Charles University in Prague

Faculty of Social Sciences
Institute of Economic Studies

MASTER'S THESIS

Bank Efficiency, Risk, and Capital in the Visegrad Group Countries

Author: **Bc. Filip Fraňo**

Supervisor: **doc. PhDr. Petr Teplý, Ph.D.**

Academic Year: **2014/2015**

Declaration of Authorship

The author hereby declares that he compiled this thesis independently, using only the listed resources and literature, and the thesis has not been used to obtain a different or the same degree.

The author grants to Charles University permission to reproduce and to distribute copies of this thesis document in whole or in part.

Prague, July, 27, 2015

Signature

Acknowledgments

I am grateful especially to doc. PhDr. Petr Teplý, Ph.D. for supervising this thesis and for his valuable comments and suggestions.
Furthermore, I would like to express gratitude to my family and friends who supported me greatly during my studies.

Abstract

The aim of the thesis is to estimate the cost efficiency of the banks from the Czech Republic, Hungary, Poland, and Slovakia during 2008–2013 using stochastic frontier analysis. In addition to this, mutual relationships between the changes in banks' cost efficiency, risk-taking, and capital position are examined. First, the literature that is concerned with these relationships is reviewed and the stochastic frontier approach towards the efficiency estimation is outlined. In the empirical analysis, the cost efficiency of the banks from the aforementioned countries is estimated. The results suggest that the Czech and the Polish banks from the sample have the highest average cost efficiency while the Hungarian banks rank the lowest. The estimated efficiency is decreasing during the sample period. No conclusive results are found to support the hypothesis that the larger banks exhibit higher cost efficiency. Subsequently, the system of simultaneous equations is applied to test the mutual relationships between the changes in the banks' cost efficiency, risk-taking, and capital position. The results suggest a negative relationship between the changes in risk-taking and cost efficiency and between the changes in capital position and risk-taking of the banks. Moreover, the results do not indicate simultaneous determination of these variables in the system.

JEL Classification	F12, G21, C30, D24
Keywords	banking sector, cost efficiency, risk, capital, stochastic frontier analysis, the Czech Republic, Hungary, Poland, Slovakia

Author's e-mail	filip.frano@gmail.com
Supervisor's e-mail	teply@fsv.cuni.cz

Abstrakt

Cieľom práce je odhad nákladovej efektívnosti bánk pochádzajúcich z Českej republiky, Maďarska, Poľska a Slovenska počas rokov 2008 až 2013 s použitím metódy stochastického odhadu nákladovej funkcie (stochastic frontier analysis). Ďalej sú v práci skúmané vzájomné vzťahy medzi zmenami nákladovej efektívnosti, rizikovosti a kapitálovej pozície bánk. V prvej časti práce je poskytnutý prehľad literatúry zaoberajúcej sa týmito vzťahmi a popísaná metóda stochastického odhadu nákladovej funkcie. V empirickej časti je odhadnutá nákladová efektívnosť bánk pochádzajúcich z hore uvedených krajín. Výsledky naznačujú, že české a poľské banky sú v priemere najviac efektívne, zatiaľ čo maďarské banky sa umiestnili najnižšie. Odhadnutá efektívnosť počas skúmaného obdobia klesala. V práci neboli dosiahnuté preukázateľné výsledky, ktoré by podporovali hypotézu tvrdiacu, že väčšie banky sú nákladovo efektívnejšie. V následnosti na odhad efektívnosti bánk bol použitý systém simultánnych rovníc k testovaniu vzájomných vzťahov medzi zmenami v nákladovej efektívnosti, rizikovosti a kapitálovej pozícii bánk. Výsledky naznačujú záporný vzájomný vzťah medzi zmenami v rizikovosti a nákladovej efektívnosti bánk a medzi zmenami v kapitálovej pozícii a rizikovosti bánk. Výsledky ďalej nepreukazujú, že tieto premenné sú v systéme určované simultánne.

Klasifikace JEL	F12, G21, C30, D24
Klíčová slova	bankový sektor, nákladová efektívnosť, riziko, kapitál, stochastic frontier analysis, Česká republika, Maďarsko, Poľsko, Slovensko

E-mail autora	filip.frano@gmail.com
E-mail vedoucího práce	teply@fsv.cuni.cz

Contents

List of Tables

List of Figures

Acronyms

2SLS Two-Stage Least Squares

3SLS Three-Stage Least Squares

CAR Capital Adequacy Ratio

DEA Data Envelopment Analysis

DFA Distribution-Free Approach

OLS Ordinary Least Squares

SFA Stochastic Frontier Analysis

TFA Thick Frontier Approach

Master's Thesis Proposal

Author	Bc. Filip Fraňo
Supervisor	doc. PhDr. Petr Teplý, Ph.D.
Proposed topic	Bank Efficiency in the Visegrad Region

Topic characteristics The banking sector is a fundamental part of modern economies. When functioning well, banks serve as financial intermediaries that enable efficient resource allocation of funds and risks, which is essential for economic growth. This especially holds in emerging economies such as Czech Republic, Hungary, Poland, and Slovakia that recently went through transformation process from centrally planned economies to market economies. The banking sector in these countries serve as a main source of corporate financing. Regulators, market participants and other stakeholders should be concerned about the performance and efficiency of the banking sector.

This calls for a need to measure and quantify the performance of banking sector and individual banks. Several methods how to measure the bank efficiency have been developed. In contemporary research, the frontier approaches towards efficiency measurement play a prominent role. They measure the efficiency of banks relative to the cost or profit frontier that is attainable with the current technology. The goal of this thesis is to calculate cost/profit efficiency of the banks in the aforementioned countries during period of 2005-2013 using Stochastic Frontier Approach, an econometric approach to efficiency estimation, which was first proposed by Aigner et al. (1977).

The studied countries, similarly to other Europeans countries, have liberalized its financial sector, which puts pressure on the competitive behavior of banks. This may serve as an incentive to extensive risk-taking which may increase short-term profits. To avoid this problem, regulators tend to cap this risk-taking by imposing minimal capital requirements. As researchers, such as Berger and De Young (1997), suggest, there exist relationships between efficiency, risk taking and capital position of banks. Hence, in addition to calculation of efficiency ratios we shall examine the relationship between these variables in our sample of banks.

Hypotheses

1. Hypothesis #1: Efficiency of banks in the Visegrad region is related to the bank's risk-taking.
2. Hypothesis #2: Efficiency of banks in the Visegrad region is related to bank's capital position.
3. Hypothesis #3: Efficiency of banks in the Visegrad region is related to the size of banks.

Methodology To estimate the bank efficiency of the banks we first use the proper specification of Stochastic Frontier Approach (SFA), which is an econometric parametric approach to efficiency estimation. The data on the inputs and outputs, as well as other bank-level variables will be obtained from Bankscope database. After obtaining results of efficiency estimation results for individual banks we shall test the hypotheses by using proper econometric model incorporating various bank-specific and country-specific variables (seemingly unrelated equations approach used for instance in Altunbas (2007) or other appropriate econometric method). In the model, non-performing loans will serve as a main proxy of bank's risk.

Expected Contribution First, I shall comprehensively review the microeconomic foundation of efficiency estimation, review the most prominent methods used in current research and discuss the application of these methods to the estimation of efficiency of financial institutions. Afterward, I shall conduct the estimation of efficiency of the banks in Visegrad region during the aforementioned period, analyze the results of this estimation and strive to determine the main determinants of this efficiency. In the second part of the empirical analysis, I shall examine what relationship and to what degree exist between bank efficiency, banks risk taking and its capitalization during the observed period. The results of this estimation might be beneficial for regulators or banking professionals when assessing the performance of banks.

Outline

1. Introduction
2. Theoretical part
   (a) Bank efficiency, risk taking, and capital
   (b) Microeconomic foundations of efficiency estimation
   (c) Efficiency estimation methods
   (d) Efficiency of financial institution: theoretical and empirical research
   (e) Stochastic Frontier Approach
3. Empirical part
   (a) Data description
   (b) Stochastic Frontier Approach specification
   (c) Results of efficiency estimation
   (d) Modeling relationship between efficiency, risk taking, and capital
   (e) Discussion of hypotheses testing results
4. Concluding Remarks

Core bibliography

1. Aigner, D., Lovell, K., and Schmidt, P., 1977. *Formulation and Estimation of Stochastic Frontier Production Function Models.* Journal of Econometrics, 6, pp. 21–37.

2. Altunbas, Y., Carbo, S., Gardener, E. P. M., and Molyneux, P., 2007. *Examining the Relationships between Capital, Risk and Efficiency in European Banking.* European Financial Management, 13, pp. 49–70.

3. Berger, A. N. and De Young, R., 1997. *Problem loans and cost efficiency in commercial Banking.* Journal of Banking and Finance, 21, pp. 849–870.

4. Berger, A. N. and Humphrey, D. B., 1997. *Efficiency of Financial Institutions: International Survey and Directions for Future Research.* Center for Financial Institutions Working Papers 97-05, Wharton School Center for Financial Institutions, University of Pennsylvania.

5. Coelli, T. J., Rao, D. S. P., O'Donnel, C. J., Battese, G. E., 2005. *An Introductionto Efficiency and Productivity Analysis.* 2nd Edition. New York: Springer Science + Business Media, Inc.

6. Freixas, X. and Rochet, J.-Ch., 2008. *Microeconomics of Banking.* 2nd edition, MIT Press.

7. Fried, H., Lovell, K., and Schmidt, S., 2008. *The Measurement of Productive Efficiency and Productivity.* Oxford University Press.

8. Girardone, C., Molyneux, P., and Gardener, E. P. M., 2004. *Analysing the Determinants of Bank Efficiency: The Case of Italian Banks.* Applied Economics, 36(3), pp. 215–227.

9. Iršová, Z., 2010. *Bank Efficiency in Transitional Countries: Sensitivity to Stochastic Frontier Design.* Working Papers IES 2010/13, Charles University Prague, Faculty of Social Sciences, Institute of Economic Studies.

10. Iršová, Z. and Havránek, T., 2010. *Measuring Bank Efficiency: A Meta-Regression Analysis.* Prague Economic Papers, 2010, issue 4, pp. 307–328.

Author Supervisor

Chapter 1

Introduction

The banking sector is a fundamental part of modern economies. When functioning well, banks serve as financial intermediaries that facilitate efficient allocation of resources and transformation of risks, which is essential for steady economic growth. Naturally, the regulators and other stakeholders are being concerned with the soundness of the banking sector since they strive to undertake the measures that make the banks operate more efficiently. Sound banking sector is especially important in the countries that underwent an economic transformation process from centrally planned to market economies, such as the Czech Republic, Hungary, Poland, and Slovakia, jointly referred to as the Visegrad Group.

The stakeholders of the banking sector need methods that may help them to assess and quantify the performance of the banks. In this respect, several options exist; their profitability, productivity or efficiency—the notions that are not interchangeable—might be examined. The cornerstone of this thesis is the measurement of the cost efficiency on the bank-specific level. The class of these measurement methods, which evaluate how efficiently the individual banks spend the resources that are needed for the production of their outputs, has its roots in microeconomic theory. In the thesis, we shall introduce one of these methods that is called *stochastic frontier analysis* and utilize it in order to calculate the efficiency of the banks from the aforementioned countries during the period spanning from the year 2008 to 2013.

Over the years, the belief that the efficiency of the banks, their risk-taking, and capital position are interrelated emerged among the researchers. In the literature, a plethora of explanations might be found why these relationships should exist between the bank efficiency, their risk-taking, and capital. For instance, less efficient banks might employ inexperienced management that has also weak control over its loan portfolio, resulting in an increased credit risk of the bank. Competitive pressure might provide incentives for the management to increase its short-term profits at the expense of increased risk exposure. To avoid this problem, regulators tend to limit the impacts of increased risk-taking by imposing the minimal capital requirements, which are believed to diminish the probability of bank failure and increase the overall safety of the banking sector. Building on the past empirical research conducted in this area of literature, we strive to examine the relationships between these variables in the aforementioned countries

The thesis is structured as follows. In the next chapter, we review the literature that is concerned with the relationships between the bank efficiency, risk-taking, and capital. Mainly, we aim to present the justifications of these mutual relationships and to present the past empirical evidence in favor of their existence.

Chapter 3 is devoted to the introduction of the cost efficiency measurement. We start with the microeconomic theory that underlies the concepts of the cost efficiency and discuss the contemporary methods that are used for its estimation. Subsequently, we move our attention to the stochastic frontier analysis, which is an estimation method that we employ in the thesis. We describe the main assumptions of this method and the procedure how the bank-specific efficiency scores are derived. Moreover, we present the main challenges that researchers face when designing an efficiency estimation study, such as the specification of the form of the cost function or the choice of outputs that the banks are assumed to produce.

The empirical analysis is provided in Chapter 4 and is divided into two parts. In the first part, we estimate the costs efficiency scores of the banks originating from the Czech Republic, Hungary, Poland, and Slovakia. Subsequently, the calculated efficiency scores are used in the second part, where we investigate the relationship between the changes in the bank's cost efficiency, risk-taking, and capital position using the system of simultaneous equations.

Chapter 2

Bank Efficiency, Risk, and Capital

Researchers have been for long interested in the measurement of the efficiency of financial institutions, especially banks. Throughout this, we are concerned with the bank-specific cost efficiency of the banks, which tells us how efficiently is the bank spending the resources that are needed to create the desired level of outputs. Several methods that can accommodate the measurement of such efficiency have been developed over the time, mostly building on the microeconomic theory.

In the contemporary research, authors are usually concerned with the efficiency derived from the frontier approach. The cost efficiency derived in such way compares the costs that the bank actually incurs in order to produce a specific level of outputs with the costs that lie on the best-practice or efficient frontier, which represents the lowest costs that are attainable when bank produces given outputs and faces the same input prices. The higher the deviation from the best-practice frontier, the lower the measured efficiency. This efficiency is usually represented by the scores ranging from 0 to 1 that are assigned to individual banks, where 1 represents the bank that lies on the efficient frontier. Description of one of such methods, the *stochastic frontier analysis*, which we use to estimate the cost efficiency of the banks from the Visegrad Group countries, is presented in Chapter 3. For the purposes of this chapter, readers do not need a detailed understanding of this method.

Being able to quantify the efficiency of the individual banks and rank them relative to their peers, it is more than natural that numerous streams of literature emerged that attempted to link the bank efficiency with other features and behaviors typically exhibited by the banks, such as the banks' risk-taking and capital position. This chapter is devoted the review of the literature examining these relationships. Let us first start with the extensively discussed literature dealing with the relationship between bank's capital position and its risk-taking.

2.1 Risk and Capital Relationship

Banking crises have a destructive effect on the financial sector and instability may easily spread to other sectors and negatively affect the real economy. The decreased lending activity and elevated interest rates have a negative impact on the output of the economy and might slow down future economic growth. Not to mention the panics induced by the turbulence in the banking sector that can eventually result in the run on banks, a phenomenon that endangers the savings of the depositors. Hence, the costs incurred under these circumstances either by public or private sectors are immense and it is in the social interest to maintain the stable banking sector.

The banking sector has been for long a subject to the regulations that intend to promote its soundness and solvency. The difference between the failure of a bank and a nonfinancial firm lies in the fact that creditors of a bank are at the same time its customers (Freixas and Rochet, 2008). Contrary to a nonfinancial firm whose debt is often held by institutional creditors, the bank debt is held to a large degree by small, dispersed, and uninformed agents that usually do not have the capacity to monitor and restrain bank's activity. The regulators and other policymakers tend to undertake the measures and policies that should promote the solvency of banks. Prudential banking regulation is thus a set of rules that should eliminate or at least reduce aforementioned threats, keep the banking sector stable, reduce the probability of bank failures, and minimize the impact of potential failures on society.

Researchers are interested in how the banking regulation actually affects the behavior of banks, their propensity to undertake the risks and their probability of failure. This stream of literature intensified after the introduction of first Basel accord in 1988. The main idea of Basel accord is to set the minimum capital requirements for banks by stipulating how much capital banks should hold against their assets. The reason that such regulations are undertaken is due to the belief that capital requirements lead to higher stability of the banking sector.

2.1.1 Capital Structure

At a first glance, the answer to the question why the capital structure of a bank should matter is not straightforward. In their famous theorem that is used in almost every textbook of corporate finance, Modigliani and Miller (1958) claim that the capital structure of the firm is irrelevant. Yet this theorem applies only under simplifying assumptions. One of many assumptions of Modigliani and Miller is that the firm—in our case the bank—is managed and owned by the same person, or that the perfect contract between shareholders and managers may be written, as is noted by Freixas and Rochet (2008). These assumptions, unfortunately, usually does not hold in the real world.

The justification of requirements on banks' capital structure may be found in the problem of allocation of control right in the banks. The capital structure of the bank determines the allocation of control rights among various claim holders such as stockholders or debt holders and govern who may intervene in the decision process inside of the bank. Dewatripont and Tirole (1993) show in their model that the right capital structure may provide managers with incentives to manage banks more safely and efficiently. Therefore, the regulation prescribing the minimum level of capital to be held may serve as a tool to discipline the managers.

In addition to this, regulators may be prone to implement the capital requirements since the equity capital serve as a buffer when the value of assets decrease. When banks are highly leveraged, even a slight decrease in asset value may undermine its solvency and create negative externalities (Admati et al., 2010). The bank capital should correspond to funds that are set aside to serve as a buffer in order to cover the expected and even unexpected losses that stem from the risks that the banks are exposed to. Hence, holding the sufficiently high capital buffer may *ceteris paribus* mitigate the risk that bank will eventually become insolvent and bankrupt. The reason why regulators should prescribe to banks how much capital they should hold may be justified by the fact that the individual banks might pay little attention to systemic risks. Or alternatively, long-term sustainability might not be the management's primary concern.

2.1.2 Bank Risk

As we lined out above, the proliferation of the capital requirements regulations made the researchers wonder what impact these requirements have on the risks that are undertaken by the banks. Generally, the banks undertake a variety of risks that are inherent to its operations. By the term risk, we usually understand a potential occurrence of a harmful event that may result in the loss of value for a bank. This might be either the decrease in earnings, capital write-offs or events that undermine the solvency or liquidity.

Management of these risks, which comprises their identification and measurement, is the core part of the bank's business. Contemporary banking institutions are exposed mainly to the following broad categories of risks:

(i) *Credit risks* is the most significant category of risks that the banks—mainly commercial ones—are exposed to. This category comprises potential losses resulting from the inability of debtors to meet its obligation to repay the debt in a timely manner. For instance, a customer may delay the repayment of the loan or ultimately fail to repay the debt at all; in other words the customer defaults on his debt. The banks are required to set aside funds, so-called *loan loss reserves*, to cover the losses related to credit risk of its loan portfolio. The size of this reserves should be set to reflect the riskiness of the provided loans.

(ii) *Market risks* represent potential losses that arise from the movements of various market factors, such as interest rates, equity prices, foreign exchange prices or commodity prices, which affect the value of banks' assets or liabilities. Commercial banks are usually largely exposed to movements of market interest rates. Interest rate risk is sometimes defined as a separate category.

(iii) *Operational risk* is arguably the most difficult to measure. This category comprises adverse events stemming from breaches of internal policies or internal control by employees, wrong setting of internal processes or systems.

(iv) *Liquidity risk* is characteristic for the banks since they serve as intermediaries that transform the maturity between assets and liabilities. Liquidity risk is a potential situation when a bank fails to meet its obligations in a timely manner. For instance, Drehmann and Nikolau (2010) define funding liquidity risk as "the possibility that over a specific horizon the bank will become unable to settle obligations with immediacy".

Several theoretical approaches have been developed that merge together the literature on the bank capital structure and its risk-taking. Generally, many authors believe that flat premium deposit insurance creates incentives for excessive risk taking for the bank management. These views are often based on an option-pricing framework; see for instance Merton (1977). When the banks are unregulated, these incentives would result in excessive risk-taking. This proposition might be viewed as a result of moral hazard problem, well-known phenomenon in economics that describes the situation when economic agent is undertaking certain risks but does not fully bear the potential costs caused by this activity. The problem of moral hazard became nowadays increasingly present in the financial markets and the banking industry. One of the first comprehensive explanations and application of this phenomenon in the theory of the firm was formulated in the seminal paper of Jensen and Meckling (1976). They assert that there exist conflicts of interest inside of firms between shareholders, debt holders, and managers and that the latter often tend to choose more risky projects than desired.

The setup of corporate governance and remuneration schemes in the banking industry may provide incentives for the management to prefer the short term profits accompanied with higher risks over the long term sustainable profits and stability. Let us mention the study of Aebi et al. (2012) who show that specific setup of corporate governance and responsibilities within a bank had an impact on the performance of banks during the recent global financial crisis. Naturally, regulators strive to prevent this behavior that may eventually end up in the failure of banks. The reason why the banking sector is so excessively regulated lies in the nature of this business, its interconnectedness, and fragility. Banks as financial intermediaries are gathering funds from creditors and these funds are subsequently lent to other parties. In this respect, capital regulation is deemed as a remedy how to cap these incentives since banks would be forced to partake in a larger portion of potential losses that may result from risky activities. Eventually, this should arguably reduce adverse investment decisions of banks.

Nevertheless, the theory does not provide a clear answer to the previous statement. In the mean-variance framework where the managers are prone to choose risky portfolios and increase the leverage, Kahane (1977) or Kim and Santomero (1988) show that the requirements on the risk-weighted capital ratios, such as prescribed by the Basel Accords, are an ineffective measure how to limit the insolvency of banks. Their approach and results were disputed by Furlong and Keeley (1989), who suggest that more stringent capital requirement do not result in increased risk-taking. Kendall and Levonian (1992) even suggest in their model that the risk-based capital requirements will in turn make banks choose riskier assets. In overall, these early studies that focused on the influence of the capital requirements on the bank solvency shows that when the requirements are combined with flat deposit insurance premium, banks may have incentives to increase the risk-taking Agoraki et al. (2011).

Shrieves and Dahl (1992) empirically study the relationship between the changes in risk and capital position represented by equity to assets ratio on the large U.S. banks using a partial adjustment framework. By employing a simultaneous equations model, they find evidence in support of the positive relationship between the changes in capital and risk-taking; their results support the hypothesis that decisions on the capital position and the risk-taking are made simultaneously inside of the bank. This suggests that leverage of bank and risk-taking are rather substitutes to each other (Shrieves and Dahl, 1992). Hence, the banks offset the increased capital position with increased risks. In addition to this, undercapitalized banks that are likely to be under regulatory pressure were found to behave differently. Jacques and Nigro (1997) build on the approach of Shrieves and Dahl (1992) with a focus on the risk-based measures of bank capital. The results suggest that risk-based capital requirements enforced the capital ratios of banks and decreased portfolio risk, which partly contradicts the findings of Shrieves and Dahl (1992). Numerous other empirical studies emerged that continue using the approach of the previous two studies, often yielding contradicting results on the sign of the relationship between changes in capital and risk-taking.

As readers might see, the theory often provides opposing explanations of the mutual relationship between the risk and capital and on the impact of the introduction of capital requirements regulation. The stream of the literature addressing these issues is vast and its full review is beyond the scope of this thesis. In short, we might find justification for both the positive and negative relationships between the risk-taking and capital, with empirical results also not yielding consistent results.

2.2 Link to the Bank Efficiency Literature

Following the literature examining the bank's capital structure and risk-taking, the stream of the literature that introduces the efficiency of banks into this framework has emerged. One of the first attempts was the study of Berger and Humphrey (1992) addressing the cost efficiency and the bank's probability of failure. They suggest that the banks that exhibit higher costs relative to its peers (and hence might be considered to be less cost efficient) may be more likely to fail due to competitive pressure. To shed light on this hypothesis, they study the sample of U.S. banks from 1981 to 1989 and show that the banks assigned to the highest cost quartile had a significantly higher probability of failure than the banks with lower cost profiles.

To explain this relationship, Berger and Humphrey (1992) suggest that the small increase in costs in highly leveraged low spread environment—in which these banks operated—may quickly reduce the earnings. Second, high costs may imply poor control of the management over the costs, which may result in poor control over loan portfolio and hence accelerate the amount of non-performing loans. Thirdly, high costs reduce expected rate of return on equity, which may serve as an incentive for increasing this return by higher involvement in riskier business activities. This again leads to already discussed moral hazard problem. Kwan and Eisenbeis (1995) follow Berger and Humphrey (1992) and use the cost efficiency estimated by stochastic frontier approach. They find a significant relationship between the risk and efficiency; banks identified as less efficient exhibited a larger portion of problem loans and higher variance of stock returns. Nevertheless, this study does not provide empirical answers to an important question on the causality of this relationship, which has a plausible explanation in both directions.

In one of the most prominent papers in this area, Berger and DeYoung (1997) introduce the bank capital into the scope of the study. They shed light on this topic by testing the hypotheses on intertemporal relationships between the bank efficiency, problem loans, and bank capital by employing Granger-causality analysis. In addition to testing a negative relationship between the capital and risk that reflects the previously discussed moral hazard problem discussed, Berger and DeYoung (1997) provide several explanations why the relationship between cost efficiency and risk-taking (represented by problem loans) should exist.

Under *bad luck* hypothesis, an external event may increase the amount of problem loans and this increase subsequently requires more effort to service these loans implying the higher incurred costs. These costs are mainly related to additional monitoring of delinquent borrowers, negotiating workout agreements, costs incurred due to seizing and disposing of the collateral, etc. (Berger and DeYoung, 1997). Hence, this hypothesis assumes a negative relationship between the cost efficiency and risk, where the increase in risk is determined exogenously and impacts the observed cost efficiency. Another hypothesis assuming the negative relationship proposed by Berger and DeYoung (1997), referred to as *bad management hypothesis*, is in line with the explanations of cost efficiency and risk-taking relationship of Berger and Humphrey (1992); under this hypothesis the lower cost efficiency is a signal of poorly performing management, which has also poor control over its loan portfolio. In this case, the fact that the bank is inefficient is determined inside of a bank.

Monitoring of loans has an impact on both the amount of nonperforming loans and cost efficiency and this would imply possible intertemporal tradeoff between the quality of loans and the cost efficiency of the bank. Higher effort (and hence costs) devoted to underwriting and monitoring of loans may decrease the cost efficiency in the short run, but may have an impact on the riskiness of the portfolio in long-term and vice versa. Hence, the bank may appear to be less cost efficient, but the effect of increased monitoring and improved underwriting standards will become apparent later. In the paper, this hypothesis is called *skimping hypothesis* and implies a positive relationship between the variables.

Finding the answer to the prevailing causation of the relationship between risk-taking and cost efficiency may be beneficial for regulators, policymakers, and other bank stakeholders. Knowing that the cost efficiency decrease precedes the relaxed lending standards of the bank might be useful information to have from the supervisory point of view. Besides this, causation is also important from efficiency research point of view. Several authors have proposed to take into account nonperforming loans in the actual design of efficiency estimation. For instance, Hughes and Mester (1993) proposed to incorporate the measures of the probability of failure and the output quality directly into the estimated cost function. Similar approach, when the ratio of nonperforming loans to total assets was included directly in the cost function to be estimated, was used by Girardone et at. (2004) when studying the efficiency of Italian banks.

Berger and DeYoung (1997) argue that whether this inclusion increases the precision of efficiency measurement depends on the causation of the above-discussed relationship. When nonperforming loans are determined exogenously, allowing the best practice cost frontier to vary with the nonperforming loans would increase the precision as this would control for extra expenditures these banks incur due to lower loan quality. On the other hand, when nonperforming loans are determined by factors inside of the firms—such as is stipulated by bad management hypothesis or skimping hypothesis—controlling for the nonperforming loans directly in the cost or profit functions may artificially increase the measured efficiency since this omits the cost inefficiencies that are associated with poor portfolio management. To conclude, the causality of this relationship matters when researchers decide to control for nonperforming loans directly in the efficiency estimation.

2.3 Past Empirical Evidence

Berger and DeYoung (1997) find in the sample of U.S. banks that intertemporal relationship between the cost efficiency and quality of loan portfolio exist in both directions. Nevertheless, they find no evidence that one of these relationships dominated the other. The results show that increase in problem loans precedes an increase in cost efficiency. In the opposite direction, they find the support of *bad management hypothesis* over *skimping hypothesis*. Furthermore, they also show that a decrease in capital ratios precedes an increase of nonperforming loans. Kwan and Eisenbeis (1997) use simultaneous equations to test the hypotheses on the relationship between efficiency, leverage and bank risk. They find in the sample of U.S. banks results that confirm that these variables are determined simultaneously but the results varied with the size of the banks.

Studies of the European banks that emerged as a response to the strand of research characterized by previous studies yield contradicting results. Williams (2004) studies the hypotheses proposed by Berger and DeYoung (1997) on European savings banks in years 1990–1998. He uses Granger causality to test these hypotheses and hence effectively replicate the design of the paper of Berger and DeYoung (1997). He finds evidence that managers in thinly capitalized banks are rather more prudent than acting on moral hazard incentives with the mixed results on the relationship between the efficiency and the risk. Generally, increase in problem loans granger-causes an increase in the capitalization and the management responds to decrease in bank efficiency by decreasing the leverage.

Altunbas et al. (2007) uses a similar approach to Kwan and Eisenbeis (1997) to investigate the sample of European banks in 1992–2000. They find no positive relationship between bank efficiency and risk-taking. Based on the empirical evidence they suggest that inefficient Europeans banks are not associated with higher risks. This contradicts the results from studies of U.S. banks. Fiordelisi (2011) contributes to these mixed results from European environment by finding no strong relationship between the efficiency and capital and the negative relationship between the bank risk and efficiency in the sample of banks from 26 European banks during the years 1995–2007.

2.4 Application in the Visegrad Region Countries

After the collapse of communism, the Czech Republic, Hungary, Poland, and Slovakia underwent a transformation from centrally planned economies into market economies. This also encompassed a difficult and inevitable task to transform their financial sectors, the measure that helps countries to set out on a path of stable economic growth. All four countries that we intend to study in this thesis are part of so-called Visegrad Group, or Visegrad Four, which is an alliance of these four states formed in 1991 in order to advance their European integration.

Although the transformation process in each country had its specific features, all countries had to face similar challenges. As former centrally planned economies with no prior experience with private banking sectors, all countries had to cope with the lack of expertise in these matters. During the transformation, all countries encountered with turbulent periods of banking crises. As Szapáry (2001) remarks, the banking crises in former centrally planned economies had the following common causes: "(i) sharp drop in aggregate demand and output in the years following the transformation, (ii) inheritance of bad loans from times when credit activity was centrally managed, (iii) lack of competition, (iv) unsound regulatory and supervisory framework, and (v) weak management of the banks, lack if internal controls and large administrative costs" (Szapáry, 2001).

According to World Bank Data, the nonperforming loans amounted to 30% of the total loans in the Czech Republic in year 2000, in Poland in peaked at 21% in 2002 and in Slovakia it represented almost 32% of total loans in the year 1998. On contrary, Hungary managed to keep the ratio considerably low during the late 1990s and early 2000s, keeping it at the levels comparable to EU average. This might be due to major clean-up of bank's balance sheet that took place in the early 1990s aiming to attract the foreign investors (Szapáry, 2001). In recent years, however, the situation is reversed. The Czech, Polish, and Slovak banks manage to protect the quality of their assets in the post-crisis period and keep the amount on the nonperforming loans on the reasonably low level. Even though the share of nonperforming loans has doubled in the Czech Republic and Slovakia since the outbreak of the crisis, it is still kept in these three countries at the level of around 5% of the total loans. On the other hand, Hungary is struggling with the significant hike in the problem loans in recent years, mainly because of sluggish recovery after the global financial crisis and depreciation of Hungarian Forint to Swiss Franc, in which large amount of mortgages was provided to households. Nonperforming loans have risen from 3% of total loans in the banking sector to almost 17% at the end of 2013.

Another feature common for these countries studied in this thesis is a very large portion of banks with foreign ownership. Many major banks ended up in foreign ownership after the banking sector restructuring in the 1990s and early 2000s. The views on whether the foreign ownership improves the performance of the banks diverge. Some authors, such as Buch (1997), claim that the entry of foreign banks increases the competitiveness of the sector and brings valuable know-how and managerial experience. This might, in turn, increase the efficiency of banks.

We see that the riskiness of banks, the quality of assets and the experience of management play important roles in the banking sectors of transition countries. Numerous studies emerged that estimate and study the efficiency of the banks in European transition countries, such as Fries and Taci (2005), Mamatzakis et. al (2007), Bonin et al. (2005). However, not so many works examine the mutual relationships between the variables that were outlined in the previous sections in the Czech Republic, Hungary, Poland or Slovakia.

One of the exceptions is Rossi et al. (2005) who study the sample of Central and Easter European countries (Czech Republic, Estonia, Hungary, Latvia, Lithuania Poland, Romania, Slovakia, and Slovenia) over the period 1995–2002. Using Granger causality approach of Berger and DeYoung (1997), they find negative relationship between bank's cost efficiency and loan quality, but this relationship was only found in the direction that favours bad luck hypothesis, i.e. that increased problem loans are determined mainly by exogenous events outside of bank's control.

Podpiera and Podpiera (2005) studied the banks in the Czech Republic from the cost efficiency point of view and examined the relation between the cost efficiency and bank's probability of failure. Their results suggest that the cost inefficiency tend to be positively related to the probability of bank's failure. The measured cost efficiency of the failing banks was decreasing prior to their failure, proving that decreasing cost efficiency might be a good signaling of future failure.

Podpiera and Weill (2008) study the relationship between the cost efficiency and nonperforming loans in the Czech Republic during 1995-2004. By extending the Granger causality approach of Berger and DeYoung (1997), they find support for bad management hypothesis. Contrary to the results of Rossi et al. (2005), bad luck hypothesis was rejected on the data.

In this thesis, we would like to continue in this line of research and investigate the relationship between bank efficiency, risk-taking and capitalization in the sample of banks from the Czech Republic, Hungary, Poland, and Slovakia during the years 2008 to 2013. Bank efficiency shall be estimated using stochastic frontier analysis, which will be described in more detail in the next chapter. Prior to this, we shall review the basic microeconomic concepts that underlie the efficiency estimation so that the readers get a proper understanding of the methods used for the calculation of the cost efficiency.

Chapter 3

Bank Efficiency Measurement

3.1 Microeconomic Fundamentals

In this chapter, we introduce the methods that are used to estimate the banks' cost efficiency with the primary focus on the stochastic frontier analysis, which we employ to calculate the efficiency scores. Besides this, we shall discuss the main approaches towards the estimation of bank's efficiency that have its roots in the microeconomic theory and the challenges that researchers usually face when employing these methods. As was already mentioned, these methods have its roots in the microeconomic theory; therefore, the aim of this section is to provide microeconomic background that will be built upon in the rest of the thesis. We start by considering the firms, which convert inputs into outputs. Later on, we restrict this generalization and focus on the efficiency of banks.

The ability to quantify the performance of firms gives decision makers' a tool to better monitor them or act upon this information. Hence, researchers, as well as managers, have long been interested in the methods that enable the measurement of the performance; one of such method is the measurement of the economic efficiency of the firm. From the microeconomic standpoint, economic efficiency has two components, technical and allocative efficiency; when these two types of efficiency are attained jointly, the firm is considered to be economically efficient.

3.1.1 Technical Efficiency

Initially, we present the first component of the economic efficiency, which is technical efficiency. As defined in the formal definition by Koopmans (1951), "a producer is technically efficient if an increase in an output requires a reduction in at least one other output or an increase in at least one input, or if a reduction in any input requires an increase in at least one other input or a reduction in at least one output". This means that the technically efficient firm produces the maximum possible output from the inputs used in the production; or alternatively, it uses as little outputs as possible in order to produce required output.

When we assume the firm that produces only one single output, currently available production technology is represented by the production function $y = f(\mathbf{x})$. It states the maximum possible output y that can be produced by the firm when employing the vector of inputs $\mathbf{x}$. Hence, when the firm produces output that lies exactly on the production function, we say that this firm is technically efficient since it produces the maximum output that can be achieved with given inputs.

In more generalized setting when the firm produces multiple outputs, the production function is no longer suitable to represent the production and the term *production set* is used instead to describe the production technology of the firm. In order to understand this term more deeply we introduce several formal definitions. The definitions that will follow in this section and Section 3.1.2 are mostly adopted from (Coelli et al., 2005) and (Fried et al., 2008).

Let us assume the firm that uses the input vector $\mathbf{x} = (x_1, \ldots, x_N) \in \mathbb{R}_+^N$ to produce the outputs $\mathbf{y} = (y_1, \ldots, y_M) \in \mathbb{R}_+^M$. The production technology is described by the production set (also called technology set), which is defined as follows:

$$T = \{(\mathbf{y}, \mathbf{x}) : \mathbf{x} \text{ can produce } \mathbf{y}\}.$$

Contrary to the production function, which determines the maximum attainable output in case of one output, the production set is the set of all possible combinations of inputs and outputs that can be achieved. Equivalently, production technology might also be represented by input and output sets. *Input set*, which is a set of all inputs $\mathbf{x}$ that can produce output $\mathbf{y}$ is defined as

$$L(\mathbf{y}) = \{\mathbf{x} : (\mathbf{y}, \mathbf{x}) \in T\}$$

and similarly, *output set*, which is a set of all outputs $\mathbf{y}$ that can be produced by input $\mathbf{x}$ is defined as

$$P(\mathbf{x}) = \{\mathbf{y} : (\mathbf{y}, \mathbf{x}) \in T\}$$

In the microeconomic theory, several assumptions are typically imposed on input and output sets.[1] Output and input sets provide an alternative description of the same underlying technology and hence, these two sets are interrelated and both contain the very same information (Coelli et al., 2005).

Distance functions, which were introduced by Shephard (1953), describe production technology in a functional form that makes the measurement of technical efficiency possible. Again, similarly as with input and output sets, we should distinguish between two types distance functions. Based on the orientation of the analysis either input-oriented (input-augmenting) or output-oriented (output-augmenting) distance functions exist. *Output distance function* represents a maximal radial expansion in all outputs that may be achieved when a firm with given technology is using given inputs $\mathbf{x}$. Equivalently, *input distance function* is defined as a maximum radial reduction in all inputs that is feasible with given technology and output (Fried et al, 2008). Let us again introduce their formal definitions. Input distance function is defined as

$$D_I(\mathbf{y}, \mathbf{x}) = \max \left\{ \lambda : \frac{\mathbf{x}}{\lambda} \in L(y) \right\}.$$

In other words, input distance function says how much we can reduce the amount of the inputs used in production while the amount of the produced outputs remains unchained. When the amount of inputs can be reduced, say by factor 1.5, this clearly says that the firm does not use the inputs to its full potential and hence, the firm is not technically efficient. From the definition of the input set, the lower bound of the input distance function's value is 1. Input oriented measure of technical efficiency may now be represented as value function $TE_I(\mathbf{y}, \mathbf{x}) = \min\{\theta : \theta\mathbf{x} \in L(y)\}$, meaning that

$$TE_I(\mathbf{y}, \mathbf{x}) = 1/D_I(\mathbf{y}, \mathbf{x}).$$

This measure has values from interval $(0, 1\rangle$, where 1 represents the most efficient firm.

Alternatively, the output distance function is defined as

$$D_O(\mathbf{x}, \mathbf{y}) = \min \left\{ \lambda : \frac{\mathbf{y}}{\lambda} \in P(x) \right\}.$$

[1] Input set is usually assumed to be closed and convex for all $\mathbf{y}$ and inputs are said to be disposable. Output set is assumed to be closed, bounded, convex for all $\mathbf{x}$, satisfies strong disposability of inputs and outputs and the property that nonzero output cannot be produced and that zero output is always possible (Coelli et al., 2005).

An output oriented measure of technical efficiency may be now represented as value function $TE_O(\mathbf{x}, \mathbf{y}) = \max\{\phi : \phi\mathbf{y} \in P(x)\}$, again meaning that

$$TE_O(\mathbf{x}, \mathbf{y}) = 1/D_O(\mathbf{x}, \mathbf{y}).$$

This time, the measure of technical efficiency is equal to 1 for technically efficiency firm and is increasing with observed levels of inefficiency.

Such measures of technical efficiency, characterized by radial expansion of outputs or reduction of inputs, were first introduced by Debreu (1951) and Farrel (1957). As Fried et al. (2008) remark, these measures do not necessarily coincide with Koompan's definition. In all situations when the producer is technically efficient according to Koopman's definition, he is technically efficient in terms of measures by Debreu (1951) and Farrel (1957) as well; however, this does not hold in the opposite direction. There might occur a case, under which Debreu's and Farrel's measure identify the firm as technically efficient while this situation would not satisfy Koompan's definition.

3.1.2 Cost Efficiency

The previous section was devoted the technical efficiency, which is only one component of the economic efficiency. When we want to measure the economic efficiency, which takes into account also allocative efficiency, we need to have information on input or output prices (or both). Measurement of the economic efficiency depends on the ultimate objective of the production, such as cost minimization, revenue maximization or profit maximization.

In the thesis we are focusing on the cost efficiency of the banks; hence, let us describe the case when the producer's goal is to minimize the production costs and hence, he ultimately seeks the cost efficiency. When nonnegative vector of input prices $\mathbf{w} \in \mathbb{R}^M_+$ is observable we can define the minimum cost function (also called cost frontier or cost function), as

$$c(\mathbf{y}, \mathbf{w}) = \min_{\mathbf{x}}\{\mathbf{w}^T\mathbf{x} : D_I(\mathbf{y}, \mathbf{x}) \geq 1\}.$$

From the definition, we see that cost function state the minimum costs that are attainable if the firm wants to produce output $\mathbf{y}$ while facing the prices $\mathbf{w}$. In order to attain these minimum costs, firm ought to choose the adequate mix of inputs that reflects their price. If the firm would produce output $\mathbf{y}$ by employing the input vector $\mathbf{x}^*$ under which the costs are minimized, we say that firm is cost efficient. The measure of *cost efficiency* for the firm that is using inputs $\mathbf{x}$ to produce output $\mathbf{y}$ is defined as

$$CE(\mathbf{x}, \mathbf{y}, \mathbf{w}) = \frac{c(\mathbf{y}, \mathbf{w})}{\mathbf{w}^T\mathbf{x}} = \frac{\mathbf{w}^T\mathbf{x}^*}{\mathbf{w}^T\mathbf{x}}. \tag{3.1}$$

This measure can be further decomposed into the measure allocative and technical efficiency, where $CE = AE_I \times TE_I$. AE is the measure of the allocative efficiency a TE_I is the measure of input-oriented technical efficiency already of input-oriented earlier in this section.

Allocative and technical may be written also in the following way:

$$AE_I = \frac{\mathbf{w}^T\mathbf{x}^*}{\mathbf{w}^T\hat{\mathbf{x}}},$$

$$TE_I = \frac{\mathbf{w}^T\hat{\mathbf{x}}}{\mathbf{w}^T\mathbf{x}},$$

where $\hat{\mathbf{x}}$ is a technically efficient vector of inputs that was derived from the vector $\mathbf{x}$ by applying a maximal achievable radial reduction while still producing output $\mathbf{y}$. In other words, when the firm is using the input $\hat{\mathbf{x}}$, it is technically efficient, but still it might employ an improper mix of these inputs when their price is taken into account; hence allocative efficiency might not be achieved.

When the producer seeks to maximize its revenues or profits, the notions of the revenue and profit efficiency might be defined in the similar fashion by utilizing the revenue and profit functions.

3.2 Estimation Approaches

In the previous section, we introduced the microeconomic foundations of the efficiency measurement. Now we may move to the next stage where we present the methods that are used to measure the efficiency of the banks in practice. As we already outlined, the efficiency measurement is a comparison of the actual observed costs, revenues or profits with the most efficient performance that is located on the efficient frontier; this efficient frontier might be represented by production, cost, revenue of profit functions. In practice, the true form of these frontiers are unknown and needs to be empirically estimated. The resulting approximation is usually called the *best-practice frontier* (Fried et al., 2008). The estimation method and specification of this frontier is a crucial part of efficiency measurement.

General distinctions of the efficiency measurement methods may be drawn between deterministic and stochastic methods. Under the deterministic methods, every deviation from the frontier is assumed to be caused by inefficiencies. On the other hand, stochastic (or econometric) methods admit the existence of the random error term that may temporarily decrease or increase output, costs or profits of some producers. According to the comprehensive review of bank efficiency measurement literature by Berger and Humphrey (1997), we may observe roughly an equal share of the application of the deterministic and the stochastic methods in the banking efficiency measurement research. The stochastic methods may be further divided between those that impose assumptions on the distribution of the error terms and the inefficiency terms. According to Berger and Humphrey (1997), another distinction may be made between the methods that assume some functional form of the efficiency frontier and those that do not.

When we turn our attention to the estimation of efficiency of banks or other financial institution, the following methods are widely used in the research (Berger and Humphrey, 1997):

- *data envelopment analysis*,
- *free disposal hull*,
- *stochastic frontier approach*,
- *distribution-free approach*,
- *thick frontier approach.*

Data envelopment analysis (DEA) and free disposal hull (FDH) are non-parametric approaches do not assume any strict structure of the best-practice frontier (Berger and Humphrey, 1997). DEA, which was formally introduced by Charnes et al. (1978), employs linear programming methods in order to construct the non-parametric best practice frontier over the data (Coelli et al., 2005). The best-practice frontier is constructed as a piecewise linear combination that connects the set of best practice observations. Under DEA, efficiency frontier is not directly observed and hence, the specification of its functional form is not necessary. FDH is a special case of DEA without the assumption of convexity that is an inherent part of DEA.

The main drawback of these two methods is that they do not consider any random error present in the observations. As Berger and Humphrey (1997) claim, this means that these methods do not assume any measurement error when constructing the frontier, no exogenous random shocks that temporarily increase or decrease the performance of some banks. Moreover, these methods do not assume any measurement errors that may arise due to varying accounting rules that may distort the information on the inputs and outputs. As already mentioned, when such deviations from the best-practice frontier are present in the data, they are assumed to be caused by inefficiency. Furthermore, these deviations may also distort the measured efficiency of all other units, even if they are present only in the observation of one single unit. This makes the use of these methods very sensitive to potential outlying observations. Nonparametric methods usually ignore prices and hence are used mainly for estimation of technical efficiency (Podpiera and Podpiera, 2005). Hence, these methods are not suitable for the measurement of allocative inefficiency as a result of misresponding to the prices of inputs or outputs (Berger and Mester, 1997).

Stochastic methods are the second class of efficiency estimation techniques. Here belong the stochastic frontier analysis (SFA), distribution-free approach (DFA), and thick frontier approach (TFA). Under SFA, the functional form of the best-practice frontier is specified and the possibility of random error is allowed in this framework; assumptions are imposed both on the random error term and also on the distribution of inefficiencies. This method has its roots in Aigner at al. (1977), who proposed that deviation from the frontier has two terms: one accounting for random error, which is assumed to follow symmetric, usually standard normal distribution and the second term corresponding to the actual inefficiencies, which follows the asymmetric distribution. We describe the stochastic frontier approach in more detail in the next section.

DFA is similar to SFA in a sense that it also specifies the functional form of the frontiers. The method is applied when panel data are available. The main difference compared to SFA lies in a fact that it does not assume any particular distribution of inefficiencies and random error. These may follow almost any distribution as long as the inefficiencies are nonnegative. DFA assumes that the inefficiency of each firm is assumed to be stable over time while the error components should be zero on average (Berger and Mester, 1997).

Last of the approaches mentioned in the list above, thick frontier approach, also specifies the functional form of the frontier. Deviations from the predicted performance within the highest and the lowest performance quartiles are assumed to represent random error while the deviations between the former and latter quartiles represent inefficiencies (Berger and Humphrey, 1997). This method is not used for the calculation of efficiency scores of individual banks, but it is rather used to measure the overall efficiency levels of some populations.

3.3 Stochastic Frontier Approach

3.3.1 Basic Production Model

In this section, we describe in more detail the stochastic frontier analysis, one of the most prominent methods used to estimate the cost efficiency of the banks or any other firms. We shall review this method to make sure that the readers are familiar with the main assumptions imposed by this method, estimation of the parameters of the cost function, and derivation of the efficiency scores for individual banks. Numerous specifications of the stochastic frontier models were proposed over time, imposing various assumptions on the distribution of error terms. We shall first start with an explanation of the most fundamental specification in cross-sectional setting.

As was already mentioned, the stochastic frontier analysis was first proposed by Aigner et al. (1977). They presented the production model in the following form:

$$y_i = f(\mathbf{x_i}; \boldsymbol{\beta}) + \varepsilon_i = f(\mathbf{x_i}; \boldsymbol{\beta}) + v_i - u_i, \tag{3.2}$$

where y_i is output of the firm (bank in our case) i, $\mathbf{x_i}$ is the vector of inputs and $f(\cdot)$ is a function with the parameter vector $\boldsymbol{\beta}$ to be estimated. Belonging to the parametric class of the stochastic estimation methods, the stochastic frontier analysis imposes distributional assumptions on the compound error term ε_i. This compound error term may be further decomposed into two separate components:

1. Term v_i reflects the stochastic nature of the production; incorporation of this symmetric idiosyncratic term allows the best practice frontier to vary in time or across banks due to the factors that are beyond their control. Hence, this implies that not all fluctuations in the outputs are caused by the bank's inefficiency; some of them might just be a result of some fortunate or unfortunate external events. Because of this, the best practice frontier has a stochastic nature and fluctuates across observations. In addition to previous reasoning, the error term v_i term may further represent a possible error in the measurement of the firm's output, for instance because of distorted accounting information.

2. Nonnegative term u_i represents the inefficiency of given bank. This term is assumed be to non-negative as this reflects the fact that each firm must lie on or below the best-practice frontier. This term this term represents the difference between maxim attainable output $(f(\mathbf{x_i};\boldsymbol{\beta}) + v_i)$ and the actual output.

Despite Aigner et al. (1977) specified the model in the form presented in Equation (3.2), the logarithmic representation is usually applied in contemporary research, i.e.

$$\ln y_i = f(\mathbf{x_i};\boldsymbol{\beta}) + v_i - u_i \quad \text{or} \quad y_i = f(\mathbf{x_i};\boldsymbol{\beta}) exp(v_i) exp(-u_i). \tag{3.3}$$

3.3.2 Cost Efficiency Model

In the thesis, we are more concerned with the cost efficiency measurement. One of the conveniences of the cost efficiency is its ability to easily incorporate several produced outputs. This would, however, require a slight adjustment of the framework presented above. If we assume that the production function satisfies necessary regularity conditions, we may derive the form of the cost function from the production function. This result stems from Shephard's lemma (Shephard, 1953). In spite of this, researchers usually directly specify the functional form of the cost function. Such specification is one of the crucial steps in the design of cost efficiency estimation, as is discussed in Section 3.4. We already know that the cost function is a function of the output quantities, the input prices, and the parameters to be estimated.[2]

Notwithstanding the specification of the functional form, we might write the basic stochastic frontier cost efficiency estimation model in the following form (Fried et al., 2008):

$$\ln C_i = c(\mathbf{y_i}, \mathbf{w_i};\boldsymbol{\beta}) + v_i + u_i, \tag{3.4}$$

or equivalently as

$$C_i = c(\mathbf{y_i}, \mathbf{w_i};\boldsymbol{\beta}) \cdot e^{v_i} \cdot e^{u_i}, \tag{3.5}$$

where C are the actual observed costs of the bank i, $\mathbf{w_i}$ is the vector of input

[2]Certain other additional variables are sometimes included directly in the cost function as well. Researchers sometimes control for other variables that are believed to alter the cost efficiency and are exogenous to the bank. Let us remind for instance Hughes and Mester (1993) who propose to control for nonperforming loans and probability of default directly in the cost function.

prices that the bank i faces, $\mathbf{y_i}$ is the vector of outputs produced by the bank i, $c(\mathbf{y_i}, \mathbf{w_i}; \boldsymbol{\beta})$ is the cost function with the functional form that we impose, and $\boldsymbol{\beta}$ are parameters of the cost function to be estimated. Please note that the inefficiency term u_i has the opposite sign compared to the basic production model shown in Equation (3.3); this stems from the fact that the costs higher than the minimal costs are considered to represent the inefficiency. Apart from this change in the sign, the same logic is applied as in the production model.

As discussed in Section 3.1.2, the cost efficiency comprises both technical and allocative efficiency; the inefficiency term u_i captures both of these concepts. In other words, let us assume that the bank is technically efficient: in case it chooses to produce the desired output using inferior combination of inputs as a result of improper reaction to the prices of these inputs, it still might be considered to be cost inefficient.

3.3.3 Distribution of Error Terms

What makes stochastic frontier approach distinct from other methods is that it imposes distributional assumptions on both components v_i and u_i of the compound error term. The most generic assumptions are that

(i) v_i follows a symmetric distribution

(ii) v_i and u_i are statistically independent of each other and,

(iii) v_i and u_i are independent and identically distributed random variables.

Aigner et al. (1977) propose v_i to be identically distributed following normal distribution $N(0, \sigma_v^2)$ and u_i is assumed to be independent of v_i and having half normal distribution $N^+(0, \sigma_u^2)$. The latter distribution might be rewritten as $u_i = |U_i|$, where $U_i \sim N(0, \sigma^2)$, i.e. this inefficiency term follows normal distribution with zero mean that is truncated at zero. The density of resulting compound term $\varepsilon_i = v_i + u_i$ is negatively skewed.

Standard normal distribution of the symmetric term is generally accepted by researchers. As for the distribution of inefficiency term, half normal distribution is the most commonly used; however, numerous alternative distributional assumptions that may be imposed on the inefficiency term. Let us mention the most prominent ones:

- In addition to half normal distribution, Aigner et al. (1977) also propose in their paper exponential distribution with mean λ, i.e. $u_i \sim iid\ G(\lambda, 0)$,

- Distribution that is the result of truncation of normal distribution with mean that is not necessarily zero, proposed by Stevenson (1980), i.e. $u_i \sim iid\, N^{+}(\mu, 0)$,

- Gamma distribution with m degrees of freedom and mean λ was introduced by Greene (1980), i.e. $u_i \sim iid\, G(\lambda, m)$.

The choice of the distribution often reflects both practical and theoretical aspects of the estimation. Critique of half normal and gamma distribution stress the fact both of these distributions assume most of inefficiency to be concentrated near zero. Truncated normal distribution and gamma distribution relax this assumption and permits a wider range of shapes of the composite error term. This, however, comes at the cost of a higher number of parameters that need to be estimated (Coelli et al., 2005). Coelli et al. (2005) further note that the choice of the distribution indeed affects the overall estimated level of efficiency; nevertheless, the ranking of firms according to the estimated efficiency scores is quite robust to the choice of distribution. Greene (1990) calculated in his study the efficiency scores of electric utility providers using half-normal, truncated normal, exponential, and gamma distributions and finds very little differences in their average efficiency.

3.3.4 Estimation of the Cost Function Parameters

Having imposed the distributional assumptions on the symmetric error term and the inefficiency terms, we may derive the log-likelihood function that is used for estimation of parameters in Equation (3.4). Below, we provide the basic steps for derivation when assuming normal-half normal combination of distributions imposed on v_i and u_i. Firstly, we need to derive the density of ε_i. Since v_i and u_i are assumed to be independent, we may write the joint density $f(u, v)$ as a product $f(u) \cdot f(v)$. Furthermore, if we take into account the fact that $v = \varepsilon - u$ and substitute this into $f(u, v)$, we obtain $f(u, \varepsilon)$. Marginal density of ε is then obtained by integrating out u from $f(u, \varepsilon)$. The resulting distribution of the error term ε_i is:

$$f_{\varepsilon}(\varepsilon) = \frac{2}{\sigma\sqrt{2\pi}} \phi\left(\frac{\varepsilon}{\sigma}\right)\left[\Phi\left(\frac{\varepsilon\lambda}{\sigma}\right)\right], \tag{3.6}$$

with $\phi(\cdot)$ being standard normal density function, $\Phi(\cdot)$ being standard normal cumulative distribution function and with parameters σ and λ equal to

$$\sigma = \sqrt{\sigma_u^2 + \sigma_v^2} \quad \text{and} \quad \lambda = \frac{\sigma_u}{\sigma_v}. \tag{3.7}$$

For a detailed derivation refer to Weinstein (1964). The parametrization from (3.6) is convenient since λ represents the relative contribution of u and v to ε. As Parmeter and Kumbhakar (2014) remark, λ is a measure of signal to noise, i.e. the amount of variation of error term that is due to the inefficiency relative to the amount of variation that is due to the noise stemming from v. When $\lambda \to 0$ we may say there is no inefficiency in the compound error term and therefore, all producers lie on production frontier. In this case simple OLS regression might be used to estimate Equation (3.4). On the other hand, $\lambda \to +\infty$ imply there is virtually no symmetric idiosyncratic error term and all deviations from the best-practice frontier are due to the inefficiency of the bank. Thus the model in Equation (3.4) would reduce to deterministic production frontier analysis. It is noteworthy to remark that σ_u^2 is not the variance of u, despite it is often confused to be (Parmeter and Kumbhakar, 2014). The variance of half normal inefficiency error term is equal to

$$var(u) = \frac{(\pi - 2)\sigma_u^2}{\pi}.$$

As we know that $\ln L = \ln(\Pi_{i=1}^n f(\varepsilon))$, log-likelihood function might be derived from Equation (3.6):

$$\ln L(\boldsymbol{\beta}, \sigma, \lambda) = -N \ln \sigma + \sum_{i=1}^{N} \left[\ln \Phi \left(\frac{\varepsilon_i \lambda}{\sigma} \right) - \frac{1}{2\sigma^2} \varepsilon_i^2 \right], \tag{3.8}$$

where $\varepsilon_i = \ln C_i - c(\mathbf{y_i}, \mathbf{w_i}; \boldsymbol{\beta})$ and N is the length of the sample. The estimates of parameters $\boldsymbol{\beta}, \sigma, \lambda$ are obtained by maximizing of the log-likelihood function in (3.8) with respect to its parameters.

Most of the traditionally proposed distributional assumptions, such as normal-half normal, normal-exponential, and normal-truncated normal models yield tractable closed or almost closed form solutions of the likelihood function which makes estimation straightforward (Parmeter and Kumbhakar, 2014). As Parmeter and Kumbhakar (2014) further note, some of the more recently proposed distributions, such as gamma distribution, does not have these features. This makes the optimization more difficult and alternative methods such as the maximum simulated likelihood need to be used. The estimated parameters provide us with the information on σ_u^2, which reveals information on the skew of disturbance term and gives information on the general level of inefficiency that is present in the overall population. However, the researchers are rather interested in the inefficiency of individual banks.

3.3.5 Bank-Level Efficiency Estimates

The final stage of the process is the calculation of the bank-specific estimates of efficiency. These estimates may further serve as a basis to rank the banks or identify the banks that operate close to or far from the best practice frontier. The main idea of this estimation is to infer what portion of each observed compound disturbance term is attributable to the noise and what portion to the actual inefficiency of the bank. Therefore, the procedure strives to decompose the compound disturbance into its two components.

Let us recall that after the log-likelihood function in Equation (3.8) is estimated, the estimates of ε_i might be easily obtained. The most widely employed method to calculate the bank-specific estimates of efficiency utilizes the information on u_i that can be inferred from these estimates of ε_i. To be more specific, estimates of u_i are calculated as an expected value of u_i conditional on the compound error term ε_i. The initial solution to this was first proposed by Jondrow et al. (1982); they derived the conditional distribution of u_i given ε_i, which reflects all the information that ε_i contains about u_i (Fried at al., 2008). Subsequently, conditional mean of the inefficiency term was derived from this distribution as

$$E(u_i|\varepsilon_i) = \mu_{*i} + \frac{\sigma_* \phi\left(\frac{\mu_{*i}}{\sigma_*}\right)}{\Phi\left(\frac{\mu_{*i}}{\sigma_*}\right)}, \tag{3.9}$$

where $\mu_{*i} = \varepsilon_i \sigma_u^2/\sigma^2$, $\sigma_* = \sigma_v \sigma_u/\sigma$, and the maximum likelihood estimates of these parameters are plugged into the equation. From the usually assumed form of the model shown in equation (3.5), we see that

$$e^{-u_i} = \frac{C_i}{c(\mathbf{y_i}, \mathbf{w_i}; \boldsymbol{\beta})}. \tag{3.10}$$

Hence, $e^{-\hat{u}_i}$ may be considered to be a suitable measure of the bank's cost efficiency as it generally corresponds to the theoretical measure of the cost efficiency defined in Equation (3.1). The efficiency score derived in such way has values between 0 and 1, with 1 representing the fully efficient firm.

Alternatively, Battese and Coelli (1988) proposed slightly modified solution and derived directly the formula for $E(e^{-u_i}|\varepsilon_i)$. As Kumbhakar and Lovell (2012) remark, the method of Battese and Coelli (1988) is preferred, since the estimate proposed by Jondrow et al. (1982) is just a first order term in the power series approximation to e^{-u_i}.

In the preceding sections, we reviewed the basic procedure that applied when researchers employ stochastic frontier approach in cross-sectional setting. As was illustrated, efficiency estimation procedure follows two steps. Firstly, the parameters of the cost function are estimated using the maximum likelihood method. Subsequently, the residual from this model is decomposed into the inefficiency terms and noise.

3.3.6 Panel Data Models

Up to this point, we only presented the stochastic frontier approach in the cross-sectional setting, i.e. all observations are treated identically and time dimension of these observations is not taken into account. Several methods that can accommodate the panel data within the stochastic frontier methods have been developed and are widely used in the literature. The advantage of these methods is the fact that in order to calculate the estimated efficiency, they accommodate more information. One of the shortcomings is that these methods allow only very limited time variability in the calculated efficiency over the sample period. Moreover, this time variability usually exhibits the similar pattern for all units.

Two of the pioneering panel data models with the time-invariant efficiency were introduced by Pitt and Lee (1981) and Battese and Coelli (1988). The time invariant nature of the previous models might be problematic, though, especially in the data sets that span over a long period of time. Time-varying extension of were proposed for instance Kumbhakar (1990) or Battese and Coelli (1992). In order to accommodate the panel data nature, we need to add time index into the cost efficiency model, i.e.

$$\ln C_{it} = c(\mathbf{y_{it}}, \mathbf{w_{it}}; \boldsymbol{\beta}) + v_{it} + u_{it}. \tag{3.11}$$

The time-varying models from above assume the inefficiency error terms to have the following form:

$$u_{it} = g(t) \cdot u_i, \tag{3.12}$$

where $g(t)$ is a function of time with the parameters to be estimated. In case of Battese and Coelli (1992), this has a form

$$g(t) = exp(-\eta(t-T)), \tag{3.13}$$

and u_i is assumed to follow truncated normal distribution. Positive η implies that the efficiency of firms is increasing over the time and vice versa. Since the specification of Battese and Coelli (1992) may easily handle unbalanced panel data and is frequently used in the banking research, we decided to employ this model later in the thesis. The estimation of the cost function parameters may be accommodated by maximization of log-likelihood function; however, the derivation of the efficiency scores is much more elaborate than for cross-sectional model and is beyond the scope of this thesis. This method together with the log-likelihood function to be maximized is provided in the appendix of paper of Battese and Coelli (1992).

We would like to assert that numerous additional specifications and treatments of panel data within the stochastic frontier approach have been developed. Let us mention for instance True Fixed Effects and True Random Effects specifications of Greene (2005) who introduces firm-specific intercepts into Equation (3.13). An additional class of the specifications are the models that assume the efficiency to be exogenously given. This means that apart from the bank inputs and outputs, other exogenous variables are assumed to determine the level of the efficiency for individual banks. Usually, this exogeneity is incorporated by modeling the mean or the variance of the inefficiency terms on the set of the exogenous variables. These extensions might applied both in cross-sectional or panel data setting; a typical example in the panel data setting would be the model of Battese and Coelli (1995), who assume the truncated normal distribution of the inefficiency terms whereas the mean of this distribution is determined as a covariate of exogenous variables.

Each of the presented models has its drawbacks and hence, no specification might be considered superior to all of the others. For a comprehensive review of panel data methods within stochastic frontier approach, we recommend the readers the summary by Parmeter and Kumbhakar (2014).

3.4 Form of the Cost Function

In the efficiency measurement research, the form of the cost function to be estimated is usually directly specified by the researchers. The trade-off between the number of parameters to be estimated and the flexibility that the function permits should always be considered. In the banking literature, two major forms are usually assumed:

- Transcendental logarithmic functional form, (usually referred to as *translog function*), which represent second-order Taylor series approximation of an arbitrary function.
- Translog functional form extended by the inclusion of trigonometric terms (referred to as Fourier-Flexible terms).

Several authors, such McAllister and McManus (1993), suggest that fitting the simple translog function may result in distorted results and suggest the application of the Fourier-Flexible terms of Gallant (1982); the rationale for this is that the resulting function is more suitable for approximation of any arbitrary function over the entire range of data. They argue that the translog function was originally developed as a local approximation of the true cost function and "may perform poorly when the global behavior of approximated function differs from its local behavior" (McAllister and McManus, 1993). Several studies have shown that the Fourier-Flexible form provide the better fit of the data. Mitchell and Onvural (1996) show on the sample of large banks that the industry cost function does not follow the translog form and that the cost function that included the Fourier-Flexible terms would be superior to the translog function. Not surprisingly, usage of the Fourier-Flexible terms gained much popularity in recent research.

The inclusion of the Fourier-Flexible terms and the research that doubts the appropriateness of the translog function emerged as a response to previous widespread usage of the translog functional form in the estimation of the bank cost efficiency. Nevertheless, the translog form has still its advocates and is still applied in contemporary research. While Cobb-Douglas function might be considered too simple, the researchers argue that the translog function provides sufficient flexibility for empirical purposes (Podpiera et Podpiera, 2005). Furthermore, some authors also point to the drawback of the inclusion of the Fourier-Flexible terms in the cost function. The inclusion of Fourier-Flexible terms is usually advocated by the fact that as a global approximation they provide a better fit of the data. Altunbas and Chakravarty (2001) warn about the use of the Fourier-Flexible terms since as they argue, the goodness of fit is not necessarily the most reliable criterion for model selection and does not ensure the goodness of prediction.

Application of the functional forms that provide a greater flexibility usually results in on average the higher predicted efficiency scores or lower inefficiencies (Berger and Humphrey, 1997). On 1990s sample of U.S. banks, Berger and DeYoung (1997) find that inclusion of the Fourier-Flexible terms into the translog function decreases inefficiencies by around 50%. On the other hand, Berger and Mester (1997) find only a marginal increase in the efficiency of U.S. banks and the goodness of fit when the Fourier-Flexible form was used. While the null hypothesis of the translog form was rejected, the improvement in the fit was not significant from an economic point of view; both functional forms yielded similar average efficiency scores and dispersion. In both studies discussed in this paragraph, rank correlation of the estimated scores between Fourier-Flexible and the translog specifications were found to be very high (approximately 0.97), implying that functional specification affects mostly the level of estimated efficiency but not relative ranking between banks. Moving to European data, Iršová (2010) study the sensitivity of stochastic frontier approach results to the variations in the estimation design on the sample of banks from the Czech Republic, Hungary, Poland, Slovenia, and Slovakia; she found the Fourier-Flexible to be jointly insignificant when used in the cost function.

When researchers are planning the design of their cost efficiency estimation studies, they should take into account findings addressed in previous paragraphs. Broadly speaking, when the level of the efficiency in the overall sample is of main concern, the researchers should rather opt for the Fourier-Flexible form of the cost function given the findings of Berger and DeYoung (1997). On the other hand, as the rank correlations between the results of the translog and the Fourier-Flexible form are very high, these two methods seem to provide very similar results in terms of the relative ranking of the banks. Hence, when researchers are interested in the relative efficiency of the individual banks or subsamples of bank, or in the dependence of the efficiency scores on other variables, omitting the Fourier-Flexible terms should not distort results to such a large extent as in the former case.

Apparently, both specifications have its proponents and opponents and both are widely used is banking literature. Since the Fourier-Flexible specification of cost function requires estimation of a considerably higher number of parameters, on top of what was discussed in the previous paragraph, this specification might be more favored in case of larger data sets. For the estimation performed on fewer observations, this specification might be deemed too demanding.

3.5 Choice of Bank Outputs and Inputs

Up to now, we focused our attention on the technical aspect of the cost efficiency estimation without providing the answer on one of the most crucial questions. What are the outputs produced by the bank and what inputs it employs? The answer varies with how we perceive the economic function of a bank and its business model. Again, several approaches and lines of thinking are promoted by the researchers.

Contrary to industrial firms, financial institutions do not produce primarily any physical outputs; this obviously leaves room for discretion when it comes to the choice of the measures that are considered to be a financial institution's outputs and inputs. In this section, we strive to outline the four most prominent approaches toward the selection of bank outputs.

3.5.1 Intermediation Approach

According to Sealey and Lindley (1977) one should look on the production of financial institution or any other firm as on transformation where certain goods cease to exist in its original form while other goods or services are being created. "The transformation process for financial firm involves the borrowing of funds from surplus spending units and lending those funds to deficit spending units" (Sealey and Lindley, 1977). This process is called financial intermediation.

Sealey and Lindley (1977) formulate in their seminal paper so-called *intermediation approach* to the production of a financial firm, sometimes also referred to as asset approach. The bank is only viewed as an institution that is intermediating funds between debtors and creditors and hence, its intermediation function is captured by this approach. Earning assets such as loans and other earning assets are considered to be outputs. The deposits and liabilities are deemed as bank inputs. Since data on the flow of funds between creditors and debtors are usually not observable, these flows are typically assumed to correspond to the monetary value of balance sheet accounts (Berger and Humphrey, 1997).

3.5.2 Value-Added Approach

Contrary to the intermediation approach, *value-added approach* acknowledges the output characteristics of all balance-sheet items, no matter if these are presents on the asset or liability side. The balance-sheet items that have significant value-added are considered to be the outputs of the bank. The value-added is measured by the required expenditures of labor and physical capital related to these balance sheet categories (Iršova and Havránek, 2010). Following this reasoning, Berger and Humphrey (1992) assert that the major type of customer deposits and loans would be considered as important bank outputs; the funds purchased on the interbank markets such as large certificates of deposits or investments into government Treasury Bills would be treated as financial inputs because they require significantly less labor and physical capital in order to be facilitated.

3.5.3 User-Cost Approach

User-cost approach determines the bank inputs and outputs based on its contribution to the bank's revenues. "If the financial return on an asset exceed the opportunity cost of funds or if the financial costs of a liability are less than opportunity cost, then the instrument is considered to be the financial output. Otherwise, it is considered to be and financial input" (Berger and Humphrey, 1992). This approach was first applied to the banking sector by Hancock (1985).

3.5.4 Production Approach

Another distinct approach towards the definition and measurement of inputs and outputs is the *production approach*, which is concerned with rather technical aspects of the bank's operations. Under this approach, the bank is viewed as a provider of services both to depositors and borrowers and these services are provided by concluding the transactions. This resembles more the approach applied to other production firms outside of the financial industry. The bank is primarily deemed as an institution that grants loan, receives deposits, processes documents, and facilitates other transactions whereas the unit of these outputs is not the monetary value, but the number of transactions facilitated. Thus, under this approach, the output would be measured as the number of transactions over a given period. Due to data unavailability, these measures

Table 3.1: Treatment of deposits

Approach	Treatment of deposits	Seminal paper
Intermediation (Asset) approach	As bank inputs	Sealey and Lindley (1977)
Value-added approach	As bank outputs	Berger et al. (1987), Berger and Humphrey (1992)
User-cost approach	As either bank outputs or inputs	Hancock (1985)
Production approach	As bank outputs	Sherman and Gold (1985), used in Kussaarri (1993)

are usually approximated by the number of accounts serviced by the bank at a certain point of time (Berger and Humphrey, 1997). To produce these outputs, banks are assumed to utilize physical inputs such as labor and capital and hence, the prices of these inputs need to be accounted for in the estimation process. This approach was used for instance by Sherman and Gold (1985) or Kussaarri (1993).

3.5.5 Treatment of Deposits

As was outlined in the previous section, various alternations of input and output combinations might be used in the cost efficiency estimation, depending on the approach that the researchers intend to pursue. The longstanding and very controversial issue in the research is the treatment of deposits. As we have already shown, under the intermediation approach deposits should be treated as inputs in the bank's production process. On the other hand, under value-added and production approach, deposits such as term deposits, savings deposit, and time deposits should be treated as bank outputs.

This treatment of deposits under the main approaches discussed in the previous section is summarized in Table 3.1. Given this diversity in their treatment as the bank outputs or inputs, in general, the researchers should adjust the selection of bank inputs and outputs so that it reflect the research question they tend to follow. No universally applied rule exists and the proper treatment of the deposits is still disputed.

Now, having described the stochastic frontier analysis, the selection of the cost function's form and the selection of the outputs and outputs, we might move on the the empirical analysis of the thesis.

Chapter 4

Empirical Analysis

The empirical analysis that is provided in this chapter is divided into two parts. The next section is devoted to the estimation of the cost efficiency scores of the banks from the Visegrad Group countries. The efficiency score calculated in the former part are subsequently used in the section 4.2 to examine the mutual relationship between the changes in the measured cost efficiency, risk-taking, and capital.

4.1 Cost Efficiency Estimation

In this section, we proceed to the estimation of cost efficiency of the banks from Visegrad Group countries, which comprise the Czech Republic, Hungary, Poland, and Slovakia. The estimation of the bank efficiency will be performed in two distinct ways:

1. First, we employ the panel data specification of Battese and Coelli (1992) that was presented in Section 3.3.6. This approach allows for variation of firm-specific efficiency over time and is frequently used in banking research. The inefficiency term of a particular bank in this setting as a monotonous function and this pattern is identical for all firms. As a result, this model specification does not allow the change of relative rank of the firm throughout the studied period. Hence, in case of a potential significant drop in actual efficiency of one particular firm compared to other, this method would not capture this change relative to the peers. We shall use these results to compare the efficiency of the countries in our sample.

2. Since we strive examine the relationship between the changes in cost efficiency risk-taking and capital in Section 4.2, the results obtained by the panel approach of Battese and Coelli (1992) would not be suitable for our purposes. Under this method, the cost efficiency estimates exhibit the same time pattern for all of the banks. In order to account for this drawback, we also estimate the models where the observations for all the banks and the time periods are pooled together and the whole sample is used in the cross-sectional estimation using procedure described in Sections 3.3.2 - 3.3.5. These results are later used in Section 4.2.

In both of these two distinct parts, we use the identical sample, form of the cost function and the inputs and output variables.

4.1.1 Data and Sample

Our data span from the year 2008 until 2013; the choice of the sample period reflects our intention to study the bank efficiency and its relationships with the risk-taking and the capital on the recent data; at the same time we need large enough dataset so that empirical analysis in Section 4.2 could be facilitated. Data on the banks' inputs, outputs, and costs were downloaded from the Bankscope database published and maintained by Bureau van Dijk. To estimate the cost function and calculate the efficiency scores, we used Stata software in all instances.

From the total sample of the banks operating in given countries during the years 2008-2013 that is covered by the Banskcope database, we excluded central banks, special government institutions, investment banks, and finance companies. The latter category comprises credit card, factoring, and leasing companies. These institutions were excluded from the sample since their operating model and the structure of the incurred costs do not coincide with the model and cost structure of ordinary banks, such as commercial or savings banks. Their inclusion in estimation might cause bias in the estimates of efficiency. Efficiency estimation methods perform well when the sample of included institution is as homogeneous as possible in its production process, operation goals and the main outputs of the production.

In addition to this, we excluded also observation with the missing values for the variables needed for the estimation of cost efficiency. Our dataset has a form of highly unbalanced panel throughout the entire sample period. Overview of a number of observations with complete information available in the Banskcope database is shown in Table 4.1. 86% of our sample is formed by the commercial banks, the rest of the included banks are cooperative banks, real estate & mortgage banks, and savings banks. Most of the banks originate from Poland; Slovakian banks are the least represented.

Table 4.1: Number of observations for cost efficiency estimation

Per country:

Year	Czech Republic	Hungary	Poland	Slovakia	Total
2008	17	21	31	12	81
2009	19	22	33	11	85
2010	19	22	37	12	90
2011	20	22	36	12	90
2012	21	23	29	13	86
2013	18	16	22	12	68
Total	114	126	188	72	500

Per bank type:

Year	Commercial	Cooperative	Real Estate & Mortgage	Savings	Total
2008	70	4	5	2	81
2009	73	4	6	2	85
2010	78	4	6	2	90
2011	79	4	5	2	90
2012	74	4	5	3	86
2013	56	4	5	3	68
Total	430	24	32	14	500

Source: Author based on Bankscope database

4.1.2 Bank Inputs and Outputs

When it comes to the choice of the bank outputs and inputs, we intend to primarily follow intermediation approached of Sealey and Lindley (1977) described in Section 3.5.1. Naturally, we are aware that some researchers might disagree with this stance.

We include two measures of the outputs in the cost function: loans and other earning assets. Loans are defined as total customer loans net of reserves for nonperforming loans; mortgage, consumer/retail, corporate, and other loans are included in this variable. Net loans are used since we want to treat only the safe loans the output of the bank; in case the bank has a large amount of nonperforming loans in its portfolio this might overstate their performance. Other earning assets are composed mainly of the loans and advances to banks and securities. The value of these outputs is measured as the year-end value of balance sheet accounts measured in thousands of Euros. Such measures of

Table 4.2: Variables used in SFA estimation

	Name	Description
Dependent variables		
OC	Operating costs	Interest, personnel, and other operating expenses
Outputs		
y_1	Loans	Net loans to customers
y_2	Other earning assets	Loans and advances to banks and securities
Inputs prices		
w_1	Price of labor	Personnel expenses/Total assets
w_2	Price of capital	Other operating expenses/Fixed Assets
w_3	Price of funds	Interest expense/Total funding
Other variables		
z	Equity	Total equity capital

box-p

Source: Author

outputs are widely used in the bank efficiency literature under intermediation approach.

We select the three fundamental inputs that are inevitable in the bank's production process: labor, physical capital, and collected funds. Optimally, the price of labor would be calculated as a ratio of personnel expenses to the number of employees. Unfortunately, Bankscope provides this information only for very limited number of observation. This forces us to use workaround solution used for instance in Altunbas and Chakravarty (2001), which is often chosen when the data on the number of employees are unavailable. More specifically, we use the ratio of the personnel expenses to total assets as a best available proxy for the price of labor. The price of funds was constructed as a ratio of total interest expense over the deposits and other funds. Price of capital was calculated as the ratio of other operating expenses (includes depreciation, amortization, occupancy costs, software costs, lease rentals, and other administrative costs) over fixed assets (property, plant, and equipment).

We use total operating costs as a measure of the costs in the thesis; these are defined as the sum of total interest expenses, personnel expenses, and other operating expenses. All variables used in the model are summarized in the Table 4.2.

4.1.3 Assumed Form of the Cost Function

As for the form of the cost function that we use, we intend to estimate the model using the translog functional form. When deciding for this specification, we took into account the size of our sample and the fact that our primary concern is not the overall efficiency in the entire sample. Furthermore, we utilized the empirical findings that the correlations between the scores derived by the translog and the Fourier-Flexible form are very high. The translog cost has the following basic form:

$$\begin{aligned}\ln C = {} & \ln\alpha_0 + \sum_j \alpha_j \ln y_j + \sum_l \beta_l \ln w_l + \frac{1}{2}\sum_j\sum_k \gamma_{jk}\ln y_j \ln y_k \\ & + \frac{1}{2}\sum_l\sum_m \delta_{lm}\ln w_l \ln w_m + \sum_l\sum_j \rho_{lj}\ln w_l \ln y_j + u + v,\end{aligned} \tag{4.1}$$

where $j, k = 1, \ldots, 2$ and $l, m = 1, \ldots, 3$. For the sake of parsimony, we do not show the time and the cross-sectional index in the equation even though the costs, the outputs, and the input prices vary across the banks and the time. In order to ensure the linear homogeneity of the cost function in input prices—the property that the cost function should satisfy by its definition—the following restrictions should be applied to the parameters:

$$\textstyle\sum_l \beta_l = 1,\ \sum_m \delta_{lm} = 0,\ \forall l;\ \text{and}\ \sum_l \rho_{lj} = 0,\ \forall j.$$

Alternatively, the linear homogeneity in input prices might be achieved by the normalization of the costs and the input prices by arbitrary input price. We follow the latter approach and normalize the costs and the input price of funds w_3. Furthermore, the output quantities and the dependent variable are scaled by equity capital. This normalization follows Berger and Mester (1997) and should tackle the potential heteroskedasticity problems and biases stemming from the varying size of the banks. Without this normalization, small firms with low costs would have a much higher variance of the error terms. The latter normalization makes the dependent variable in our estimation to be of similar magnitude across the observations. The employment of both of these normalizations results in the following form of the model to be estimated:

$$
\begin{aligned}
\ln \frac{C}{w_3 z} =& \ln \alpha_0 + \sum_j \alpha_j \ln \frac{y_j}{z} + \sum_l \beta_l \ln \frac{w_l}{w_3} + \frac{1}{2} \sum_j \sum_k \gamma_{jk} \ln \frac{y_j}{z} \ln \frac{y_k}{z} \\
&+ \frac{1}{2} \sum_l \sum_m \delta_{lm} \ln \frac{w_l}{w_3} \ln \frac{w_m}{w_3} + \sum_l \sum_j \rho_{lj} \ln \frac{w_l}{w_3} \ln \frac{y_j}{z} + u + v,
\end{aligned}
\tag{4.2}
$$

where $j, k, l, m = 1, \ldots, 2$. Furthermore, in order to satisfy the symmetry of the cost function's second order derivatives (Young's Theorem), we need to impose the parameter restrictions $\gamma_{jk} = \gamma_{kj}$ and $\delta_{lm} = \delta_{ml}$ for all i, j, m, l.

Having selected the input and output variables and the functional form of the cost function, we may move to the actual estimation of efficiency scores. We start by the estimation of panel data specification.

4.1.4 Panel Data Estimation

We employ the panel data specification of Battese and Coelli (1992); the inefficiency term might be written in the following form:

$$u_{it} = exp(-\eta(t - T)) \cdot u_i,$$

where we shall assume half normal distribution of u_i, i.e. $u_i \sim N^+(0, \sigma_u^2)$. The symmetric error term v_{it} is assumed to follow standard normal distribution, i.e. $v_i \sim N(0, \sigma_v^2)$

Parametrization of Battese and Corra (1977) is usually applied in connection with this specification, where likelihood function is expressed by the parameters $\sigma^2 = \sigma_v^2 + \sigma_u^2$ and $\gamma = \sigma_u^2/(\sigma_v^2 + \sigma_u^2)$. To estimate the parameters of the cost function, the maximum likelihood estimation employed; the log-likelihood function to be maximized together with the method how to derive the bank-level efficiency scores is presented in Battese and Coelli (1992).

The results of the cost function estimation of our sample are shown in Table 4.3. The estimate of parameter η is negative and significant on 5% level. This result implies that when we assumed the cost function to be stationary over time, the estimated cost efficiency is decreasing over time. Parameter γ is equal to 0.89, meaning that most of the total variance of the compound error term in our sample is due to the inefficiency component. Kernel density estimate of the estimated efficiency scores is shown in Figure 4.1.

Since we are using normalization by the price of labor and equity capital in the cost function, interpretation of estimated cost function parameters is not

Table 4.3: Results of cost function estimation using panel data approach

	Coef.		Std. Err.	z	P> |z|
α_1	0.5004	***	0.06940	7.21	0.0000
α_2	0.7001	***	0.04115	17.01	0.0000
β_1	0.6130	***	0.03879	15.80	0.0000
β_2	0.1277	***	0.03803	3.36	0.0010
γ_{11}	0.1037	***	0.00989	10.48	0.0000
γ_{12}	-0.1729	***	0.01105	-15.65	0.0000
γ_{22}	0.0486	***	0.00229	21.23	0.0000
δ_{11}	0.0656	***	0.00558	11.76	0.0000
δ_{12}	0.0087		0.00699	1.25	0.2120
δ_{22}	-0.0036		0.00322	-1.11	0.2690
ρ_{11}	-0.0389	***	0.01050	-3.71	0.0000
ρ_{12}	-0.0038		0.00830	-0.46	0.6470
ρ_{21}	-0.0056		0.01099	-0.51	0.6090
ρ_{22}	-0.0281	***	0.00650	-4.33	0.0000
α_0	1.1916	***	0.13629	8.74	0.0000
η	-0.0293	**	0.01466	-2.00	0.0450
σ^2	0.0774		0.01235		
γ	0.8948		0.01943		
σ_u^2	0.0693		0.01244		
σ_v^2	0.0081		0.00061		
Number of observations:			500		
*** $p < 0.01$, **$p < 0.05$, *$p < 0.1$					

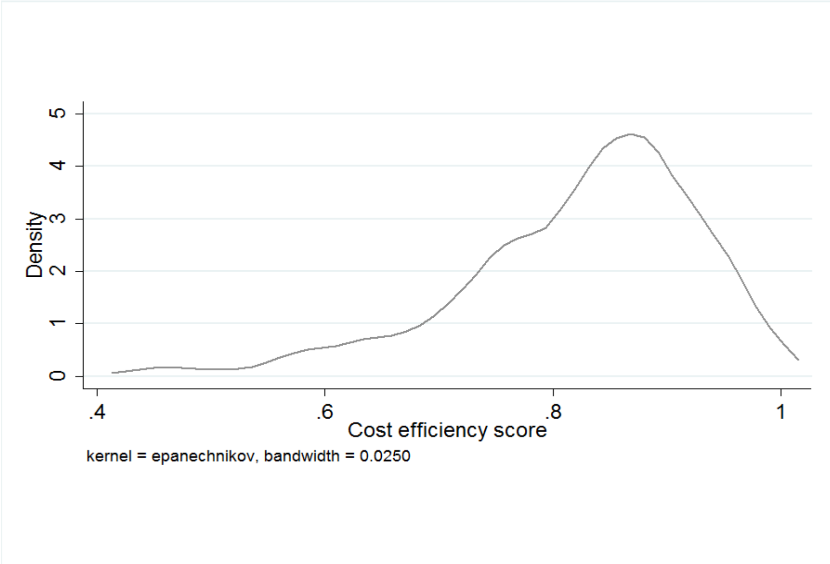
Source: Author's calculations based on Stata software

straightforward. In order to understand the results of efficiency estimation, we need to examine the estimated efficiency scores.

When inspecting the box plots of the estimated efficiency scores across countries in our sample that are shown in Figure 4.2 we observe that the Czech Republic and Poland have the highest median efficiency score. The upper and the lower edge of the square box show the first and the third quartile of given sample, the band inside of the box is the median value of the sample. The bands that are ending the whiskers mark the upper and lower adjacent values.[1] The banks from the Czech Republic have the highest concentration around the median value. The median efficiency of the Hungarian banks is the lowest; the upper edge of the third quartile of the estimated efficiency scores of the Hungarian banks is even lower than the lower edge of the first quartile of the Czech banks.

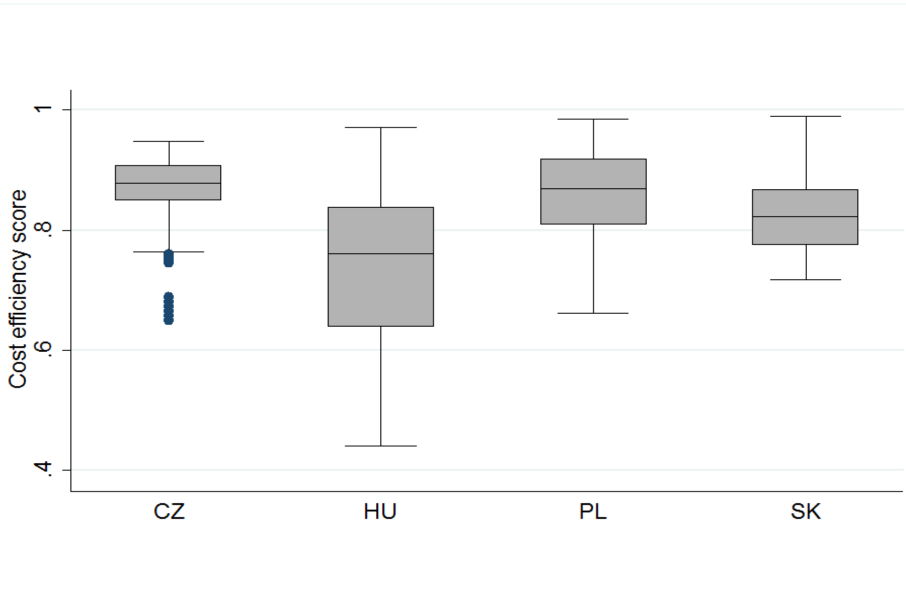
[1]Upper adjacent value is equal to third quartile plus $1.5 \cdot IQR$, where IQR is the interquartile range, i.e. the difference between third and first quartile of the sample. Lower adjacent value is equal to the first quartile minus $1.5 \cdot IQR$.

Figure 4.1: Kernel density of cost efficiency scores from panel data model



Source: Author's calculations based on Stata software

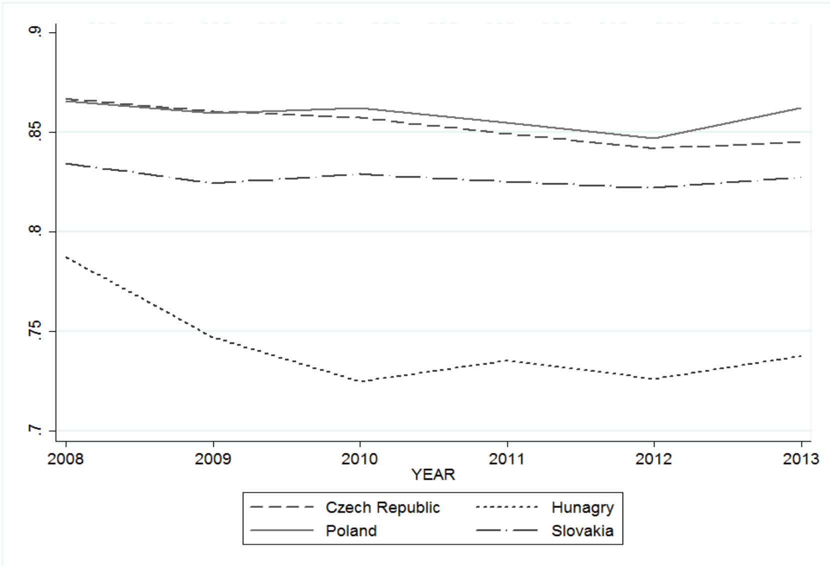
Figure 4.2: Box-Plot of estimated efficiency scores across countries



Source: Author's calculations based on Stata software

The mean efficiency in the entire sample is 82%. the mean efficiency in the Czech Republic, Hungary, Poland, and Slovakia is 85%, 74%, 86%, and 83% respectively. This reinforces our observation that Poland and the Czech Republic has the banks with the highest efficiency in our sample, while Hungary has the worst performing banks in terms of cost efficiency. Still, we need to be very cautious in the interpretation of these results since the sample might suffer from selection bias; several observations had to be removed because of incomplete data.

Figure 4.3: Mean of efficiency scores

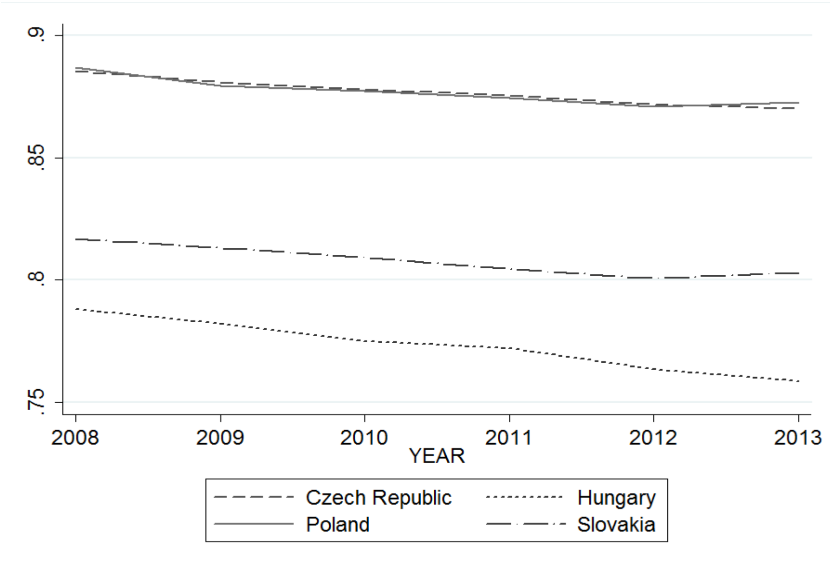


Source: Author's calculations based on Stata software

The time evolution of mean efficiency scores across countries is provided in Figure 4.3 and also in Table 4.4. If our dataset had the form of balanced panel, the mean efficiency score would be steadily decreasing over time (provided the estimate of the parameter η would still be negative). This would be a consequence of the specification of Battesse and Coelli (1992), where the estimated efficiency scores for one particular bank are the monotonic function of time. Our dataset has the form of the unbalanced dataset and hence, it is possible to observe slight increases in mean efficiencies across certain periods. This is caused by the introduction of new banks with higher than average cost efficiency to the sample in given year or alternatively, removal of relatively less efficient banks from the sample.

Naturally, the examination of the mean efficiency score the across countries does not take into account the size of individual banks. In order to complement the information that was provided in the previous paragraphs, we provide an evolution of weighted means of the efficiency scores in Figure 4.4 and Table 4.5, where the weight is the value of assets of given bank compared to the total bank assets in given year and country from our sample. This information should provide valuable information on the efficiency of the banking sectors in given countries as a whole since the efficiency of very small banks (in terms of total assets) contributes to the weighted mean just marginally; on the other hand, the mean efficiency would be mostly determined by the efficiency scores of the largest banks that represent the major portion of the banking assets in given countries.

Figure 4.4: Mean of efficiency scores weighted by bank's total assets



Source: Author's calculations based on Stata software

In case of the Czech Republic, Poland, and Hungary, weighted means are slightly higher than in Figure 4.3. On the contrary, the weighted mean of Slovak Banks is slightly lower; we observe this because the largest Slovak banks in our sample exhibit lower than average efficiency. In all four countries, the ranking of the countries based on this weighted mean efficiency remains unchanged. For instance, when we compare weighted means calculated in the year 2010, the weighted mean of Czech and Polish Bank is equal to 88%, the weighted mean of Hungarian banks is 77%, and weighted mean of Slovak banks is equal to 81%.

What was presented in the previous paragraphs reinforces our observation that the sample of Polish and Czech Banks has on average the highest cost efficiency, Hungarian the lowest, and Slovakian banks placed somewhere in between these two categories; this holds also when the size of the banks is taken into account.

Having the efficiency scores at hand, we are interested whether economies

Table 4.4: Mean efficiency scores

Year	Czech Republic	Hungary	Poland	Slovakia	Total
2008	0.87 (0.08)	0.79 (0.12)	0.87 (0.07)	0.83 (0.08)	0.84 (0.09)
2009	0.86 (0.08)	0.75 (0.13)	0.86 (0.08)	0.82 (0.07)	0.83 (0.10)
2010	0.86 (0.08)	0.72 (0.13)	0.86 (0.08)	0.83 (0.08)	0.82 (0.11)
2011	0.85 (0.08)	0.74 (0.14)	0.85 (0.08)	0.83 (0.08)	0.82 (0.11)
2012	0.84 (0.08)	0.73 (0.14)	0.85 (0.07)	0.82 (0.08)	0.81 (0.11)
2013	0.85 (0.08)	0.74 (0.13)	0.86 (0.06)	0.83 (0.07)	0.82 (0.10)
Total	0.85 (0.08)	0.74 (0.13)	0.86 (0.07)	0.83 (0.07)	0.82 (0.10)

Note: standard deviations provided in parentheses

Source: Author's calculations based on Stata software

Table 4.5: Weighted mean efficiency scores

Year	Czech Republic	Hungary	Poland	Slovakia
2008	0.89	0.79	0.89	0.82
2009	0.88	0.78	0.88	0.81
2010	0.88	0.77	0.88	0.81
2011	0.88	0.77	0.87	0.80
2012	0.87	0.76	0.87	0.80
2013	0.87	0.76	0.87	0.80

Note: total assets used as a weight

Source: Author's calculations based on Stata software

of scale are present in our dataset; i.e. whether the larger banks tend to exhibit higher cost efficiency as well. This relationship is often tested in empirical research. In overall, the results are rather mixed. See for instance Girardone et al. (2004) who do not find any clear relationship between the cost efficiency and the asset size in the sample of Italian Banks. Berger and Mester (1997) find positive scale economies on 1990s US data while results for 1980s sample implies constant or negative scale economies.

In order to examine this relationship, we examine the Spearman's rank correlation between the bank's cost efficiency represented by the efficiency scores calculated in this section and the size of the bank, represented by total assets. Spearman's rank correlation is a nonparametric test to test the monotonic association between two variables proposed by Spearman (1904). The test does not assume any statistical distribution of variables. Calculation formula for the value of Spearman's correlation for two variables X and Y is

$$\rho_{Spearman} = 1 - \frac{6\sum_i (x_i - y_i)^2}{n(n^2-1)}, \tag{4.3}$$

where x_i and y_i are the ranks of the values X_i and Y_i in the sample. The null hypothesis of the test is that these two variables are independent.

When we perform the test on the calculated cost efficiencies and the value of total assets for the separate years, we obtain the values of Spearman's correlation ranging from 0.06 in 2008 to 0.27 in 2012. The results are shown in Table 4.6. We reject the null hypothesis of independence on 10% level of significance for years from 2009 to 2012. In case of 2008 and 2013, we cannot reject the null hypotheses even on 10% level. Test results reveal there exists relationship, albeit weak, between bank the cost efficiency and the size of the bank between 2009 and 2012. We cannot conclude this for observations from the year 2008 and 2013. This being said, the relationship between bank size and its efficiency do not seem to be persistent over the time and we cannot conclude that the larger banks are more efficient in the overall sample period.

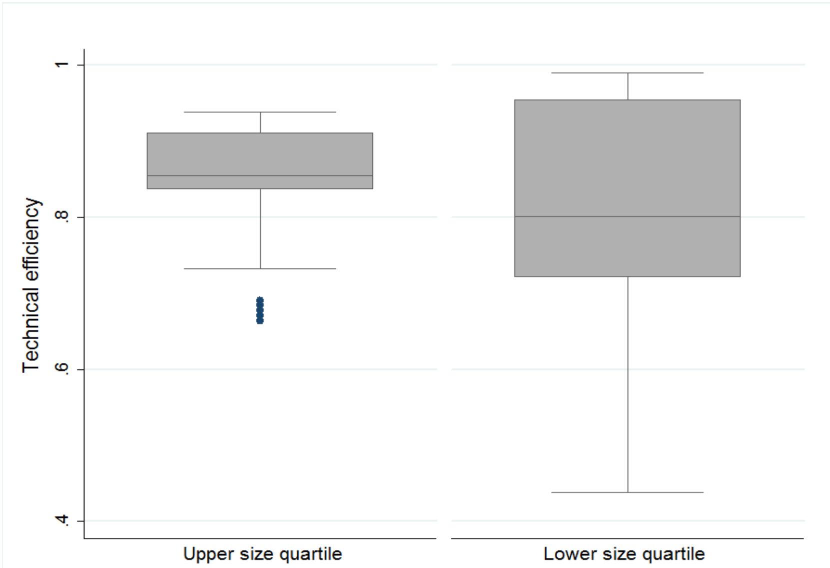
Table 4.6: Spearman's correlations between cost efficiency and asset size

Year	Spearman's ρ	p-value	Observations
2008	0.0663	0.5566	81
2009	0.1837	0.0924	85
2010	0.1857	0.0798	90
2011	0.1864	0.0785	90
2012	0.2736	0.0108	86
2013	0.1107	0.3688	68

Source: Author based on Bankscope database

Another method that might give us glimpse whether larger banks tend to be more efficient is to sort the data into categories based on its size and estimate the mean efficiency of each group. The mean cost efficiency of banks from the fourth size quartile is equal to 85.44% while the mean cost efficiency of the banks belonging to lowest size quartile is 80.87%. After inspecting box plot of the efficiency scores of these two groups, which is provided in Figure 4.5, we see that variance of the lower size quartile group is much higher than for the group of large banks, which makes economic interpretation of the difference in the mean efficiencies cumbersome. We see that even some of the most efficient banks belong to the small size group. Taking into account the results from the previous paragraphs, we cannot conclude there is a clear evidence that the larger banks are also more cost efficient, which would imply that the banks in our sample take advantage of the economies of scale.

Figure 4.5: Box-Plot of estimated efficiency scores of upper and lower size quartiles



Source: Author's calculations based on Stata software

Apart from the estimation of the efficiency of the banks from the Visegrad Group countries, the other aim of this thesis is to examine the relationship between the changes in the cost efficiency, risk-taking, and capital of the banks from our sample. Under the method that we used in this section, the estimated efficiency scores exhibit the same time for all banks. This makes the efficiency scores derived in this section not suitable for the purposes of econometric analysis that will follow in Section 4.2. This problem is addressed in the next section.

4.1.5 Cross-Sectional Estimation

In order to obtain the efficiency scores that are further used in Section 4.2, we decided to pool all the observation together and estimate the cost efficiency scores using the methodology for cross-sectional estimation described in Sections 3.3.2 - 3.3.5. We decided for this specification since we want the estimated cost efficiency scores to vary over time; this comes at the cost that the fulfillment of all the assumption of the cross-sectional stochastic frontier model might be challenged. The estimation of the efficiency scores was tackled in a similar fashion also in other papers that examine the relationships between the cost efficiency, risk-taking, and capital, such as in Altunbas et al. (2007) and Kwan and Eisenbeis (1995).

The symmetric random error v_{it} is assumed to follow the normal distribution $N(0, \sigma_v)$ and the inefficiency term u_{it} is assumed to follow half normal distribution $N^+(0, \sigma_u)$. To estimate the parameters of the cost function we employ the maximum likelihood estimation as described in Section 3.3.4. The efficiency scores are calculated using the modification of mean-conditional method of Jondrow et al. (1982) that was proposed by Battese and Coelli (1988).

Since these scores are further used the econometric analysis in the next section, we want to examine how these scores are sensitive to certain changes in the specification of this estimation method. Hence, apart from the base model, several other deviations from the base specification were estimated. The correlation between the scores derived by various specifications will be examined. In overall, the following pooled cross-sectional base model and its deviations are estimated:

(A) Base model as described by Equation (4.2) assuming normal distribution $N(0, \sigma_v^2)$ of the symmetric error term v and half normal distribution $N^+(0, \sigma_u^2)$ of the inefficiency error term.

(B) Time variable (together with corresponding products with other cost function variables) is included directly into the cost function. Again, normal distribution $N(0, \sigma_v^2)$ of the symmetric term v and half normal distribution $N^+(0, \sigma_u^2)$ of the inefficiency term is assumed.

$$\begin{aligned}\ln \frac{C}{w_3 z} = & \ln \alpha_0 + \tau_1 t + \tau_2 t^2 + \sum_j (\alpha_j + \phi_j t) \ln \frac{y_j}{z} \\ & + \sum_l (\beta_l + \theta_l t) \ln \frac{w_l}{w_3} + \frac{1}{2} \sum_j \sum_k \gamma_{jk} \ln \frac{y_j}{z} \ln \frac{y_k}{z} \\ & + \frac{1}{2} \sum_l \sum_m \delta_{lm} \ln \frac{w_l}{w_3} \ln \frac{w_m}{w_3} + \sum_l \sum_j \rho_{lj} \ln \frac{w_l}{w_3} \ln \frac{y_j}{z} \\ & + u + v\end{aligned} \tag{4.4}$$

(C) Total deposits are included in cost function as output (together with the corresponding products with other cost function variables) as is promoted by value-added approach, i.e. one additional output is added into the cost

Table 4.7: Results of cost function estimation of pooled model (A)

	Coef.		Std. Err.	z	P> |z|
α_1	0.5820	***	0.07882	7.38	0.0000
α_2	0.6981	***	0.04398	15.87	0.0000
β_1	0.6343	***	0.03579	17.72	0.0000
β_2	0.1606	***	0.04873	3.30	0.0010
γ_{11}	0.1075	***	0.00964	11.16	0.0000
γ_{12}	-0.1803	***	0.01226	-14.71	0.0000
γ_{22}	0.0485	***	0.00216	22.48	0.0000
δ_{11}	0.0761	***	0.00589	12.92	0.0000
δ_{12}	0.0093		0.00731	1.27	0.2040
δ_{22}	-0.0053		0.00455	-1.16	0.2450
ρ_{11}	-0.0189	*	0.01144	-1.65	0.0990
ρ_{12}	-0.0331	***	0.00891	-3.71	0.0000
ρ_{21}	-0.0210	*	0.01258	-1.67	0.0950
ρ_{22}	-0.0325	***	0.00718	-4.53	0.0000
α_0	1.1127	***	0.16416	6.78	0.0000
σ_u	0.2287		0.01471	15.55	0.0000
σ_v	0.0854		0.00898	9.50	0.0000
λ	2.6788		0.02176	123.13	0.0000
Number of observations:			500		
*** $p < 0.01$, **$p < 0.05$, *$p < 0.1$					

Source: Author's calculations based on Stata software

function. Again, normal distribution $N(0, \sigma_v^2)$ of the idiosyncratic term v and half normal distribution $N^+(0, \sigma_u^2)$ of the inefficiency term is assumed.

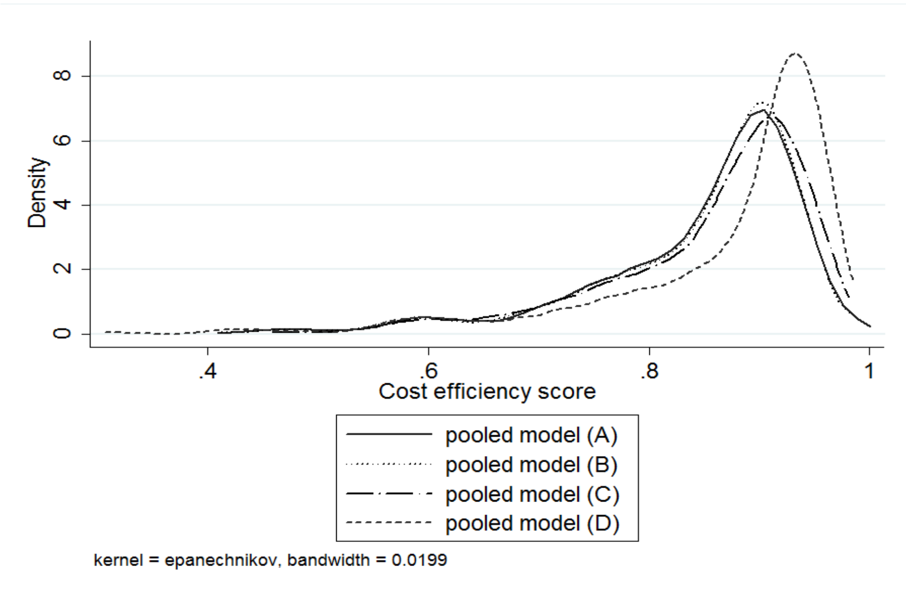
(D) The same as the base model (A) but the inefficiency term is assumed to follow truncated normal distribution as proposed by Stevenson (1980).

$$u_{it} \sim N^+(\mu, \sigma_u)$$

The cost function estimation results of the base model (A) are shown in Table 4.7. The results of the deviations from the base model are shown in Appendix.

In order to see the impact of the deviations from the base model on the estimated score, we plot he kernel densities of the estimated efficiency scores using the specifications described above. In the Figure 4.6, kernel densities of the base model (A) and the deviations are shown. We see that kernel density of deviations (B) and (C) are very similar to the base model (A). The shape of these kernel densities are very similar because the half normal distributions is assumed in the first three specifications and the signal to noise ratio, represented by coefficient λ, is very similar across these three specifications. To remind the readers, coefficient λ is the share of the standard deviation of the symmetric term v and of the coefficient σ_u, i.e. $\lambda = \sigma_u/\sigma_v$. Coefficient λ is equal to 2.68 for the base model, 2.71 for model (B), and 2.97 for model (C). This implies similar overall estimated level of (in)efficiency. Compared to the first three specifications from Figure 4.6, the estimated kernel density of the deviation (D) has different shape, Figure 4.6 implies that according to the results of this specification, the banks are concentrated closer to the best-practice frontier, i.e. the overall estimated level of efficiency is higher when using the assumption of truncated normal distribution compared to half-normal distribution.

Figure 4.6: Kernel densities of cost efficiency scores from pooled models (A), (B), (C), (D)



Source: Author's calculations based on Stata software

To obtain the understanding how the deviations (B), (C), and (D) affect the relative ranking of the banks based on the estimated cost efficiency scores, we examine the Spearman's rank correlation coefficients and product-moment correlation coefficients (referred to as Pearson's correlation coefficient) between the efficiency scores estimated using all four cross-sectional specifications. The correlation coefficients are shown in Table 4.8.

We observe high correlations between the base model and all three deviations. The deviation (B) has the highest correlation with the base model, this

Table 4.8: Correlation between efficiency scores estimated using pooled models (A), (B), (C), (D)

Spearman correlation:

	(A)	(B)	(C)	(D)
(A)	1.0000			
(B)	0.9890	1.0000		
(C)	0.9343	0.9283	1.0000	
(D)	0.9887	0.9774	0.9328	1.0000

Pearson correlation:

	(A)	(B)	(C)	(D)
(A)	1.0000			
(B)	0.9955	1.0000		
(C)	0.9339	0.9284	1.0000	
(D)	0.9867	0.9840	0.9169	1.0000

Source: Author's calculations based on Stata software

Table 4.9: Correlations between yearly differences in efficiency scores estimated using pooled models (A), (B), (C), (D)

Spearman's correlation:

	(A)	(B)	(C)	(D)
(A)	1.0000			
(B)	0.9920	1.0000		
(C)	0.9372	0.9311	1.0000	
(D)	0.9881	0.9783	0.9346	1.0000

Pearson's correlation:

	(A)	(B)	(C)	(D)
(A)	1.0000			
(B)	0.9961	1.0000		
(C)	0.9144	0.9131	1.0000	
(D)	0.9840	0.9802	0.9119	1.0000

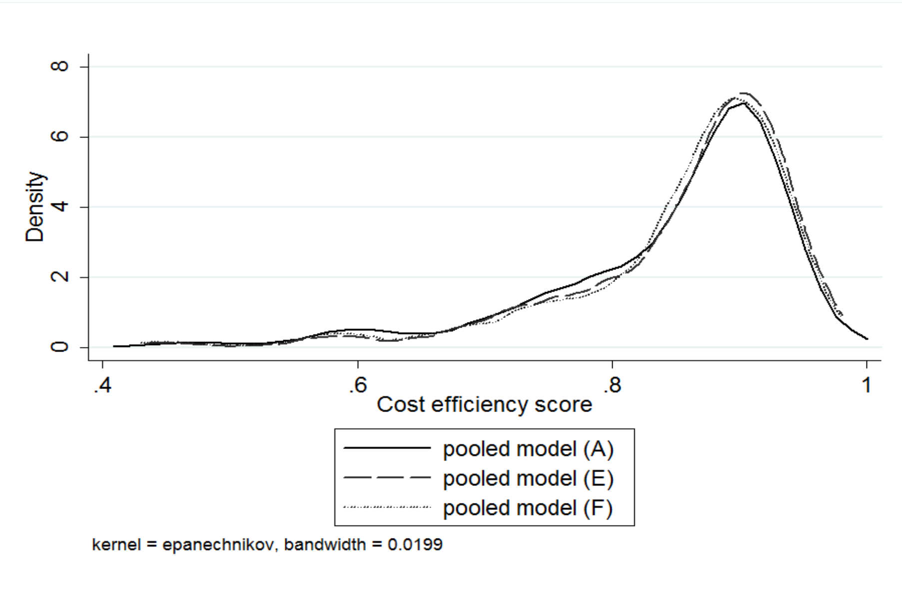
Source: Author's calculations based on Stata software

is further supported by the fact that all the coefficients associated with the time variables that were added into cost function are insignificant (see Table A.1 in Appendix). The lowest correlations of around 0.93 with other specifications are observed for the model (C), which includes the customer deposits as output in the cost function. This is partly in line with our expectation, since the introduction of deposits as a new output variable alters significantly the cost function. Interestingly, we see that despite the fact that the kernel density of the model (D) assuming truncated normal distribution of was much more shifted towards 1, Spearman's and Pearson's correlations with the base model

(A) have value of almost 0.99. This shows that the alternation in the distributional assumption on the inefficiency term u_{it} had an impact on the overall estimated level of efficiency, but the ranking of banks according to estimated efficiency remained almost identical. The value of Pearson's correlation suggests a very strong linear relationship between these two specifications. Hence, for the purposes of econometric modeling, these two specifications are almost identical.

Since in the next chapter we use the yearly differences of the calculated efficiency scores as dependent variables, we provide in the Table (4.9) also the correlations between yearly changes in the efficiency scores. Again, the calculated correlations are very high ranging from 0.91 to 0.99 with similar interpretation as in the previous paragraph.

Figure 4.7: Kernel densities of cost efficiency scores from pooled models (A), (E), (F)



Source: Author's calculations based on Stata software

In addition to the previously discussed deviations from the base model, we also estimated 2 deviations that assume different estimation period, namely:

(E) The same specification as in (A) but estimated on data from the year 2009 to 2013.

(F) The same specification as in (A) but estimated on data from the year 2010 to 2013.

Comparison of the kernel densities of these deviations from the base model (A) that assume the same distributional assumptions and cost function, but use the data from shorter time period are shown in Figure 4.7. We see that the densities are almost identical, again implying very similar overall level of estimated (in)efficiency. Spearman's and Pearson's correlations between the efficiency scores derived by the base model (A) and the specifications (E) and (F) are all equal to 0.92. Hence, we see that the reduction of our sample by omitting the year 2008 or the years 2008–2009 has an impact on estimated efficiency of the banks. Despite this, the value of the correlation coefficients might be still deemed high and implying only a minor impact on the overall ranking of the banks.

Correlations between the estimated efficiency scores using various specifications are considerably high, which assures us that estimated efficiency score are rather robust to the specification. For these reasons, we decide to use the efficiency score estimated from the base model (A) as a measure of cost efficiency in the next section, where we examine relationship between cost efficiency of the banks in our sample, their risk-taking, and capital position using the system of simultaneous equations.

4.2 Simultaneous Equations Model

Possessing the cost efficiency estimates from Section 4.1.5, we proceed to the part where we examine the relationships between the cost efficiency of banks from the Visegrad Group countries, their risk-taking, and capital position. The main goal is to examine whether these variables are determined simultaneously and inspect the relationship between the bank efficiency and risk-taking. To be more specific, we want to test whether there is a negative relationship between the changes in measured cost efficiency and bank's risk taking represented by problem loans as was suggested by some of the past empirical research. Throughout this section, we shall be primarily concerned with the credit risk that the banks undertake. As Berger and DeYoung (1997) propose in their paper, negative relationship between these two variables might be explained by two hypotheses with different causality: *bad management hypothesis* and *bad luck hypothesis*. Additionally, we also want to examine whether a negative relationship between changes in capital and risk-taking might be observed, which might suggest the exploitation of moral hazard incentives by the management.

Bad Luck Hypothesis

Bad luck hypothesis stipulates that the external events out of the bank's control might cause a sudden increase in the problem loans that are present on the bank's balance sheet. Servicing portfolio with increased portion of nonperforming loans is more costly for the bank since the additional costs are incurred. Such costs comprise the monitoring of the borrowers, negotiation of workaround arrangement with delinquent borrowers, costs related to the collection of overdue loans, costs related to seizure of collateral, etc. (Berger and DeYoung, 1997). Increased problem loans impose numerous types of additional costs and require increased management efforts and hence, the banks hit by such external event are identified as less cost efficient compared to its peers.

Bad Management Hypothesis

Bad management hypothesis also stipulates negative relationship between the cost efficiency and the problem loans. But contrary to the former hypothesis, the causality is altered. The low cost efficiency is a sign of a poor performing management in a bank; i.e. senior management lacks inevitable skills needed for the management of the bank. Such poor management that does not have sufficient control over the cost of the bank might also perform poorly in terms on the underwriting of new loans and monitoring of existing loans.

4.2.1 Model and Data

In order to examine the aforementioned relationships, we employ simultaneous equations modeling approach and examine the relationship between the changes in all three variables of interest. Particularly, we build on the modeling approach of Shrieves and Dahl (1992), Jacques and Nigro (1992), Rime (2001), or Matejašák et al. (2009), and we extend this approach so that the model takes into account also changes in bank's cost efficiency.

Shrieves and Dahl (1992) assume in their model that decision on the bank's capital position and risk taking are determined simultaneously and mutually related. Using a system of simultaneous equation, they model the observed annual change in bank risk and capital while they decompose this change into discretionary adjustment and change that is due to exogenous factors. In a single period, however, the bank may not be able to fully adjust these variables to its target rates as desired. To account for this fact, partial adjustment framework is used, where the discretionary change is proportional to the difference between previous period's amount of capital (or risk) and the unobservable target rate. Even though the target rates are unobservable, they are believed to depend on the certain set of observable variables. Along the other explanatory variables, the change in the capital is assumed to depend on the change in risk-taking and vice versa.

The past studies of Berger and DeYoung (1997) or Kwan and Eisenbeis (1997) carried out on US data promote the idea that bank efficiency, risk-taking, and capital position are interrelated. Hence, we incorporate this finding into the model of Shrieves and Dahl (1992). To be more specific, we use the similar logic as above also for the changes of the cost efficiency of the bank and include the separate equation that reflects the changes in the cost efficiency of the bank. We assume that changes in capital position and risk-taking are related to the change in the cost efficiency of the bank and vice versa. In the logic of model Shrieves and Dahl (1992), we assume that there exists a certain target rate of the cost efficiency.

We propose to estimate the system of three simultaneous equation, written in the structural form as:

$$\begin{aligned} \Delta EFF_{i,t} =& \alpha_0 + \alpha_1 EFF_{i,t-1} + \alpha_2 \Delta RISK_{i,t-1} + \alpha_3 \Delta CAP_{i,t-1} \\ &+ \alpha_4 SIZE_{i,t} + \alpha_5 LGROWTH_{i,t} + \alpha_6 LGROWTHSQ_{i,t} \\ &+ \alpha_7 Dum2010 + \cdots + \alpha_{10} Dum2013 + e_{i,t} \end{aligned} \tag{4.5}$$

$$\begin{aligned} \Delta RISK_{i,t} =& \beta_0 + \beta_1 RISK_{i,t-1} + \beta_2 \Delta EFF_{i,t-1} + \beta_3 \Delta CAP_{i,t-1} \\ &+ \beta_4 SIZE_{i,t} + \beta_5 LGROWTH_{i,t} + \beta_6 LGROWTHSQ_{i,t} \\ &+ \beta_7 NIM_{i,t} + \beta_8 REGP_{i,t-1} \\ &+ \beta_9 Dum2010 + \cdots + \beta_{12} Dum2013 + u_{i,t} \end{aligned} \tag{4.6}$$

$$\begin{aligned} \Delta CAP_{i,t} =& \gamma_0 + \gamma_1 CAP_{i,t-1} + \gamma_2 \Delta EFF_{i,t-1} + \gamma_3 \Delta RISK_{i,t-1} \\ &+ \gamma_4 SIZE_{i,t} + \gamma_5 ROAA_{i,t} + \gamma_6 REGP_{i,t-1} \\ &+ \gamma_7 Dum2010 + \cdots + \gamma_{10} Dum2013 + v_{i,t} \end{aligned} \tag{4.7}$$

All three equations satisfy the order condition needed for the identification in simultaneous equations system. First of all, the variables that represent the risk-taking and the capital position of the bank need to be selected. For the

Table 4.10: Description of variables included in model

Variable	Description
EFF	Cost efficiency score estimated by Base model (A)
$RISK$	Loan-loss reserves to total assets
CAP	Equity to Assets
$LGROWTH$	Rate of annual growth of loans
$LGROWTHSQ$	Rate of annual growth of loans, squared
$SIZE$	Natural logarithm of total assets
NIM	Net interest margin
$ROAA$	Return on average assets
$REGP$	Regulatory pressure dummy variabe
$Dum2010$–$Dum2013$	Yearly dummy variables

Source: Author

measure of the cost efficiency (EFF) we shall use the efficiency scores derived from the base specification (A) from Section 4.1.5. The scores are ranging from 0 to 1 whereas 1 represents the bank that is identified as the most cost efficient. All three endogenous variables in the system are the yearly changes in the measures of the efficiency, risk, and capital position.

Measure of Capital Position

Following Shrieves and Dahl (1992), Berger and DeYoug (1997) and others, the bank's capital position (CAP) will be represented by Equity to Assets ratio. Nowadays, much less attention is paid to simple measures of bank's capital position, such as Equity to Assets ratio or Leverage Ratio. This is partly because of the introduction of Basel accords that promote risk-weighted Capital Adequacy Ratio, which is defined as the ratio of Tier 1 capital to the risk-weighted assets. Nevertheless, calculation of Basel Capital Adequacy Ratio might be opaque and much less transparent than Equity to Assets. The latter measure still provides valuable information on bank's capital position. Let us point to Basel's recent introduction of the minimum requirements on Leverage Ratio—a ratio that is not subject to any risk-weighting—within Basel III.

Measure of Bank Risk

The selection of the measure of risk is the widely discussed issue. Generally, we may distinguish between the market and the accounting measures of the risk that are used in empirical research. The argument against accounting measures is that these measures are subject to the certain managerial discretion and hence might be biased. On the other hand, market measures of risk are only feasible for the banks with regularly traded securities. In our sample, utilizing such market measure of the of risk is thus not applicable. An alternative solution might be to use the measures published by renowned rating agencies, such as Moody's KMV. Unfortunately, we did not have access to such measures. Rimes (2001) and others use ratio of risk-weighted assets to total assets as a measure of risk. In our sample, we would not obtain a sufficient number of observations for this variable.

We decided to follow the approach of numerous bank efficiency studies, such as Williams (2004), Berger and DeYoung (1997) or Kwan and Eisenbeis (1997). The credit risk covers the significant portion of the risks that commercial banks undertake and might be considered the inherent risk related to primary business function of banks. Hence, credit risk stemming from the loans portfolio captures the vast majority of the bank-specific risk that commercial banks are exposed to. We choose nonperforming loans as a measure of bank's asset risk such as in Altubnas et el. (2007). Hence, the measure of the risk of the bank ($RISK$) is defined as loan loss reserves to total assets.

Explanatory variables

When selecting the explanatory variables in our model, we build on the studies of Shrieves and Dahl (1992), Jacques and Nigro (1992), Kwan and Eisenbeis (1997), Rime (2001), or Altunbas et. al (2007).

In most of the studies examining mutual capital and risk adjustments, the size of the bank is included as explanatory variable. The size of the bank might have the impact on target rates of capital and risk due to nature of bank's investment opportunity set, its ownership characteristics, and access to equity capital (Shrieves and Dahl, 1992). Furthermore, the economies of scale are believed to exist in the banking industry; hence, the cost efficiency might be influenced by the size of the bank as well. Therefore, we choose to control for bank size in all three equations. Bank size ($SIZE$) is defined as the logarithm of total assets.

Following Kwan and Eisenbeis (1997), we introduce two variables describing the growth of loans into Equations (4.5) and (4.6). These two variables are the yearly growth rate of loans $LGROWTH$ and the square of this variable $LGROWTHSQ$. The latter variable is added in order to account for a possible U-shaped relationship as described below. Steady and sustainable loan growth might be a sign of healthy growth of loans and sign of good managerial quality, which is linked to the cost efficiency of the firm. On the other hand, excessive growth might be the sign of relaxed underwriting standards resulting in the higher share of nonperforming loans and ultimately in the higher risk of the bank. A sudden increase in the loans of the bank might have also imposed the additional costs on the bank that were spent on the underwriting and scoring of the new clients. This might result in the lower cost efficiency of such bank compared to its peers with the same amount of loans but provided in the past.

In Equation (4.6), along with $SIZE$, $LGROWTH$, and $LGROWTHSQ$, we also include the measure of the net interest margin (NIM). Kit (1997) shows that the net interest margin is positively related to the bank's credit risk. When the bank is facing higher interest spreads in the market, it might be tempted to relax its underwriting standards in order to monetize this opportunity. Higher margins may also indicate that higher share of loans with inferior quality was provided in given year.

In Equation (4.7), we include current year's profit measured by the return on average assets ($ROAA$) as proposed by Rime (2001). Return on capital might have a positive impact on bank's capital in case the bank retains its earnings. He argues that financial institutions might prefer this way of capital increase to equity issuance as "the latter may convey negative information to the market about bank's value in the presence of asymmetric information" (Rime, 2001).

Moreover, in line with Shrieves and Dahl (1992), Jacques and Nigro (1992), and others, we include the regulatory pressure variable into Equations (4.6) and (4.7). Banks that are close to the minimum capital requirement tend to behave in a different manner than the rest of the banks; this might be caused by the active pressure of local bank regulators and supervisor. We consider the banks with Basel II capital adequacy ratio (CAR) below 8% to be undercapitalized. To constructs the regulatory pressure variable, we select the simplified approach and assume that bank is under regulatory pressure when its CAR is lower than 12%.

$$\begin{aligned} REGP &= 1 \quad \text{if} \quad CAR < 0.1 \\ &= 0 \quad \text{otherwise} \end{aligned}$$

We do not possess the information on CAR for all of the observations in our data; therefore, we decided to assign zero value to $REGP$ in case we are lacking the information on the capital adequacy ratio.

Yearly dummies were included in each equation to account for common exogenous shocks in given years that might affect the dependent variables. We included dummy variables for the year 2010 and onwards in order to avoid the perfect multicollinearity in explanatory variables.

Data on the variables were again obtained from Bankscope database. Since we use yearly differencing of dependent variables, the data set is spanning from the year 2009 to 2013. Due to the differencing of the dependent variables and the introduction of the new variables, our data set has shrank to 320 observations in total. Summary statistics of the variables presented above are shown in Table 4.11.

Table 4.11: Summary statistics of variables included in simultaneous equations model

Variable	No. Obs.	Mean	Std. Dev.	Min	Max
ΔEFF_t	320	0.0016	0.0526	-0.2693	0.1756
$\Delta RISK_t$	320	0.0049	0.0160	-0.1172	0.1223
ΔCAP_t	320	0.0034	0.0182	-0.0961	0.0790
EFF_{t-1}	320	0.8636	0.0719	0.4815	0.9681
$RISK_{t-1}$	320	0.0321	0.0345	0.0004	0.2361
CAP_{t-1}	320	0.0934	0.0405	0.0286	0.2913
$LGROWTH_t$	320	0.0001	0.0040	-0.0050	0.0006
$SIZE_t$	320	15.1910	1.3497	11.1425	17.6859
NIM_t	320	0.0326	0.0182	0.0022	0.1460
$ROAA_t$	320	0.0064	0.0152	-0.0760	0.0443
$REGP_{t-1}$	320	0.2844	0.4518	0.0000	1.0000

Source: Author's calculations based on Stata software

4.2.2 Estimation Method

In the system of equations represented by (4.5), (4.6), and (4.7), endogenous variables are included in the right-hand side of all three equations. Such endogenous variables might be correlated with disturbances, which is a violation of orthogonality assumption, one of the basic assumptions underlying OLS. As a result of a violation of this assumption, OLS is not be the unbiased and consistent estimator in simultaneous equations setting. This problem is often referred to as *simultaneity bias* (Cipra, 2008).

Hence, more sophisticated methods should be used in order cope with simultaneity bias. Two-Stage Least Squares (2SLS) or Three-Stage Least Squares (3SLS) estimators are among the most frequently used methods to estimate the systems of simultaneous equations that address this problem. Both 2SLS and 3SLS address the endogeneity of explanatory variables and thus are preferred to OLS. The difference between the two is that 3SLS takes into account also potential correlation between disturbances from the separate equations, while 2SLS does not. Because of this, 2SLS is assigned to the class of *limited information estimators* and 3SLS belong to the class of *full information estimators*.

2SLS is analogous to the instrumental variables estimation methods applied separately to each of the equations in the system, i.e. the right-hand side endogenous variables are replaced with the variables that are correlated with the explanatory variables but uncorrelated with disturbances. The estimation process follows two steps separately for each equation, hence the name Two-Stage Least Squares. In the first stage, each right-hand side endogenous variable is regressed on exogenous variables from the entire system using OLS. In the second stage, the original values of the right-hand side endogenous variables are replaced by predicted values from the first stage. Subsequently, OLS is applied to these equations. When asymptotic assumptions hold, such estimator is consistent and asymptotically efficient among single-equation estimators (Cipra, 2008).

3SLS is the estimator of the full system of simultaneous equations. Since 3SLS takes into account also the correlation structure between disturbances of the individual equations, it is an asymptotically efficient estimator of the entire system of equations (Cipra, 2008). This is achieved by introduction of the third step, where parameters of the structural form are estimated using Feasible Generalized Least Square (FGLS). Naturally, the estimates of the covariances between disturbances from the individual equations are needed. These are estimated using the error terms derived from the first two stages, as suggested by Zellner and Theil (1962).

As noted in Baltagi (2011), 3SLS is more efficient that 2SLS in case that all equations in the system are specified properly. However, in case one of the equations is improperly specified, parameter estimates of the entire system derived from 3SLS will be contaminated due to this misspecification; 2SLS estimates of the properly specified individual equations will not be affected by this bias. Due to this fact, even though we estimate the system of Equations (4.5) - (4.7) primarily using 3SLS, the results are validated by running 2SLS estimation as well.

4.2.3 Results

The results of the estimation using 3SLS estimation are provided in Tables 4.12, 4.13, and 4.13. As discussed, we also estimated the system using 2SLS estimator; the results are shown in Appendix and their interpretation is similar to the results of 3SLS.

Efficiency Equation

Table 4.12: 3SLS Results of Equation (4.5)

depvar = ΔEFF_t	Coef.		Std. Err.	z	P> |z|
ΔCAP_t	-0.56214		0.47570	-1.18	0.237
$\Delta RISK_t$	-1.65657	***	0.39295	-4.22	0.000
EFF_{t-1}	-0.34303	***	0.04482	-7.65	0.000
$LGROWTH_t$	0.03406		0.02179	1.56	0.118
$LGROWTHSQ_t$	-0.00675	*	0.00351	-1.92	0.055
$SIZE_t$	0.00127		0.00209	0.61	0.543
$Dum2010$	-0.01756	*	0.00968	-1.81	0.070
$Dum2011$	-0.01406		0.01011	-1.39	0.164
$Dum2012$	-0.02026	**	0.00966	-2.10	0.036
$Dum2013$	-0.03591	***	0.01139	-3.15	0.002
$cons$	0.30390		0.04819	6.31	0.000
Number of Observations		320			
*** $p < 0.01$, **$p < 0.05$, *$p < 0.1$					

Source: Author's calculations based on Stata software

We start with the results of the first equation in our system, where the change in the bank's cost efficiency is the dependent variable. The coefficient ΔCAP_t variable is not significant; based on this result we do not observe an impact of the change in the capital on the yearly change in efficiency. We are particularly interested in the estimated coefficient of $\Delta RISK_t$ variable since this estimate is related to the hypothesis that the changes in bank efficiency and its risk-taking are negatively related. This coefficient is negative with the value of -1.66 and significant on 1% level. We may infer from this that the negative relationship between the change in the riskiness of the bank's loan portfolio and the change in measured cost efficiency of the bank exists. In terms of this equation, the change in bank's cost efficiency is negatively affected by the change in the portion of nonperforming loans. This might be explained by unskilled management that is losing control over both the cost structure of the bank and the administration of its loan portfolio. Alternatively, this relationship might be explained by exogenous shocks to default rates that eventually impact the costs that need to be exerted to deal with this situation.

Based on the estimate of $SIZE_t$ variable coefficient, we might observe that the changes in the cost efficiency are not related to the size of the bank. This might suggests that behavior of the banks with respect to cost efficiency does not vary with increasing balance sheet size, or at least no linear relationship exists between these two variables. From the coefficients of the growth in loans variables, only the coefficient of squared loan growth is significant (on 5% level). Hence, the nonlinear relationship might be observed, albeit very small.

Risk Equation

Contrary to the previous equation, the results of Equation (4.6) do not support a negative relationship between the changes in bank's risk position and measured efficiency in the opposite direction. The estimated coefficient is negative but insignificant. This might perhaps suggest that positive relationship exist only in one direction and that the change in bank's risk-taking in not explained by changes in cost efficiency, which would favour more the bad luck over bad management hypothesis. Nevertheless, we cannot draw the conclusion on this causation from our analysis. The estimated coefficient of ΔCAP_t variables is significantly negative on 5% level, suggesting that the changes in risk and capital are negatively related. As pointed by Shrieves and Dahl (1992) and Jacques and Nigro (1997), a positive relationship is consistent with several hypotheses, such as risk aversion of managers, regulatory cost, bankruptcy cost avoidance or unintended results of capital requirements regulation. On the other hand, the negative relationship would be explained by mispriced deposit insurance and exploitation of this scheme by the management, which is a consequence of moral hazard problem.

Moving to other explanatory variables from the Equation (4.6), the change in the risk position is positively dependent to the net interest margin of given year. This might be for instance suggest that when banks are facing favorable interest rate environment, they might be tempted to increase the amount of loans provided at the expense of decreased quality of such loans. Surprisingly, the results do not imply that the change in $RISK$ variable is determined by the loan growth. Again, we observe the same behavior for banks of all sizes since the parameter of $SIZE$ variable is insignificant. The regulatory pressure variable is significant on 5% level, hence the banks with lower Basel capital ratio

Table 4.13: 3SLS Results of Equation (4.6)

depvar = $\Delta RISK_t$	Coef.		Std. Err.	z	P> |z|
ΔEFF_t	-0.03860		0.04325	-0.89	0.372
ΔCAP_t	-0.51156	***	0.16599	-3.08	0.002
$RISK_{t-1}$	-0.04126		0.03245	-1.27	0.204
$LGROWTH_t$	-0.00562		0.00821	-0.68	0.494
$LGROWTHSQ_t$	0.00139		0.00131	1.06	0.291
NIM_t	0.30088	***	0.06731	4.47	0.000
$SIZE_t$	0.00035		0.00073	0.48	0.629
$REGP_{t-1}$	0.00554	**	0.00226	2.45	0.014
$Dum2010$	-0.00631	**	0.00334	-1.89	0.059
$Dum2011$	-0.00878	***	0.00341	-2.58	0.010
$Dum2012$	-0.00859	***	0.00321	-2.68	0.007
$Dum2013$	-0.01269	***	0.00363	-3.50	0.000
$cons$	-0.00117		0.01133	-0.10	0.918
Number of Observations		320			
*** $p < 0.01$, **$p < 0.05$, *$p < 0.1$					

Source: Author's calculations based on Stata software

adjust their risk position in a different way than the well-capitalized banks. The coefficient is positive, which means that worse capitalized banks decreased their position slower than well capitalized banks; Heid et al. (2003) who was studying German savings banks, obtained similar results. This contradicts the results usually obtained by the empirical studies that utilize the methodology of Shieves and Dahl (1992), where the negative sign of this relationship is usually observed, which would suggest that banks subject to potential pressure of regulator tend to cap their risks.

Capital Equation

Let us move to the results of Equation 4.7 that represents the adjustments in the capital position of the bank. The results do not show any relationship between change in capital and change in efficiency of a bank and risk taking. Similarly to the previous equations, results suggest no dependence on the size of a bank. In line with previous research, the change in the bank capital is positively related to the bank's return on assets in given year. The coefficient of regulatory pressure is positive and significant of 10% level, which is in line with the previous research and implies that the banks under the supposed regulatory pressure increased their capital quicker than the rest of the sample.

Similarly to the previous studies applying the approach of Shrieves and Dahl (1992), the coefficients of determination of all three equations are considerably

Table 4.14: 3SLS Results of Equation (4.6)

depvar = ΔCAP_t	Coef.		Std. Err.	z	P> |z|
ΔEFF_t	-0.01328		0.03965	-0.33	0.738
$\Delta RISK_t$	-0.09049		0.13678	-0.66	0.508
CAP_{t-1}	-0.08498	***	0.02536	-3.35	0.001
$ROAA_t$	0.39689	***	0.07907	5.02	0.000
$REGP_{t-1}$	0.00423	*	0.00218	1.94	0.053
$SIZE_t$	-0.00022		0.00071	-0.31	0.756
$Dum2010$	-0.00823	***	0.00301	-2.73	0.006
$Dum2011$	-0.00809	***	0.00312	-2.60	0.009
$Dum2012$	-0.00170		0.00322	-0.53	0.597
$Dum2013$	-0.00869	**	0.00344	-2.53	0.012
$cons$	0.01672		0.01112	1.50	0.133
Number of Observations		320			
*** $p < 0.01$, **$p < 0.05$, *$p < 0.1$					

Source: Author's calculations based on Stata software

low, implying a very low predictive power of our model. The coefficient determination of the second equation is even negative, which might happen when 2SLS or 3SLS estimation is employed and the predictive power of the model is low.

In addition to the full sample estimation, we estimated the model also for the subsample of commercial banks. The results, which are provided in Appendix, are mostly in line with the full sample estimation. The only significant difference is that the loan growth variables are significant in the second equation.

Discussion

In Table 4.15 we briefly summarize the findings of the prominent papers that examined the relationships between bank efficiency, risk, and capital.[2] The mixed results obtained in this section contribute to the literature represented by these studies. In overall, our results do not imply that the changes in the cost efficiency, risk-taking, and capital would be determined simultaneously in our model; the results do not indicate two-way relationships between these variables. Instead, based on results the structure of the relationship seem to

[2] In the table, only the studies concerned with the relationship between the cost efficiency and the risk. We do not include the papers that study only the relationship between the risk and capital, which build on the approach of Shrieves and Dahl (1992). For an overview of the results of such empirical studies please refer to Matejašák et. al. (2009).

be rather recursive, starting with the bank capital that is affecting the risk position of the bank, which in turns affects the cost efficiency of the bank.

In the light of the recent economic crisis, the negative relationship between the changes is loan-loss reserves and the cost efficiency that was found in the model might be to some degree explained by exogenous macroeconomic shocks that affected the loan portfolios of the banks. According to the bad luck hypothesis, these exogenous shocks are reflected in the decreased cost efficiency. Hence, if the relationship proposed by this hypothesis was prevailing in the sample, the observed decrease in the overall cost efficiency of the banks in our sample shown in Section 4.1.4 might be explained by these events. However, this observation does not limit also the possible presence of the relationship corresponding to the bad management hypothesis. Furthermore, the observed finding that the changes in the loan-loss reserves are to some degree negatively determined by the changes in the capital position of the bank might introduce aspect of endogeneity into the changes in the bank's credit risk. The negative sign of the relationship is generally in line with the hypothesis of the moral hazard incentives of the management proposed by the past studies. Still, this result somewhat contradicts the deleveraging tendencies observed for instance in Hungary, which are characterized by the declined lending activity that ultimately result in increased amount of nonperforming loans compared to total assets.

Table 4.15: Summary of past findings

Paper	**Used sample**	**Methodology**	**Efficiency–Risk relationship**	**Risk–Capital relationship**
Berger and DeYoung (1997)	US commercial banks (1985–1994)	Granger causality technique	Mainly negative, evidence for skimping hypothesis among consistently most efficient banks	Capital negatively Granger cause nonperforming loans; nonperforming loans positively Granger cause capital of low-capitalized banks
Kwan and Eisenbeis (1997)	US large banks (1986–1995)	Simultaneous equations (level data)	Both positive and negative depending on bank size	Negative
Williams (2004)	European savings banks (1990–1998) (DK, FR, GER, IT, ESP, UK)	Granger causality technique	Both negative and positive depeneding on the direction and country	Capital negatively Granger cause nonperforming loans; Capital positively Granger cause nonperforming loans (Strong evidence for GER and ESP, weaker for others)
Rossi et al. (2005)	CEE countries (1995–2002)	Granger causality technique	Negative (Only bad luck hyp.)	Not studied
Altunbas et al. (2007)	EU 15 countries (1992–2000)	System of seemingly unrelated regressions (both level data and yearly differences)	Weak positive	Positive
Podpiera and Weil (2008)	Czech Banks (1995-2004)	Granger causality technique	Negative (Only bad management hyp.)	Not studied
Fiordelisi et al. (2011)	26 EU countries (1995–2007)	Granger causality technique	Negative	No strong relationship
This study	CZ, HU, PL, SK (2008–2013)	Simultaneous equations (yearly differences)	Negative	Negative

Source: Author's compilation

Chapter 5

Conclusion

This thesis was devoted to the measurement of the cost efficiency of the banks from the Czech Republic, Hungary, Poland, and Slovakia and to the examination of the relationships between their cost efficiency, risk-taking, and capital. Prior the empirical analysis, the literature studying the mutual relationships between these variables was reviewed. By doing this, we provided a rationale why these relationships should exist in the banking sector and what results were obtained in the empirical studies.

We decided to use the stochastic frontier analysis to calculate the cost efficiency of the banks. This method has its roots in the microeconomic theory and permits the stochastic fluctuation of the best-practice cost frontier over the time and observations. In order to make sure that the readers are familiar with this method, we reviewed its main assumptions and described the procedure that is applied to derive the bank-specific efficiency scores. In addition to this, we also outlined certain specific issued that need to be addressed during the estimation of the bank's cost efficiency, such as the choice of the form of the cost function or the decision whether to treat the customer deposits as the inputs or the outputs of the bank's production.

The empirical analysis of this thesis comprised two parts. In the first part, we used the stochastic frontier approach to estimate the cost efficiency of the banks from the aforementioned countries during the period spanning from 2008 to 2013. Both the cross-sectional specification of Aigner et al. (1977) and the panel data specification of Batesse and Coelli (1992) were applied. Based on the means of the calculated efficiency scores, the Hungarian banks from our sample were identified to be the least cost efficient. On the other hand, the Czech and the Polish banks exhibit the highest average cost efficiency. The sample of the Slovak banks is placed between these two groups. The similar results were obtained when the relative size of the banks was taken into account in the calculation of the overall efficiency in given country. The measured efficiency was found to be decreasing over the studied period. Moreover, we examined the relationship between the cost efficiency and the size of the banks but we did not find any conclusive results that would support the hypothesis that the larger banks exhibit higher cost efficiency.

The second part of the empirical analysis was devoted to the examination of the relationships between the changes in the bank's cost efficiency, risk-taking, and capital position. We were mainly building on the past research of Berger and DeYoung (1997), Kwan and Eisenbeis (1997) and Altunbas et al. (2007); partial adjustment simultaneous equation framework was used following Shrieves and Dahl (1992). We extended their approach by introducing the change in the cost efficiency into the system of simultaneous equations. Loan-loss reserves were used as a proxy for the bank risk since we assume the credit risk to represent the major portion of the risks that the banks from this region undertake.

Our results suggest a negative relationship between the changes in risk-taking and cost efficiency and between the changes in capital position and risk-taking of the banks. According to the results, the behavior of the banks is not affected by the size of the banks. Nevertheless, we did not find support for the hypothesis that the changes in the efficiency, risk, and capital are determined simultaneously in our model. Instead, the result suggests that the recursive relationship is governing these variables.

We ought to interpret our results with caution since the estimated efficiency scores might be sensitive to the applied estimation approach. In this regard, a suggestion for the future research might be to study these relationships using the efficiency scores derived from other efficiency estimation methods, or to modify the choice of bank inputs and outputs. Furthermore, a more profound dataset might be gathered that would cover all the banks from the Visegrad Group countries; this might limit a potential selection bias that is inherent to the usage of Bankscope database.

Bibliography

[1] Agoraki, M.-E. K., Delis, M. D., Pasiouras, F., 2011. *Regulations, competition and bank risk-taking in transition countries*. Journal of Financial Stability, Elsevier, vol. 7(1), pp. 38–48.

[2] Aebi, V., Sabato, G., Schmid, M., 2012. *Risk management, corporate governance, and bank performance in the financial crisis*. Journal of Banking & Finance, 36(12), pp. 3213–3226.

[3] Aigner, D., Lovell, K., and Schmidt, P., 1977. *Formulation and Estimation of Stochastic Frontier Production Function Models*. Journal of Econometrics, 6, pp. 21–37.

[4] Altunbas, Y., Carbo S., Gardener, E. P. M., Molyneux, P., 2007. *Examining the Relationships between Capital, Risk and Efficiency in European Banking*. European Financial Management, 13, 1, pp. 49–70.

[5] Altunbas, Y. and Chakravarty, S. P., 2001. *Frontier cost functions and bank efficiency*. Economics Letters, Elsevier, vol. 72(2), pp. 233–240.

[6] Baltagi, B. H., 2011. *Econometrics*. Springer Texts in Business and Economics.

[7] Battese, G. and Coelli, T., 1988. *Prediction of firm-level technical efficiencies with a generalized frontier production function and panel data*. Journal of Econometrics 38, pp. 387–399.

[8] Battese, G. and Coelli, T., 1992. *Frontier production functions, technical efficiency and panel data: with application to paddy farmers in India*. Journal of Productivity Analysis 3(1–2): pp. 153–169.

[9] Battese, G. and Coelli, T., 1995. *A model for technical inefficiency eeffects in a stochastic frontier production function for panel data*. Empirical Economics, 20, pp. 325–332.

[10] Battese, G. and Corra, G. S., 1977. *Estimation of a Production Frontier Model: With Application to the Pastoral Zone of Eastern Australia*. Australian Journal of Agricultural Economics, 21, pp. 169–179.

[11] Berger, A. N. and DeYoung, R., 1997. *Problem loans and cost efficiency in commercial banks*. Journal of Banking & Finance, Elsevier, vol. 21(6), pp. 849–870.

[12] Berger, A. N., Hanweck, G. A., and Humphrey, D. B., 1987. *Competitive viability in banking: Scale, scope, and product mix economies*. Journal of Monetary Economics, Elsevier, vol. 20(3), pp. 501–520.

[13] Berger, A. N. and Humphrey, D. B., 1992. *Measurement and Efficiency Issues in Commercial Banking*. NBER Chapters, in: Output Measurement in the Service Sectors, National Bureau of Economic Research, pp. 245–300.

[14] Berger, A. N. and Humphrey, D. B., 1997. *Efficiency of Financial Institutions: International Survey and Directions for Future Research*. Center for Financial Institutions Working Papers 97-05, Wharton School Center for Financial Institutions, University of Pennsylvania.

[15] Berger, A. N. and Mester, L., 1997. *Inside the black box: What explains differences in the efficiencies of financial institutions?*. Journal of Banking & Finance, 21, issue 7, pp. 895–947.

[16] Bonin, J. P., Hasan, I., Wachtel, P., 2005. *Bank performance, efficiency and ownership in transition countries*. Journal of Banking & Finance, 29(1), pp. 31–53.

[17] Buch, C. M., 1997. *Opening up for foreign banks: How Central and Eastern Europe can benefit*. The Economics of Transition, The European Bank for Reconstruction and Development, 5(2), pp. 339–366.

[18] Charnes, A., Cooper, W. W., Rhodes, E., 1978. *Measuring the efficiency of decision making units*. European Journal of Operational Research, 2, pp. 429–444.

[19] Cipra, T., 2008. *Finanční ekonometrie*. Ekopress.

[20] Coelli, T., Rao, D. S. P., O'Donnel, C. J., Battese, G., 2005. *An Introduction to Efficiency and Productivity Analysis*. 2nd Edition. New York: Springer Science + Business Media, Inc.

[21] Debreu, G., 1951. *The Coefficient of Resource Utilization*. Econometrica 19(3), pp. 273–292.

[22] Dewatripont, M. and Tirole, J., 1993. *The Prudential Regulation of Banks*. MIT Press.

[23] Diewert, W. E., 1992. *Fisher Ideal Output, Input and Productivity Indexes Revisited*. Journal of Productivity Analysis, 3, pp 211–248.

[24] Drehmann, M. and Nikolau, K., 2010. *Funding liquidity risk: definition and measurement*. BIS Working Papers No. 316, Bank for International Settlements.

[25] Farrell, M. J., 1957. *The Measurement of Productive Efficiency*. Journal of the Royal Statistical Society, Series A, General, 120(3), pp. 253–282.

[26] Fiordelisi, F., Marques-Ibanez, D., Molyneux, P., 2011. *Efficiency and risk in European banking*. Journal of Banking & Finance, 35(5), pp. 1315–1326.

[27] Freixas, X. and Rochet, J.-Ch., 2008. *Microeconomics of Banking*. 2nd edition, MIT Press.

[28] Fried, H., Lovell, K., and Schmidt, S., 2008. *The Measurement of Productive Efficiency and Productivity*. Oxford University Press.

[29] Fries, S. and Taci, A.,2005. *Cost efficiency of banks in transition: Evidence from 289 banks in 15 post-communist countries.* Journal of Banking & Finance, 29(1), pp.55–81

[30] Furlong, F. T. and Keeley, M. C., 1989. *Capital regulation and bank risk-taking: A note*. Journal of Banking and Finance 13(6), pp. 883–891.

[31] Gallant, A., 1982. *Unbiased determination of production technologies*. Journal of Econometrics, 20(2), pp. 285–323.

[32] Girardone, C., Molyneux, P., and Gardener, E., 2004. *Analysing the determinants of bank efficiency: the case of Italian banks*. Applied Economics, Taylor & Francis Journals, 36(3), pp. 215–227.

[33] Greene, W., 1980. *Maximum likelihood estimation of econometric frontier functions*. Journal of Econometrics 13, pp. 27–56.

[34] Greene, W., 1990. *A Gamma-distributed stochastic frontier model*. Journal of Econometrics, 46(1-2), pp. 141–163.

[35] Greene, W., 2005. *Fixed and random effects in stochastic frontier models*. Journal of Productivity Analysis, 23, pp. 7–32.

[36] Hancock, D., 1985. *The Financial Firm: Production with Monetary and Nonmonetary Goods*. Journal of Political Economy, University of Chicago Press, 93(5), pp. 859–980.

[37] Heid F., Porath, D., and Stolz, S., 2003. *Does Capital Regulation Matter for Bank Behavior? Evidence for German savings banks*. Working Papers 1192.Kiel: Institute for World Economics.

[38] Hughes, J. P., and Mester, L. J., 1993. *A Quality and Risk-Adjusted Cost Function for Banks: Evidence on the 'Too-Big-To-Fail' Doctrine*. The Journal of Productivity Analysis 4, pp. 293–315.

[39] Iršová, Z., 2010. *Bank Efficiency in Transitional Countries: Sensitivity to Stochastic Frontier Design*. William Davidson Institute Working Papers Series wp998, William Davidson Institute at the University of Michigan.

[40] Iršová, Z. and Havránek, T., 2010. *Measuring Bank Efficiency: A Meta-Regression Analysis*. Prague Economic Papers, issue 4, pp. 307–328.

[41] Jacques, K. and Nigro, P., 1997. *Risk-based capital, portfolio risk, and bank capital: A simultaneous equations approach*. Journal of Economics and Business, 49(6), pp. 533–547.

[42] Jensen, M., and Meckling, W. R., 1976. *Theory of the firm, managerial behavior, agency costs and ownership structure*. Journal of Financial Economics 3, pp. 305–360.

[43] Jondrow, J., Lovell, K., Materov, I. S., Schmidt, P., 1982. *On the estimation of technical efficiency in the stochastic frontier production function model*. Journal of Econometrics 19 (2/3), pp. 233–238.

[44] Kahane, Y., 1977. *Capital adequacy and the regulation of financial intermediaries*. Journal of Banking and Finance, 1(2), pp. 207–217.

[45] Kit, P. W., 1997. *On the determinants of bank interest margins under credit and interest rate risks*. Journal of Banking & Finance, 21(2), pp. 251–271.

[46] Kumbhakar, S. C., 1990. *Production frontiers, panel data and time-varying technical inefficiency*. Journal of Econometrics, 46, pp. 201–212.

[47] Kumbhakar, S. C. and Lovell, K., 2012. *Stochastic Frontier Analysis*. Cambridge University Press.

[48] Kuussaari, H., 1993. *Productive efficiency in Finnish local banking during 1985 – 1990*. Bank of Finland discussion papers, 14/93.

[49] Kwan, S. H. and Eisenbeis, R. A., 1995. *An analysis of inefficiencies in banking: a stochastic cost frontier approach*. Working Papers in Applied Economic Theory No. 95-12, Federal Reserve Bank of San Francisco.

[50] Kwan, S. H. and Eisenbeis, R. A., 1997. *Bank risk, capitalization and operating efficiency*. Journal of Financial Services Research 12, pp. 117–131.

[51] Mamatzakis, E., Staikouras, C., and Koutsomanoli-Filippaki, A., 2007. *Bank effciency in the new European Union member states: Is there convergence?*. International Review of Financial Analysis, 17, pp. 1156–1172.

[52] Matejašák, M., Teplý, P., Černohroský, J., 2009. *The impact of regulation of banks in the US and the EU-15 countries*. E+M Economics & Management, 2009/3, pp. 58–68.

[53] McAllister, P. and McManus, D. A., 1993. *Resolving the Scale Efficiency Puzzle in Banking*. Journal of Banking and Finance, Vol. 17(2-3), pp. 389–405.

[54] Merton, R. C., 1977. *An analytic derivation of the cost of deposit insurance and loan guarantees An application of modern option pricing theory*. Journal of Banking & Finance, 1(1), pp. 3–11.

[55] Mitchell, K, and Onvural, N. M., 1996. *Economies of Scale and Scope at Large Commercial Banks: Evidence from the Fourier Flexible Functional Form*. Journal of Money, Credit and Banking, 28(2), pp. 178–99.

[56] Modigliani, F. and Miller, M., 1958. *The Cost of Capital, Corporation Finance and the Theory of Investment*. American Economic Review, 48(3), pp. 261—297.

[57] Parmeter, C. F. and Kumbhakar, S. C., 2014. *Efficiency Analysis: A Primer on Recent Advances*. Foundations and Trends in Econometrics, 7(3-4), pp. 191–385.

[58] Pitt, M. and Lee., L., 1981. *The measurement and sources of technical inefficiency in the Indonesian weaving industry*. Journal of Development Economics 9, pp. 43–64.

[59] Podpiera, A. and Podpiera, J., 2005. *Deteriorating Cost Efficiency in Commercial Banks Signals an Increasing Risk of Failure*. Working Papers 2005/06, Czech National Bank, Research Department.

[60] Podpiera, J. and L. Weill. 2008. *Bad Luck or Bad Management? Emerging Banking Market Experience*. Journal of Financial Stability, 4(2), pp. 135–148.

[61] Rime, B., 2001. *Capital Requirements and Bank Behavior: Empirical Evidence of Switzerland*. Journal of Banking and Finance, 25, pp. 789–805.

[62] Rossi S. P. S., Schwaiger, M., Winkler, G., 2005. *Managerial Behavior and Cost/Profit Efficiency in the Banking Sectors of Central and Eastern European Countries*. Working Papers 96, Oesterreichische Nationalbank (Austrian Central Bank).

[63] Santos, J. A. C., 2001. *Bank Capital Regulation in Contemporary Banking Theory: A Review of the Literature*. Financial Markets, Institutions & Instruments, 10, pp. 41–84.

[64] Sealey, C. W. J. and Lindley, J. T, 1977. *Inputs, Outputs, and a Theory of Production and Cost at Depository Financial Institutions*. Journal of Finance, American Finance Association, 32(4), pp. 1251–1266.

[65] Shephard, R. W., 1953. *Cost and Production Functions*. Princeton: Princeton University Press.

[66] Sherman, H. D. and Gold, F., 1985. *Bank branch operating efficiency: Evaluation with Data Envelopment Analysis*. Journal of Banking & Finance, 9(2), pp. 297–315.

[67] Shrieves, R. E. and Dahl, D., 1992. *The relationship between risk and capital in commercial banks.* Journal of Banking & Finance, 16(2), pp. 439–457.

[68] Spearman, C. E., 1904. *The proof and measurement of association between two things.* American Journal of Psychology 15, pp. 72–101.

[69] Stevenson, R., 1980. *Likelihood Functions for Generalized Stochastic Frontier Estimation.* Journal of Econometrics, 13, pp. 58–66.

[70] Szapáry, G., 2001. B*anking Sector Reform in Hungary: Lessons Learned, Current Trends and Prospects.* MNB Working Papers 2001/5, Magyar Nemzeti Bank (The Central Bank of Hungary).

[71] Weinstein, M., 1964. *The Sum of Values from a Normal and a Truncated Normal Distribution.* Technometrics, 6, pp. 104–105.

[72] Williams, J., 2004. *Determining management behaviour in European banking.* Journal of Banking and Finance, 28, pp. 2427–2460.

[73] World Bank. [online] Available at:<http://data.worldbank.org/indicator/FB.AST.NPER.ZS/countries> [Accessed 12 April 2015].

[74] Zellner, A. and Theil, H., 1962. T*hree-Stage Least Squares: Simultaneous Estimation of Simultaneous Equations.* Econometrica, 30, pp. 54–78.

Appendix A

Additional Estimation Results

Table A.1: Results of cost function estimation of pooled model (B)

	Coef.		Std. Err.	z	P> |z|
alpha_1	0.5631	***	0.08286	6.80	0.0000
alpha_2	0.6832	***	0.04542	15.04	0.0000
beta_1	0.6529	***	0.03633	17.97	0.0000
beta_2	0.1488	***	0.05045	2.95	0.0030
gamma_11	0.1085	***	0.01027	10.57	0.0000
gamma_12	-0.1806	***	0.01230	-14.69	0.0000
gamma_22	0.0483	***	0.00260	18.55	0.0000
delta_11	0.0784	***	0.00625	12.54	0.0000
delta_12	0.0108		0.00734	1.47	0.1410
delta_22	-0.0063		0.00467	-1.35	0.1780
rho_11	-0.0182		0.01197	-1.52	0.1280
rho_12	-0.0346	***	0.00900	-3.85	0.0000
rho_21	-0.0207		0.01294	-1.60	0.1100
rho_22	-0.0303	***	0.00771	-3.93	0.0000
tau_1	-0.0375		0.02942	-1.27	0.2030
tau_2	-0.0004		0.00275	-0.15	0.8820
phi_21	0.0055		0.00787	0.70	0.4830
phi_22	0.0017		0.00483	0.35	0.7230
theta_21	-0.0063		0.00488	-1.29	0.1970
theta_22	0.0056		0.00386	1.46	0.1450
alpha_0	1.2289	***	0.18187	6.76	0.0000
sigma_u	0.2282		0.01472	15.50	0.0000
sigma_v	0.0842		0.00906	9.29	0.0000
lambda	2.7118		0.02188	123.97	0.0000
Number of observations:			500		

Source: Author's calculations based on Stata software

Table A.2: Results of cost function estimation of pooled model (C)

	Coef.		Std. Err.	z	P> |z|
alpha_1	0.5792	***	0.08260	7.01	0.0000
alpha_2	0.6781	***	0.06610	10.26	0.0000
alpha_3	-0.1494	***	0.05435	-2.75	0.0060
beta_1	0.6368	***	0.05679	11.21	0.0000
beta_2	0.1173	**	0.05181	2.26	0.0240
gamma_11	0.0961	***	0.01063	9.04	0.0000
gamma_12	-0.2270	***	0.01779	-12.76	0.0000
gamma_13	0.0384	***	0.01463	2.62	0.0090
gamma_22	0.0458	***	0.00222	20.58	0.0000
gamma_23	0.0413	***	0.00619	6.67	0.0000
gamma_33	-0.0078	***	0.00254	-3.06	0.0020
delta_11	0.0770	***	0.00908	8.49	0.0000
delta_12	0.0143		0.01074	1.33	0.1830
delta_22	-0.0059		0.00482	-1.23	0.2170
rho_11	-0.0344	***	0.01082	-3.18	0.0010
rho_12	-0.0542	***	0.01234	-4.39	0.0000
rho_13	0.0187	**	0.00862	2.17	0.0300
rho_21	-0.0173		0.01256	-1.37	0.1690
rho_22	-0.0267	**	0.01065	-2.50	0.0120
rho_23	0.0208	**	0.00818	2.55	0.0110
alpha_0	1.3408		0.15885	8.44	0.0000
sigma_u	0.2112		0.01230	17.17	0.0000
sigma_v	0.0712		0.00749	9.50	0.0000
lambda	2.9668		0.01787	165.98	0.0000
Number of observations:			486		

Source: Author's calculations based on Stata software

Table A.3: Results of cost function estimation of pooled model (D)

	Coef.		Std. Err.	z	P> |z|
alpha_1	0.5494	***	0.07557	7.27	0.0000
alpha_2	0.6929	***	0.04203	16.49	0.0000
beta_1	0.6093	***	0.03225	18.89	0.0000
beta_2	0.1685	***	0.04542	3.71	0.0000
gamma_11	0.1117	***	0.00839	13.32	0.0000
gamma_12	-0.1981	***	0.01113	-17.80	0.0000
gamma_22	0.0472	***	0.00196	24.14	0.0000
delta_11	0.0813	***	0.00528	15.41	0.0000
delta_12	0.0171	**	0.00669	2.56	0.0100
delta_22	-0.0095	**	0.00426	-2.22	0.0260
rho_11	-0.0205	**	0.00963	-2.13	0.0330
rho_12	-0.0297	***	0.00823	-3.61	0.0000
rho_21	-0.0122		0.01165	-1.05	0.2960
rho_22	-0.0222	***	0.00724	-3.07	0.0020
alpha_0	1.1634	***	0.15522	7.50	0.0000
Mu	-208.2969		242.33930	-0.86	0.3900
sigma_u	5.5635		3.23670	1.72	0.0860
sigma_v	0.0784		0.00681	11.51	0.0000
lambda	70.9453		3.23693	21.92	0.0000
Number of observations:			500		

Source: Author's calculations based on Stata software

Table A.4: Results of cost function estimation of pooled model (E)

	Coef.		Std. Err.	z	P> |z|
alpha_1	0.5373	***	0.08249	6.51	0.0000
alpha_2	0.5162	***	0.04811	10.73	0.0000
beta_1	0.6109	***	0.04252	14.37	0.0000
beta_2	0.1532	***	0.04446	3.45	0.0010
gamma_11	0.1211	***	0.01065	11.37	0.0000
gamma_12	-0.1686	***	0.01397	-12.07	0.0000
gamma_22	0.0932	***	0.00476	19.60	0.0000
delta_11	0.0857	***	0.00679	12.61	0.0000
delta_12	0.0150	**	0.00759	1.98	0.0480
delta_22	-0.0079	**	0.00391	-2.02	0.0430
rho_11	-0.0127		0.01393	-0.91	0.3620
rho_12	-0.0110		0.00948	-1.16	0.2480
rho_21	-0.0190		0.01331	-1.43	0.1530
rho_22	-0.0072		0.00769	-0.94	0.3460
alpha_0	1.2207	***	0.15649	7.80	0.0000
sigma_u	0.2094		0.01315	15.92	0.0000
sigma_v	0.0801		0.00758	10.56	0.0000
lambda	2.6145		0.01849	141.40	0.0000
Number of observations:			419		

Source: Author's calculations based on Stata software

Table A.5: Results of cost function estimation of pooled model (F)

	Coef.		Std. Err.	z	P> |z|
alpha_1	0.5111	***	0.11293	4.53	0.0000
alpha_2	0.4865	***	0.06094	7.98	0.0000
beta_1	0.6042	***	0.05852	10.32	0.0000
beta_2	0.1468	***	0.05323	2.76	0.0060
gamma_11	0.1293	***	0.01552	8.33	0.0000
gamma_12	-0.1732	***	0.01830	-9.47	0.0000
gamma_22	0.0968	***	0.00616	15.72	0.0000
delta_11	0.0919	***	0.00857	10.73	0.0000
delta_12	0.0168	**	0.00958	1.75	0.0790
delta_22	-0.0077		0.00476	-1.62	0.1060
rho_11	-0.0007		0.01981	-0.04	0.9720
rho_12	-0.0237	*	0.01212	-1.96	0.0500
rho_21	-0.0144		0.01660	-0.87	0.3870
rho_22	-0.0049		0.00922	-0.54	0.5920
alpha_0	1.2463		0.19650	6.34	0.0000
sigma_u	0.2169		0.01457	14.89	0.0000
sigma_v	0.0812		0.00824	9.85	0.0000
lambda	2.6700		0.02011	132.75	0.0000
Number of observations:			334		

Source: Author's calculations based on Stata software

Table A.6: 2SLS Results of equations (4.5) - (4.7)

depvar = ΔEFF_t	Coef.		Std. Err.	z	P> |z|
ΔCAP_t	-0.44212		0.48458	-0.91	0.362
$\Delta RISK_t$	-1.23402	***	0.40748	-3.03	0.003
EFF_{t-1}	-0.35801	***	0.04572	-7.83	0.000
$LGROWTH_t$	0.02247		0.02230	1.01	0.314
$LGROWTHSQ_t$	-0.00551		0.00360	-1.53	0.126
$SIZE_t$	0.00094		0.00212	0.44	0.659
$Dum2010$	-0.01437		0.00986	-1.46	0.145
$Dum2011$	-0.00978		0.01031	-0.95	0.343
$Dum2012$	-0.01614		0.00986	-1.64	0.102
$Dum2013$	-0.02991	**	0.01164	-2.57	0.010
$cons$	0.31674	***	0.04912	6.45	0.000
Nobs:	320				
depvar = $\Delta RISK_t$	Coef.		Std. Err.	z	P> |z|
ΔEFF_t	-0.00131		0.04535	-0.03	0.977
ΔCAP_t	-0.52226	***	0.17151	-3.05	0.002
$RISK_{t-1}$	-0.05046		0.03833	-1.32	0.188
$LGROWTH_t$	-0.02589	***	0.00903	-2.87	0.004
$LGROWTHSQ_t$	0.00416	***	0.00146	2.84	0.005
NIM_t	0.36612	***	0.07194	5.09	0.000
$SIZE_t$	0.00015		0.00075	0.20	0.842
$REGP_{t-1}$	0.00560	**	0.00242	2.31	0.021
$Dum2010$	-0.00502		0.00342	-1.47	0.143
$Dum2011$	-0.00784	**	0.00349	-2.25	0.025
$Dum2012$	-0.00853	**	0.00330	-2.58	0.010
$Dum2013$	-0.01159	***	0.00374	-3.10	0.002
$cons$	0.00087		0.01158	0.07	0.940
Nobs:	320				
depvar = ΔCAP_t	Coef.		Std. Err.	z	P> |z|
ΔEFF_t	0.02074		0.04082	0.51	0.612
$\Delta RISK_t$	0.07683		0.14193	0.54	0.588
CAP_{t-1}	-0.12915	***	0.02719	-4.75	0.000
$ROAA_t$	0.36429	***	0.08113	4.49	0.000
$REGP_{t-1}$	0.00232		0.00227	1.03	0.305
$SIZE_t$	-0.00026		0.00073	-0.36	0.720
$Dum2010$	-0.00748	**	0.00307	-2.44	0.015
$Dum2011$	-0.00749	**	0.00317	-2.36	0.018
$Dum2012$	-0.00015		0.00329	-0.05	0.963
$Dum2013$	-0.00659	*	0.00352	-1.87	0.061
$cons$	0.02031	*	0.01134	1.79	0.074
Nobs:	320				

Source: Author's calculations based on Stata software

Table A.7: 3SLS Results of equations (4.5) - (4.7) for subsample of commercial banks

depvar = ΔEFF_t	Coef.		Std. Err.	z	P> |z|
ΔCAP_t	-0.43056		0.50208	-0.86	0.391
$\Delta RISK_t$	-1.58292	***	0.42033	-3.77	0.000
EFF_{t-1}	-0.33957	***	0.04867	-6.98	0.000
$LGROWTH_t$	0.04220	*	0.02367	1.78	0.075
$LGROWTHSQ_t$	-0.00798	**	0.00380	-2.10	0.036
$SIZE_t$	0.00140		0.00236	0.59	0.555
$Dum2010$	-0.01985	*	0.01090	-1.82	0.068
$Dum2011$	-0.01616		0.01142	-1.42	0.157
$Dum2012$	-0.01990	*	0.01087	-1.83	0.067
$Dum2013$	-0.03889	***	0.01280	-3.04	0.002
$cons$	0.29921	***	0.05315	5.63	0.000
Nobs:	273				
depvar = $\Delta RISK_t$	Coef.		Std. Err.	z	P> |z|
ΔEFF_t	-0.04239		0.04701	-0.90	0.367
ΔCAP_t	-0.48060	***	0.17801	-2.70	0.007
$RISK_{t-1}$	-0.04399		0.03584	-1.23	0.220
$LGROWTH_t$	-0.00531		0.00926	-0.57	0.567
$LGROWTHSQ_t$	0.00133		0.00148	0.90	0.368
NIM_t	0.30740	***	0.07296	4.21	0.000
$SIZE_t$	0.00032		0.00084	0.38	0.700
$REGP_{t-1}$	0.00569	**	0.00269	2.12	0.034
$Dum2010$	-0.00682	*	0.00379	-1.80	0.072
$Dum2011$	-0.00951	**	0.00386	-2.47	0.014
$Dum2012$	-0.00882	**	0.00368	-2.40	0.017
$Dum2013$	-0.01330	***	0.00420	-3.17	0.002
$cons$	0.00007		0.01311	0.01	0.996
Nobs:	273				
depvar = ΔCAP_t	Coef.		Std. Err.	z	P> |z|
ΔEFF_t	-0.02607		0.04317	-0.60	0.546
$\Delta RISK_t$	-0.09910		0.14625	-0.68	0.498
CAP_{t-1}	-0.09022	***	0.02777	-3.25	0.001
$ROAA_t$	0.40010	***	0.08439	4.74	0.000
$REGP_{t-1}$	0.00460	*	0.00260	1.77	0.077
$SIZE_t$	-0.00076		0.00082	-0.93	0.352
$Dum2010$	-0.00876	**	0.00345	-2.54	0.011
$Dum2011$	-0.00833	**	0.00362	-2.30	0.021
$Dum2012$	-0.00171		0.00371	-0.46	0.646
$Dum2013$	-0.00919	**	0.00403	-2.28	0.022
$cons$	0.02636	**	0.01278	2.06	0.039
Nobs:	273				

Source: Author's calculations based on Stata software