071	0.8816	0.7991	0.8393	0.8599	**0.8537**
2020	0.9022	0.8988	0.8437	0.8988	0.8378	0.8737	0.8802	**0.8782**
2021	0.9040	0.9257	0.8569	0.9081	0.8514	0.8811	0.8923	**0.8889**
Total	0.8887	0.9193	0.8146	0.8893	0.8156	0.8624	0.8653	**0.8644**
PTE								
Current	**V4**	**B3**	**B4**	**Ecomer**	**Lcomer**	**Listed**	**Unlisted**	**Total**
2013	0.9350	0.9413	0.8517	0.9219	0.8654	0.9343	0.8893	**0.9028**
2014	0.9385	0.9354	0.8756	0.9240	0.8909	0.9438	0.8995	**0.9128**
2015	0.9457	0.9524	0.8544	0.9279	0.8758	0.9464	0.8949	**0.9104**
2016	0.9504	0.9794	0.8824	0.9412	0.9029	0.9497	0.9191	**0.9283**
2017	0.9634	0.9516	0.8736	0.9437	0.8895	0.9475	0.9159	**0.9254**
2018	0.9593	0.9744	0.8881	0.9563	0.8887	0.9454	0.9284	**0.9335**
2019	0.9596	0.9534	0.9121	0.9511	0.9166	0.9541	0.9332	**0.9395**
2020	0.9562	0.9630	0.9313	0.9519	0.9388	0.9474	0.9475	**0.9474**
2021	0.9647	0.9720	0.9286	0.9631	0.9288	0.9503	0.9520	**0.9515**
Total	0.9525	0.9581	0.8886	0.9423	0.8997	0.9465	0.9200	**0.9279**
SE								
Current	**V4**	**B3**	**B4**	**Ecomer**	**Lcomer**	**Listed**	**Unlisted**	**Total**
2013	0.9463	0.9767	0.9539	0.9584	0.9474	0.9474	0.9578	**0.9547**
2014	0.9351	0.9793	0.9399	0.9526	0.9293	0.9325	0.9500	**0.9448**
2015	0.9456	0.9620	0.9352	0.9531	0.9271	0.9259	0.9522	**0.9443**
2016	0.9213	0.9446	0.9195	0.9330	0.9083	0.8845	0.9419	**0.9246**
2017	0.9158	0.9462	0.9110	0.9287	0.9006	0.8866	0.9331	**0.9192**
2018	0.9275	0.9894	0.8987	0.9489	0.8834	0.8927	0.9414	**0.9268**
2019	0.9213	0.9328	0.8903	0.9277	0.8779	0.8804	0.9240	**0.9109**
2020	0.9436	0.9332	0.9083	0.9444	0.8948	0.9216	0.9303	**0.9277**
2021	0.9381	0.9520	0.9246	0.9434	0.9190	0.9278	0.9383	**0.9351**
Total	0.9327	0.9573	0.9202	0.9434	0.9097	0.9110	0.9410	**0.9320**

The Malmquist index is also introduced to capture the movement of the efficiency frontier, which is calculated by the technology efficiency. There is technical progress when technology efficiency is larger than 1. The technology here is different from that in the BCC and SBM models. The technology efficiency in the BCC and SBM model corresponds to the Efficiency change (EC) in Malmquist. Both the adjacent and global reference Malmquist index imply the adjacent reference in EC. The difference is that global Malmquist implies global reference in TC whereas the adjacent reference implies the adjacent reference in TC. The Malmquist works like converting the current DEA efficiency score into an index for the EC part, and the calculation of the TC is what makes it unique, and the TC is this paper’s main focus.

Table 11 Malmquist index – adjacent

Technology change								
Adjacent	**V4**	**B3**	**B4**	**Ecomer**	**Lcomer**	**Listed**	**Unlisted**	**Total**
2013-14	1.0069	0.9932	1.0146	1.0101	1.0026	1.0223	1.0013	**1.0076**
2014-15	0.9731	0.9487	1.0238	0.9752	1.0165	1.0168	0.9772	**0.9891**
2015-16	1.0756	1.1765	1.0195	1.0967	1.0200	1.0406	1.0838	**1.0708**
2016-17	1.0304	1.0150	1.0025	1.0254	0.9991	1.0188	1.0156	**1.0165**
2017-18	1.0062	0.9041	1.0012	0.9738	1.0109	0.9823	0.9880	**0.9863**
2018-19	1.0144	1.0239	0.9826	1.0142	0.9821	1.0064	1.0020	**1.0033**
2019-20	0.9321	0.9181	0.9667	0.9327	0.9648	0.9418	0.9443	**0.9435**
2020-21	1.1208	1.0487	1.0565	1.0989	1.0500	1.0941	1.0774	**1.0824**
Total	1.0199	1.0035	1.0084	1.0159	1.0057	1.0154	1.0112	**1.0125**

Table 12 Malmquist index – global

Technology change								
Global	**V4**	**B3**	**B4**	**Ecomer**	**Lcomer**	**Listed**	**Unlisted**	**Total**
2013-14	0.9966	1.0212	1.0029	1.0065	0.9975	1.0076	1.0017	**1.0035**
2014-15	0.9469	0.9861	0.9887	0.9627	0.9857	0.9856	0.9640	**0.9705**
2015-16	1.0417	1.0313	1.0107	1.0315	1.0196	1.0419	1.0213	**1.0275**
2016-17	1.0174	0.9981	1.0110	1.0129	1.0088	1.0117	1.0114	**1.0115**
2017-18	1.0114	0.9602	1.0054	0.9906	1.0185	0.9977	1.0010	**1.0000**
2018-19	1.0192	1.0176	0.9796	1.0223	0.9653	1.0116	0.9994	**1.0031**
2019-20	0.9202	0.9604	0.9767	0.9344	0.9800	0.9365	0.9555	**0.9498**
2020-21	1.1021	1.0441	1.0322	1.0794	1.0338	1.0835	1.0556	**1.0640**

Total	1.0069	1.0024	1.0009	1.0050	1.0011	1.0095	1.0012	**1.0037**

Focusing on the year-on-year technical change which is shown in the adjacent reference Malmquist index, the technical efficiency increased from 2013 to 2014 but decreased from 2014 to 2015 (1.0076 in 2013/14 and 0.9891 in 2014/15). After that, the CEE banks experienced technical progress from 2015 to 2017 with an index of 1.0708 in 2015/16 and 1.0165 in 2016/17. The TC fluctuated afterwards until a sharp decrease in 2019-20 may be because of the COVID with an index of 0.9435. However, the technology efficiency recovered quickly, increasing to 1.0824 for the period of 2020/21.

Back to the global reference Malmquist index, the global BCC Malmquist index indicates that there is technological progress in the overall CEE banking sector and individual regions during the nine years (1.1021, 1.0441, 1.0322 and 1.0640 for V4, B3, B4 and overall regions in 2021). Using the technology level in 2013 as the benchmark, the technology level over the period of 2014-2015, and 2019-2020 are lower than the benchmark since the indexes are less than 1.

The TC is 6.4% overall, while the TC of V4 groups changes the most with a percentage of 10.21%, followed by Baltic 3 and Balkan 4 countries with a ratio of 4.41% and 3.22%, respectively. The EU earlycomers showed more technological progress compared with the EU latecomers over the nine years (7.94% for earlycomers and 3.38% for latecomers).

When dividing the banks into listed and unlisted bank groups. The Malmquist index shows that there is technological progress over the nine years for both listed and unlisted banks, but the listed banks indicate more changes (8.35% for listed and 5.56% for unlisted banks). Furthermore, the lowest technology efficiency occurred between 2019 and 2020 for both groups (0.9365 for listed and 0.9555 for unlisted banks).

3.3 Results and robust of the second stage Bootstrap regression

3.3.1 Basic linear model

Table 13 Basic regression models with robust - 1

	Tobit TE	**Tobit PTE**	**Truncated TE**	**Truncated PTE**	**SBTR TE**	**SBTR PTE**
lnTA	0.0210***	0.0440***	0.0288***	0.0632***	0.0288***	0.0632***
	(0.00420)	(0.00462)	(0.00372)	(0.00621)	(0.00374)	(0.00615)
ETA	0.944***	0.831***	0.781***	0.716***	0.781***	0.716***
	(0.151)	(0.164)	(0.140)	(0.201)	(0.141)	(0.195)
LCTA	-0.157**	-0.248***	-0.0195	-0.109	-0.0195	-0.109
	(0.0487)	(0.0528)	(0.0443)	(0.0623)	(0.0434)	(0.0623)
LLRA	-0.928***	-0.382	-0.828***	-0.331	-0.828***	-0.331
	(0.185)	(0.200)	(0.162)	(0.221)	(0.167)	(0.219)
NIIOR	-0.242***	-0.223***	-0.166***	-0.159**	-0.166***	-0.159**
	(0.0490)	(0.0526)	(0.0449)	(0.0588)	(0.0452)	(0.0591)
DTA	0.156**	0.183***	0.158***	0.187**	0.158**	0.187**
	(0.0513)	(0.0553)	(0.0477)	(0.0627)	(0.0485)	(0.0619)
HH	0.0746	0.0972	0.0940*	0.132*	0.0940*	0.132*
	(0.0477)	(0.0519)	(0.0443)	(0.0655)	(0.0452)	(0.0655)
CPI	0.328	-0.672	0.433	-0.933	0.433	-0.933
	(0.632)	(0.679)	(0.557)	(0.768)	(0.569)	(0.754)
GDPP	-0.668*	0.00468	-0.362	-0.737	-0.362	-0.737
	(0.284)	(0.311)	(0.241)	(0.387)	(0.242)	(0.382)
2013.year	0	0	0	0	0	0
	(.)	(.)	(.)	(.)	(.)	(.)
2014.year	0.0142	-0.0292	0.0154	0.0211	0.0154	0.0211
	(0.0265)	(0.0286)	(0.0240)	(0.0330)	(0.0246)	(0.0332)
2015.year	-0.0275	-0.0727*	-0.00690	0.000281	-0.00690	0.000281
	(0.0286)	(0.0309)	(0.0255)	(0.0356)	(0.0263)	(0.0354)
2016.year	-0.0176	-0.0528	-0.00653	0.0167	-0.00653	0.0167
	(0.0280)	(0.0303)	(0.0253)	(0.0357)	(0.0261)	(0.0351)
2017.year	-0.0240	-0.0419	-0.0352	0.0196	-0.0352	0.0196
	(0.0272)	(0.0294)	(0.0243)	(0.0345)	(0.0243)	(0.0348)
2018.year	-0.0280	-0.0301	-0.0155	0.0482	-0.0155	0.0482
	(0.0270)	(0.0293)	(0.0241)	(0.0345)	(0.0243)	(0.0337)
2019.year	-0.0481	-0.0280	-0.0382	0.0159	-0.0382	0.0159
	(0.0262)	(0.0285)	(0.0233)	(0.0332)	(0.0238)	(0.0338)
2020.year	-0.131***	-0.0797**	-0.0896***	-0.0616	-0.0896***	-0.0616
	(0.0284)	(0.0308)	(0.0253)	(0.0371)	(0.0254)	(0.0368)
2021.year	0.00497	0.0196	-0.0165	0.0527	-0.0165	0.0527
	(0.0372)	(0.0405)	(0.0336)	(0.0485)	(0.0343)	(0.0478)
_cons	0.462***	0.218*	0.182*	-0.240	0.182*	-0.240
	(0.0961)	(0.104)	(0.0872)	(0.128)	(0.0885)	(0.126)
N	720	720	633	545	633	545

Table 14 Basic regression models with robust - 2

	DBTR TE	DBTR PTE	DBTR TE	DBTR PTE
lnTA	0.0299***	0.0578***	0.0312***	0.0591***
	(0.00302)	(0.00334)	(0.00304)	(0.00342)
ETA	0.834***	0.788***	0.859***	0.799***
	(0.109)	(0.120)	(0.109)	(0.121)
LCTA	-0.0528	-0.128***	-0.0666	-0.141***
	(0.0349)	(0.0381)	(0.0341)	(0.0372)
LLRA	-0.758***	-0.326*	-0.815***	-0.335*
	(0.130)	(0.141)	(0.128)	(0.137)
NIIOR	-0.222***	-0.189***	-0.241***	-0.199***
	(0.0354)	(0.0364)	(0.0356)	(0.0372)
DTA	0.124***	0.154***	0.160***	0.167***
	(0.0362)	(0.0387)	(0.0369)	(0.0385)
HH	0.0560	0.0946*	0.0878*	0.119**
	(0.0337)	(0.0380)	(0.0343)	(0.0368)
CPI	-0.233	-0.294	0.207	-0.703
	(0.263)	(0.286)	(0.441)	(0.479)
GDPP	0.0255	0.120	-0.458*	-0.257
	(0.110)	(0.115)	(0.200)	(0.223)
2013.year			0	0
			(.)	(.)
2014.year			0.0137	-0.00318
			(0.0192)	(0.0205)
2015.year			-0.0250	-0.0391
			(0.0206)	(0.0226)
2016.year			-0.0171	-0.0203
			(0.0201)	(0.0221)
2017.year			-0.0282	-0.0128
			(0.0194)	(0.0210)
2018.year			-0.0245	0.00223
			(0.0187)	(0.0211)
2019.year			-0.0451*	-0.0112
			(0.0189)	(0.0204)
2020.year			-0.105***	-0.0671**
			(0.0200)	(0.0214)
2021.year			-0.00969	0.0204
			(0.0266)	(0.0301)
_cons	0.179**	-0.176*	0.163*	-0.177*
	(0.0684)	(0.0744)	(0.0694)	(0.0758)
N	720	720	720	720

Table 15 Non-linear regression models with robust

	Tobit PTE	**Truncated PTE**	**SBTR PTE**	**DBTR PTE**
main				
lnTA	-0.394***	-0.647***	-0.647***	-0.243***
	(0.0697)	(0.106)	(0.102)	(0.0552)
TAS	0.0147***	0.0243***	0.0243***	0.0102***
	(0.00234)	(0.00366)	(0.00354)	(0.00188)
ETA	0.882***	0.736***	0.736***	0.812***
	(0.160)	(0.189)	(0.191)	(0.117)
LCTA	-0.204***	-0.0540	-0.0540	-0.114**
	(0.0516)	(0.0589)	(0.0572)	(0.0369)
LLRA	-0.525**	-0.646**	-0.646**	-0.434**
	(0.195)	(0.216)	(0.211)	(0.141)
NIIOR	-0.222***	-0.150**	-0.150**	-0.202***
	(0.0511)	(0.0555)	(0.0551)	(0.0357)
DTA	0.158**	0.126*	0.126*	0.148***
	(0.0537)	(0.0597)	(0.0619)	(0.0381)
HH	0.0939	0.0825	0.0825	0.108**
	(0.0506)	(0.0631)	(0.0610)	(0.0378)
CPI	-0.465	-0.649	-0.649	-0.570
	(0.662)	(0.733)	(0.704)	(0.490)
GDPP	-0.0218	-0.615	-0.615	-0.270
	(0.303)	(0.374)	(0.380)	(0.222)
2013.year	0	0	0	0
	(.)	(.)	(.)	(.)
2014.year	-0.0254	0.0173	0.0173	0.000239
	(0.0279)	(0.0316)	(0.0311)	(0.0204)
2015.year	-0.0683*	-0.00577	-0.00577	-0.0341
	(0.0301)	(0.0340)	(0.0334)	(0.0224)
2016.year	-0.0488	0.00935	0.00935	-0.0159
	(0.0295)	(0.0341)	(0.0336)	(0.0215)
2017.year	-0.0423	0.00752	0.00752	-0.0119
	(0.0287)	(0.0332)	(0.0333)	(0.0209)
2018.year	-0.0342	0.0274	0.0274	0.00162
	(0.0285)	(0.0331)	(0.0336)	(0.0214)
2019.year	-0.0337	-0.00259	-0.00259	-0.0133
	(0.0278)	(0.0318)	(0.0331)	(0.0208)
2020.year	-0.0867**	-0.0717*	-0.0717*	-0.0698**
	(0.0300)	(0.0358)	(0.0354)	(0.0220)
2021.year	0.0125	0.0346	0.0346	0.0166
	(0.0395)	(0.0464)	(0.0466)	(0.0297)
_cons	3.433***	4.963***	4.963***	2.028***
	(0.520)	(0.775)	(0.746)	(0.407)
N	720	545	545	720

In the linear model, the regression results indicate that bank size has a significant positive relationship with both TE and PTE at 0.001 level. This positive significant relationship between bank size and bank efficiency is consistent with the findings of (Pancurová and Lyócsa, 2013; Sufian, 2016; Kamarudin et al., 2017; Fernandes, Stasinakis and Bardarova, 2018; Paleckova, 2019). The probable explanation is that larger banks may benefit from the economics of scale (Goddard, Molyneux and Wilson, 2004). In addition, bigger banks are capable of lowering the costs of collecting and processing information. (Staub, da Silva e Souza and Tabak, 2010; Fernandes, Stasinakis and Bardarova, 2018). According to Alhassan and Tetteh (2017), compared to smaller banks with limited off-balance sheet (OBS) activities, large banks are better equipped to leverage cutting-edge technology with greater potential to develop and expand more successful OBS activities. (Lieu, Yeh and Chiu, 2005; Reddy and Nirmala, 2013). The result contrasts with the opinion of Guidi (2022) who argued that large banks face the problems of bureaucracy which results the scale diseconomies, thus affecting the bank performance. This theory does not hold in this study probably because the asset scale of the CEE banks is not huge enough to cause the scale diseconomies.

Focusing on the equity ratio, the results show that the relationship between bank capitalisation and bank efficiency (for both TE and PTE) is positively significant at 0.001 level. This result contrasts with the finding of Sufian (2009), who suggested that banks with less efficiency are involved in more risky investments and operations. Thus, these banks tend to hold more capital due to bank safety concerns and regulatory pressures. (Shawtari, Ariff and Abdul Razak, 2015). Also, this finding contrasts with the findings of Goddard, Molyneux and Wilson (2004), who argued that highly capitalised banks are more likely to operate with more caution and ignore rewarding opportunities (Guidi, 2022). Tecles and Tabak (2010a) suggested that managers are more motivated to monitor bank efficiency when there is a high equity ratio based on the moral hazard theory (Shawtari, Ariff and Abdul Razak, 2015). This positive relationship also can be explained that more efficient banks generate more profits, thus, more earnings are retained as bank capital” (Carvallo and Kasman, 2005). Furthermore, another possible explanation is that banks with larger equity ratio have greater cushioning and these banks are capable of investing in more profitable investment portfolios with higher risks.

The relationship between LCTA and efficiency is negative and significant for PTE in both the basic linear and non-linear DBTR models, but the relationship is not significant for TE under the DBTR model at a 0.05 significance level. Naceur and Ghazouani (2007) argue that banks with higher loans in investment portfolios are associated with higher costs of monitoring and screening while more loan placement is related to higher operational costs. Similarly, Pancurová and Lyócsa (2013) suggested that the negative relationship is due to the higher loan risk and worse credit management. Specifically, they thought that extremely high loan placement is associated with poor risk management policy. This negative relationship is contrary to the explanation of Palečková (2016), who suggested that less liquid banks (higher LCTA) are more efficient, since holding fewer liquid assets means that banks can invest and then earn more, which increases banks’ output.

The relationship between the loan loss reserve ratio and the efficiency is negative and significant for TE (at 0.001 level) and PTE (at 0.05 level), which is consistent with the assumption of Barr et al. (2002), who argued that banks with more risk tolerance are likely to have lower performance (Kamarudin et al., 2017). Furthermore, the probable explanation for this negative relationship is that problematic loans are associated with more costs regarding monitoring and loan repayment enforcement (Havrylchyk, 2006). Intuitively, the higher loan loss reserve ratio indicates the management holds the belief that banks operate with higher risk regarding the loans, and investment or they think banks operate in an unfavourable external environment, which often involves higher investment loss and non-performing loans.

In terms of income diversification, the result shows that more diversified banks are associated with lower efficiency. It consistent with the finding of Stiroh (2004a, b) who suggested that bank diversification results in worse risk-adjusted bank performance. Stiroh (2004a, b) argued that non-interest income activities provide little risk diversification benefits, which increase bank risks. Laeven and Levine (2007) explained the diversification discount from the perspective of agency theory. To be more specific, banks with diversified activities have severe agency problems. Therefore, diversified banks are outperformed by banks that only focus on specific activities. The finding of this study contrasts the finding of Vallascas, Crespi, and Hagendorff (2012), who argued that income diversification benefits to bank performance since the banks' income sources are not bound to a narrow activity.

The deposits-to-asset ratio represents how much of the bank funds are covered by public deposits (Mwangi, Muturi and Ombuki, 2015). The finding indicates that the deposit ratio impacts the bank's efficiency positively at 0.001 significance level. A possible explanation is that banks with high customer-deposit-rate have a larger proportion of customer deposit funds rather than relying on expensive short-term borrowing in the financial market, which leads to lower capital costs for the bank and thus achieves higher profit efficiency (Helms, 2006).

The relationship between market concentration and bank efficiency is positive and significant. This is not in line with the finding of Lieu, Yeh and Chiu (2005), who argued that banks will not be efficient without competition (Pancurová and Lyócsa, 2013). Based on this theory, banks tend to operate less efficiently in a highly concentrated market. However, this theory does not hold in this study. The result of this study, however, is in line with the structure–conduct–performance (SCP) paradigm, which suggests that the higher concentration ratio will result in collusive behaviours among huge banks, resulting in higher prices and profitability because of increased market power (Williams, 2012; Mirzaei, Moore and Liu, 2013; Sufian, 2016).

3.3.2 Non-linear relationship between size and efficiency

Apart from the linear relationship, this study also verifies that a non-linear relationship exists between bank size and efficiency. Under the DEA formula, the technical efficiency (TE) equals pure technical efficiency (PTE) times scale efficiency (SE) which includes the information on the size effect. Therefore, in this part, this study decides to regress the pure technical efficiency (PTE) but not the TE (technical efficiency) to eliminate the consideration of the scale in the dependent variable. The coefficient of bank size (lnTA) is significantly negative while that of the square of bank size (TAS) is significantly positive. Unlike the bell-shaped curve found by Eichengreen and Gibson (2001), a U-shaped curve is found in this study. All four empirical regression (Tobit, Truncated, SBTE and DBTR) techniques indicate similar results. It shows that the PTE decreases for smaller banks but the PTE increases for larger banks when size increases. This result is reasonable and the possible explanation is that the economics of scale appears after achieving a certain size for banks. In other words, allocation, decision-making, and communication inefficiency dominate the smaller banks compared with the scale economics. Like what is discussed in the linear model, the result does not show a negative relationship for square term is probably because the banks in CEE are not large enough to result in scale diseconomies. In other words, many banks in CEE countries are still expanding towards achieving scale economies. Thus, the findings in this study are not contradictory to Eichengreen and Gibson (2001), but provide a more accurate explanation of bank size and bank efficiency, especially for smaller banks.

3.3.3 Robust check

The double bootstrap truncated regression (DBTR) model is used as the main model. The parameters for bootstrapping are designed to be 1000 and 2000 for biased corrected efficiency score and regression, respectively. Following the approach proposed by (Badunenko and Tauchmann, 2019), this paper uses Tobit, Truncated and single bootstrap truncated regression (SBTR) techniques as robust. The single bootstrap approach means that the efficiency score is not biased-corrected but utilises the bootstrap approach only in the regression stage. Also, the Double-Bootstrap Truncated Regression without the time dummy is presented for comparison. Like what was discussed by (Badunenko and Tauchmann, 2019), the coefficients for the truncated model and SBTR model are almost the same, which indicates the correct use of the models. Although considering the non-linear relationship of bank size, the non-linear models also verify similar results with the linear models for most core explanatory variables. The results of the robust indicate that the signs of significance for explanatory variables are almost the same for most of the models with few minor exceptions. Specifically, in Table 13, columns 1-2 show the Tobit model for TE and PTE, columns 3-4 show the Truncated model for TE and PTE, and columns 5-6 show the SBTR model for TE and PTE. In Table 14, columns 7-8 show the DBTE model but exclude the time effect, while columns 9-10 show the main DBTR model. The results indicate that lnTA and ETA, are highly significant (in 0.001 level) in all the ten models. However, the significance of LCTA decreased in the truncated type model compared with the Tobit model. To be more specific, the relationship between LCTA and TE is not significant at 0.05 level under all models except for Tobit, while the relationship between LCTA and PTE is not significant at 0.05 level in truncated and SBTR models. The relationship between LCTA and PTE is only significant in the DBTR and Tobit model. In terms of the relationship between LLRA and efficiency, all DBTR models revealed a negative significant relationship, but the significance level is higher for TE than PTE. And the similar result can be seen for the relationship between NIIOR and efficiency. The relationship between H-H and bank efficiency is not significant (at 0.05 level) in Tobit, but the relationship becomes significant when the truncated models and the year dummy are utilised. However, the significant level is low at only 0.05. When using the DBTR technique without the year effect, the relationship between H-H and TE turns insignificant (at 0.05 level). When incorporating the year dummy, the relationship between H-H and TE turns significant (0.05 in level) while the significance level between H-H and PTE is enhanced (in 0.01 level). Furthermore, most models show that the year effect is significant in 2020, indicating the significant effect of COVID-19 on bank efficiency. The robust test shows that the use of the DBTR technique and the incorporation of the year dummy is robust, which helps to explain the bank efficiency determinants.

3.3.2 Heterogeneity analysis of the Bootstrap regression

Table 16 Group regression with three regions

	DBTR TE-V4	**DBTR PTE-V4**	**DBTR TE-B3**	**DBTR PTE-B3**	**DBTR TE-B4**	**DBTR PTE-B4**
lnTA	0.0178^{***}	0.0556^{***}	0.0488^{***}	0.0591^{***}	0.0416^{***}	0.0565^{***}
	(0.00405)	(0.00453)	(0.0113)	(0.0112)	(0.00478)	(0.00577)
ETA	0.870^{***}	1.120^{***}	0.599	0.810^{*}	0.637^{**}	0.700^{**}
	(0.149)	(0.167)	(0.361)	(0.361)	(0.195)	(0.228)
LCTA	-0.146^{***}	-0.164^{***}	0.112	0.118	0.0959	-0.000464
	(0.0424)	(0.0460)	(0.121)	(0.114)	(0.0537)	(0.0656)
LLRA	-0.739^{***}	-0.416^{*}	-1.136	-1.325^{*}	-0.335	0.0823
	(0.181)	(0.191)	(0.623)	(0.585)	(0.190)	(0.226)
NIIOR	-0.479^{***}	-0.296^{***}	0.111	0.153	-0.247^{***}	-0.243^{***}
	(0.0490)	(0.0490)	(0.128)	(0.122)	(0.0566)	(0.0667)
DTA	0.0567	0.0379	0.106	0.240	0.218^{**}	0.372^{***}
	(0.0393)	(0.0423)	(0.160)	(0.150)	(0.0728)	(0.0843)
HH	-0.00387	0.0305	0.0700	0.137	-0.746^{***}	-0.0160
	(0.0600)	(0.0664)	(0.107)	(0.100)	(0.145)	(0.170)
CPI	1.379	2.920^{*}	-1.282	-2.196	-0.404	-2.155^{**}
	(1.199)	(1.401)	(2.398)	(2.320)	(0.587)	(0.716)
GDPP	-2.057^{**}	-1.200	0.577	-0.0644	-0.00901	0.205

	(0.667)	(0.751)	(1.418)	(1.384)	(0.227)	(0.279)
2013.year	0	0	0	0	0	0
	(.)	(.)	(.)	(.)	(.)	(.)
2014.year	0.0623	0.0617	0.0101	0.0127	0.0152	-0.0473
	(0.0345)	(0.0386)	(0.0557)	(0.0524)	(0.0270)	(0.0328)
2015.year	0.0583	0.0579	-0.0334	-0.0237	0.0109	-0.0957*
	(0.0436)	(0.0499)	(0.0684)	(0.0667)	(0.0306)	(0.0376)
2016.year	0.0174	0.0375	0.00183	0.0307	-0.000714	-0.0939*
	(0.0306)	(0.0357)	(0.0551)	(0.0532)	(0.0322)	(0.0395)
2017.year	0.0328	0.00814	-0.00899	0.0399	-0.00702	-0.0671
	(0.0341)	(0.0375)	(0.0840)	(0.0779)	(0.0285)	(0.0347)
2018.year	0.0436	0.0178	0.00675	0.0624	0.00756	-0.0286
	(0.0347)	(0.0378)	(0.0701)	(0.0674)	(0.0273)	(0.0331)
2019.year	0.0126	-0.00848	-0.0490	-0.0196	0.0119	-0.0262
	(0.0315)	(0.0352)	(0.0592)	(0.0558)	(0.0297)	(0.0354)
2020.year	-0.184***	-0.161**	-0.0719	-0.0975	0.0196	-0.0292
	(0.0456)	(0.0520)	(0.0986)	(0.0949)	(0.0335)	(0.0403)
2021.year	0.0665	-0.0250	-0.0464	0.0463	0.0690	0.00387
	(0.0524)	(0.0570)	(0.112)	(0.108)	(0.0400)	(0.0501)
_cons	0.622***	-0.00159	-0.233	-0.515*	0.309*	-0.297
	(0.0860)	(0.0915)	(0.237)	(0.232)	(0.149)	(0.176)
N	306	306	126	126	288	288

The countries can be divided into three categories, V4 group, Baltic-3 and Balkan-4 countries. Compared with the basic DBTR model with year effect, Table 13 shows that the bank size and equity ratio significantly impact both the TE and PTE. However, the significant level between ETA and bank efficiency is lower in the B4 countries (at 0.01 level) and the relationship between ETA and TE is not significant at 0.05 level for B3 countries. The LCTA, LLRA, NIIOR, DTA and market concentration (HH) are heterogeneous across different regions. The LCTA is only negatively significant in V4 countries but not in other regions while only the PTE is significant in the basic model. The NIIOR is only negatively significant in V4 and B4 countries but the relationship is not significant in B3 countries at 0.05 level. Furthermore, the market concentration shows a negative significance with the efficiency (TE) in B4 countries while this relationship is generally positive but not significant for other regions. The LLRA is only significant for both TE and PTE for V4 and B3 countries, whereas the DTA does not show significant results for V4 and B3 countries. To sum up, when dividing the sample into three subgroups, it can be seen that the sign of the correlation is almost the same as the basic model, but the significance level of the explanatory variable varies. The negative significant relationship between H-H and TE is found in B4 countries probably because the banks in B4 countries benefit from the competition but suffer less from the collusion behaviours. Focusing on the year dummy, it shows that the year 2020 is only significant in V4 groups. Moreover, the overall significance level of V4 countries is much more similar to the regression results of the whole sample. The results of Table 16 indicate that the determinants of different country groups vary, thus, CEE-level policies may not suit all the subgroups and region-specific policies and regulation approaches are essential.

Table 17 Group regression with two regions

	DBTR TE-EC	**DBTR PTE-EC**	**DBTR TE-LC**	**DBTR PTE-LC**
lnTA	0.0211***	0.0577***	0.0388***	0.0562***
	(0.00376)	(0.00401)	(0.00492)	(0.00633)
ETA	0.945***	1.083***	0.309	0.439
	(0.129)	(0.138)	(0.224)	(0.274)
LCTA	-0.114**	-0.181***	0.228**	0.115
	(0.0385)	(0.0393)	(0.0775)	(0.0974)
LLRA	-0.809***	-0.469**	-0.517*	-0.132
	(0.178)	(0.171)	(0.219)	(0.268)
NIIOR	-0.310***	-0.198***	-0.173*	-0.202*
	(0.0397)	(0.0410)	(0.0742)	(0.0918)
DTA	0.135***	0.127**	0.171*	0.335***
	(0.0390)	(0.0411)	(0.0813)	(0.0984)
HH	0.0847*	0.0858*	-0.994***	-0.206
	(0.0362)	(0.0369)	(0.165)	(0.211)
CPI	-0.000871	0.801	-0.247	-2.456**
	(0.652)	(0.670)	(0.643)	(0.791)
GDPP	-0.985*	-0.298	-0.0764	0.101
	(0.436)	(0.460)	(0.244)	(0.307)
2013.year	0	0	0	0
	(.)	(.)	(.)	(.)
2014.year	0.0201	0.0200	0.0190	-0.0591
	(0.0236)	(0.0246)	(0.0298)	(0.0369)
2015.year	-0.0167	-0.00901	0.0444	-0.0849*
	(0.0253)	(0.0260)	(0.0346)	(0.0430)
2016.year	-0.0139	0.00441	0.0193	-0.0955*
	(0.0227)	(0.0240)	(0.0361)	(0.0440)

2017.year	-0.000275	-0.0144	0.0189	-0.0524
	(0.0278)	(0.0287)	(0.0311)	(0.0389)
2018.year	0.0137	0.00800	0.0300	-0.0127
	(0.0268)	(0.0275)	(0.0304)	(0.0382)
2019.year	-0.0146	-0.0125	0.0254	-0.0184
	(0.0244)	(0.0253)	(0.0312)	(0.0391)
2020.year	-0.117***	-0.0776*	0.0378	-0.0182
	(0.0291)	(0.0302)	(0.0352)	(0.0459)
2021.year	0.0307	-0.0130	0.102*	0.0401
	(0.0390)	(0.0391)	(0.0456)	(0.0583)
_cons	0.397***	-0.127	0.461**	-0.187
	(0.0839)	(0.0847)	(0.167)	(0.204)
N	477	477	243	243

From the perspective of EU accession, all 11 countries can be divided into two categories, early-comers and late-comers. As early comers, the V4 group, Baltic-3 countries and Slovenia joined the EU in 2004. As latecomers, Romania and Bulgaria joined the EU in 2007 while Croatia joined the EU in 2013. The results of the EU latecomers are more similar to the B4 groups, while the results of the EU earlycomers are more similar to the V4 groups and the whole sample. Specifically, the relationship between bank size and efficiency keeps a high significance level (0.001) across all models. However, this relationship is not significant at 0.05 level for latecomers. The LCTA is significant for TE for latecomers and significant for both TE and PTE for earlycomers. The relationship between H-H and efficiency is positively significant for earlycomers (TE and PTE) while the sign of significance is negative for TE for latecomers. Similar to B4 groups, the year effect of 2020 is not significant for the EU latecomers. The difference between the B4 group and the EU latecomers is the incorporation of Slovenia. The results of Table 17 indicated that the EU early comers and the EU late comers have many differences in terms of bank determinants. The removal of Slovenia in the EU latecomers shows that the characteristics of Slovenia banks are different from those in Romania, Bulgaria, and Croatia, but similar to banks in V4 groups. It is probably because Slovenia is closer to the V4 countries although located in Balkan or due to the early EU accession.

Table 18 Group regression with quoted status

	DBTR TE-UL	DBTR PTE-UL	DBTR TE-L	DBTR PTE-L
lnTA	0.0382^{***}	0.0563^{***}	0.0310^{***}	0.0633^{***}
	(0.00400)	(0.00467)	(0.00455)	(0.00533)
ETA	0.809^{***}	0.738^{***}	1.359^{***}	1.273^{***}
	(0.126)	(0.139)	(0.211)	(0.251)
LCTA	-0.0664	-0.134^{**}	-0.174^{*}	-0.300^{***}
	(0.0397)	(0.0433)	(0.0693)	(0.0802)
LLRA	-0.668^{***}	-0.209	-1.659^{***}	-1.061^{***}
	(0.159)	(0.167)	(0.221)	(0.240)
NIIOR	-0.217^{***}	-0.181^{***}	-0.340^{***}	-0.436^{***}
	(0.0384)	(0.0421)	(0.0821)	(0.0940)
DTA	0.146^{***}	0.144^{**}	0.451^{***}	0.309^{**}
	(0.0427)	(0.0442)	(0.0888)	(0.0960)
HH	0.0400	0.131^{*}	0.116^{*}	0.139^{**}
	(0.0459)	(0.0515)	(0.0470)	(0.0523)
CPI	-0.226	-0.735	0.425	-0.797
	(0.558)	(0.598)	(0.699)	(0.768)
GDPP	-0.262	-0.0959	-0.763^{**}	-0.738^{*}
	(0.265)	(0.289)	(0.261)	(0.290)
2013.year	0	0	0	0
	(.)	(.)	(.)	(.)
2014.year	0.00138	-0.00987	0.0303	0.0159
	(0.0239)	(0.0259)	(0.0249)	(0.0292)
2015.year	-0.0436	-0.0506	0.00883	-0.00257
	(0.0264)	(0.0281)	(0.0290)	(0.0320)
2016.year	-0.0305	-0.0204	-0.0128	-0.0222
	(0.0255)	(0.0275)	(0.0276)	(0.0317)
2017.year	-0.0369	-0.0171	-0.0273	-0.00905
	(0.0246)	(0.0265)	(0.0256)	(0.0283)
2018.year	-0.0256	0.00773	-0.0355	-0.0213
	(0.0248)	(0.0267)	(0.0260)	(0.0286)
2019.year	-0.0466	-0.0104	-0.0557^{*}	-0.0238
	(0.0245)	(0.0258)	(0.0246)	(0.0280)
2020.year	-0.0974^{***}	-0.0543	-0.132^{***}	-0.116^{***}
	(0.0269)	(0.0291)	(0.0266)	(0.0300)
2021.year	-0.0253	0.0135	0.0174	0.0391
	(0.0337)	(0.0371)	(0.0378)	(0.0424)
_cons	0.108	-0.139	-0.00455	-0.187
	(0.0827)	(0.0920)	(0.137)	(0.149)
N	504	504	216	216

Considering the quoted condition of banks, both listed and unlisted banks show similar results with the basic model. However, for unlisted banks, there is no significant relationship between LCTA, HH and TE, and between LLRA and PTE. In terms of time effect, both listed and unlisted banks show a significant relationship for TE. Thus, the heterogeneity between listed and unlisted banks is not obvious.

In summary, the robust test shows that bank determinant significances vary across different geographical regions although the relationship is consistent overall. Moreover, banks in Slovenia are different from banks in the EU latecomers although located in Balkan. Considering the quoted status, there is no obvious heterogeneity among list quoted sample, unlisted sample and the whole sample.

3.4 Discussion and policy implication

In the past decades, research on banks in transition economies such as CEE countries has become popular, since the banking sector in CEE countries involved the privatization, recapitalisation and liberalization during the reforms (Andries & Capraru, 2013; Antoun, Coskun and Georgievski, 2018). Moreover, the EU's accession and market development are the focuses of researchers in CEE countries. Specifically, Havrylchyk (2006) suggested that the initiation of the banking reforms began in 1989 featured by an extreme liberal licensing policy. This policy led to the creation of many private small banks as well as banks with foreign owners. In this period, foreign banks have incentives of tax holidays and they are permitted to keep the equity in a well-accepted currency. However, the main customers of foreign banks are foreign companies initially and their competitiveness is limited when facing the domestic banks. For instance, in Poland, after 1992, conditional licensing was adopted, which means that foreign banks can get a license if they agree to restore a domestic bank in trouble. Over the years, liberalisation, privatisation and restructuring intertwined, while the foreign investors can also have some shares of banks. In some countries, the state still played an important role and kept the controlling ownership and actively involved in the daily operation of banks (Abarbanell and Bonin, 1997). The wave of bank mergers took place at the beginning of the 21st century when a number of newly created banks merged the domestic banks. Since then, the pace of the bank reforms slowed down. As a complex sector, a well-established Banking system is significant to the financial stabilisation, economic growth as well as wealth accumulation of countries. (Cetorelli and Gambera, 2001; Paradi, Rouatt, & Zhu, 2011). Different from other business sectors, the banking industry plays a more crucial role in the economic system since banks are public interest institutions. Specifically, bank performance affects a wide range of stakeholders, including but not limited to regulators, depositors, shareholders, and especially the general public even if without direct connection with banks (Fethi & Pasiouras, 2010). Thus, the importance of bank stability gained wider attention, especially during the 2007 GFC, (LaPlante & Paradi, 2015; Henriques et al., 2020) the Euro Debt Crisis as well as the covid. Moreover, bank failure may result in significant implications as the banking crises expand with a contagion effect (Antoun, Coskun and Georgievski, 2018). Specifically, banks can transfer risks from one nation to another (Kalemli-Ozcan et al., 2013), and banking crises always trigger more harmful debt or even currency crises (Laeven and Valencia, 2013; Dungey and Gajurel, 2015).

This study has many implications for the bank's management and banking sector regulation. The first stage utilises the simple DEA approach to calculate the bank efficiency scores in CEE countries. The technical efficiency, pure technical efficiency, scale efficiency and technology change all show a decreasing trend in 2020, followed by a slight recovery in 2021. Thus, it shows that bank management should focus on the macro risk such as COVID-19 and make early preparations because the efficiency impact of the macroeconomic changes is extensive. Moreover, the efficiency composition of different regions varies. Specifically, banks in V4 countries perform the best in pure technical efficiency but low in scale efficiency.

However, banks in B4 countries ranked the lowest overall efficiency due to the lowest pure technical efficiency, while banks in B3 countries achieved the highest overall efficiency due to the balanced pure technical efficiency and scale efficiency. And the pure technical efficiency of early comers is higher than the late comers obviously. From a similar perspective, listed banks have an advantage in pure technical efficiency but have a disadvantage in scale efficiency. The banks in the EU latecomers had the lowest pure technical efficiency in 2015 rather than 2020, which indicated that the external environment such as the covid is not the only trigger of the efficiency decrease, probably because the inefficient bank management. Thus, banks with lower pure technical efficiency and scale efficiency should find ways to optimise the efficiency level. In terms of scale efficiency, the banks in V4 countries and listed banks should identify why banks are not operated at an optimal level, in other words, to identify the scale inefficiency of banks caused by too small size or too large size. Furthermore, various ways can be used for banks in B4 countries and unlisted banks to improve pure technical efficiency. Specifically, banks with low pure technical efficiency should consider introducing advanced IT systems and artificial intelligence technology. These technologies can be used to optimise risk management and get investment advice. Moreover, process optimisation and resource allocation techniques can be used to optimise the costs, which decreases the inputs of banks. Additionally, banks with low pure technical efficiency can optimise the employee training and evaluation approaches to improve the professional skills of employees. Last but not least, more advanced customer management approaches can be utilised to improve customer satisfaction and loyalty, which improves bank efficiency by increasing the outputs (revenues).

The second stage finds out the bank efficiency determinants. Specifically, the bank managers should keep the bank size at a reasonable level. The non-linear regression result shows that too small size is associated with lower pure technology efficiency while bank efficiency increases with the bank size for larger banks. However, it is not saying that the larger the better for the bank's pure technical efficiency. The reason is that too large a bank size may result in the diseconomy of scale theoretically although it is not shown in this study. The possible explanation is that banks in CEE are not big enough to suffer the scale diseconomy. Regarding bank capitalisation, the result indicates that banks should keep a higher level of equity to be efficient. Banks should focus on risk management to keep their efficiency since the loan loss reserve ratio which is the proxy of the bank risk level negatively affects the bank efficiency. Moreover, the bank should balance the loan placement and liquidity since the LCTA is negatively associated with efficiency. The positive relationship between DTA and efficiency indicates that banks should rely more on cheaper fund sources such as customer deposits to be efficient while the bank management should consider the activity diversification cautiously since the negatively significant relationship. At the industry level, the structure–conduct–performance (SCP) paradigm is confirmed, which suggests that the monopoly benefits profit efficiency. However, from the perspective of the regulator and the stakeholders, the profit efficiency is not the only consideration while the monology may result in other problems. Therefore, regulators should be cautious when facing market concentration. The heterogeneity analysis shows that the signs and the significances are highly consistent with the whole sample for listed banks and V4 banks, but the effect of size and bank capitalisation is stable across samples. Thus, it means that the characteristics of banks in different regions are not the same, and policymakers should not use identical policies in the EU or the whole CEE level. Policies should be formulated based on the situations and characteristics of different regions.

To build competitiveness, CEE countries should construct a well-designed and well-functioning banking system. Ideally, banks should try their best to operate efficiently to avoid extra costs. However, it is common to see that bank management utilizes high-risk strategies to capture better financial profit and personal benefits. To solve these problems, the assessment of the bank's efficiency can be used to set the rules and to control the risk. Specifically, examining the efficiency of banks helps bank management and financial regulators to measure the multi-dimensional performance of a specific bank and to find out what can be done to improve the bank efficiency, which is useful for the banking decision-making process. In that case, the risky behaviour (Fioderlisi, Marques-Ibanez and Molyneux; 2011) and the moral hazard can be alleviated, which benefits the stability of the whole banking sector (Svitalkova, 2014). The capital market and banking sector are two of the most important components of the financial market. Different from the early developed economies like the US with advanced capital markets, the banking sector dominates the financial markets for a long time in CEE countries as transition economies and their capital markets are relatively undeveloped (Wachtel, Haselmann and Sobott, 2016). Thus, the efficiency of banks attracts special interest from regulatory authorities, bank customers, bank management and the whole stakeholders in CEE countries (Pancurová and Lyócsa, 2013).

3.5 Limitations and future directions

This thesis contributes to the DEA analysis of the banking sector in CEE. However, a few things can be improved in future research. Firstly, in terms of DEA analysis, some scholars adopted an internal two-stage or saying network DEA approach to overcome the block box problem (Färe and Grosskopf, 1996; Kao and Hwang, 2008; Chen et al., 2009; Chen et al., 2010; Li et al., 2012). These internal two-stage model can be combined with the external Bootstrap model when evaluating the efficiency of banks in CEECs, to better decompose the whole process following the design of Gulati and Kumar (2017). Secondly, to better consider the efficiency improvements, the super-efficiency DEA model can be considered when evaluating the bank efficiency in CEECs. It allows an efficiency score higher than 1, which is particularly useful when further differentiation between the best-performing units is required

(Andersen and Petersen, 1993). Moreover, the BCC, SBM and MPI scores are just the basic methods to calculate the efficiency, further studies can utilise the more advanced approach such as EBM or network DEA to calculate the efficiency score. Also, apart from the output-orientated DEA assumption, the input-orientated DEA can be considered on some occasions for further studies. Additionally, this study focuses on the data from 2013 to 2021, longer timespan or years after 2022 can also be considered for further studies. In this study, although the time effect is incorporated, the individual effect is not included in the regression due to the applicability of the DBTR methodology.

Conclusions

Using data from 2013 to 2021, this paper finds out the determinants of the efficiency of commercial banks in Central and Eastern European (CEE) countries using the external two-stage DEA method under the profit approach. The empirical results show that the efficiency of the banking sector fluctuated over the years, reaching the lowest level in 2020, but recovered quickly in 2021. The findings of external regression show that the relationship between bank size and bank efficiency is positively significant in the linear model while this relationship is a U-shape between the bank size and the pure technical efficiency in the non-linear model. Moreover, the equity ratio and the deposit ratio impact the bank efficiency positively and significantly, while the loan/asset ratio, loan loss reserve ratio as well as income diversification affect the bank efficiency negatively and significantly. Considering the banking industry, market concentration is found to impact bank efficiency significantly and positively. Interestingly, significance levels across different regions in CEE are different.

This study contributes to the DEA study in several ways. Firstly, a two-stage DEA method is introduced to control the environment variables with high explanatory power. In stage two, this article follows the Bootstrap approach proposed by Simar and Wilson (2007) to get a less biased coefficient estimator. Moreover, the literature review part indicates that most papers focus on the period between 2006 and 2016, and few focus on the period after 2017. Therefore, this study uses data from 2013 to 2021. Many scholars conduct single-country DEA analyses. This thesis, however, is a cross-country analysis incorporating 11 CEE countries inside the EU, including Bulgaria, Croatia, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia, and Slovenia. Moreover, this paper employs the non-performing loan as the undesirable outputs, which provide a more comprehensive bank efficiency evaluation. At last, this paper decomposes the operating incomes into three parts not only getting the sum. Thus, the activities of banking sectors are well presented. This thesis makes a comparison analysis and identifies the reason why banks experience low efficiency in some regions. Specifically, low efficiency may be the result of low administrative capacity (PTE) or the bank operating on an inappropriate scale (SE). Thus, this thesis provides some insight into bank management.

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