LISBON SCHOOL OF ECONOMICS & MANAGEMENT
UNIVERSIDADE DE LISBOA

Master's Final Work

Project

The impact of liquidity and solvency constraints in European banks' efficiency

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Master
Finance

October, 2017

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October, 2017

Abstract

The purpose of this study is to analyse the relationship between bank efficiency and some Basel III regulatory measures. It presents and discusses the effectiveness of recent liquidity and capital global standards imposed by the Basel Committee on Banking Supervision (BCBS).

Our empirical analysis relies on two distinct methodologies: (i) multiple linear regressions; (ii) a non parametric method called Data Envelopment Analysis (DEA).

The efficiency in the banking sector is measured in two different perspectives – through simple accounting ratios and, alternatively, through the concept of technical efficiency which consists of the relative distance to a best-practice efficient frontier.

Our findings point to the presence of effects of Basel regulation on bank efficiency, although these effects are not consistent throughout the three-year analysis. Evidence from both methodologies suggest a conflicting impact on the efficiency of European banks.

Keywords: Basel III, Liquidity Coverage Ratio, Common Equity Tier 1 Ratio, Ordinary Least Squares, Data Envelopment Analysis, Technical Efficiency

Resumo

O objetivo deste estudo é analisar a relação entre a eficiência bancária e algumas das medidas regulatórias do Basileia III. É feita uma apresentação e discussão da eficácia das normas globais de liquidez e capital, recentemente impostas pelo Comité de Supervisão Bancária do Basileia (BCBS - Basel Committee on Banking Supervision).

A nossa análise empírica baseia-se em duas metodologias distintas: (i) regressões lineares múltiplas; (ii) um método não paramétrico designado de Análise de Dados em Envelope (DEA - Data Envelopment Analysis).

A eficiência no setor bancário é medida a partir de duas perspetivas diferentes – com base em simples rácios contabilísticos e, alternativamente, a partir do conceito de eficiência técnica que consiste na distância relativa a uma fronteira de eficiência padrão.

Os nossos resultados apontam para a presença de efeitos da regulação do Basileia na eficiência bancária, embora estes efeitos não sejam consistentes durante os três anos em análise. Os resultados de ambas as metodologias sugerem impactos contraditórios na eficiência dos bancos europeus.

Palavras-chave: Basileia III, Liquidity Coverage Ratio, Common Equity Tier 1, Método dos Quadrados Mínimos, Análise de Dados em Envelope, Eficiência Técnica

Acknowledgement

I would like to express my gratitude to my supervisor, Raquel M. Gaspar, for the continuous guidance and counselling given during my research project. Her supervising method and rules have been crucial in establishing priorities and carrying on with my research.

My friends and family have given me support at all times.

I want to specially thank Pedro Cananão for the advice and friendship in the most challenging phases of my research. His help was also crucial on learning *latex* to write my MFW.

I want to thank my father, Emérico Gonçalves, for the valuable advice and patience which helped me tackle difficulties and challenges in my research work.

Finally, I want to thank Eduardo Parreira for the advice, counselling and friendship he showed me when discussing the methodology for my MFW.

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Abbreviations

BCBS	**B**asel **C**ommittee on **B**anking **S**upervision (see page 5)
BCC	**B**anker **C**harnes and **C**ooper (see page 26)
CAR	**C**apital **A**dequacy **R**atio (see page 12)
CCR	**C**harnes **C**ooper and **R**hodes (see page 26)
CDS	**C**redit **D**efault **S**wap (see page 9)
CET1	**C**ommon **E**quity **T**ier 1 (see page 8)
CRS	**C**onstant **R**eturns to **S**cale (see page 27)
CTI	**C**ost **T**o **I**ncome (see page 10)
DEA	**D**ata **E**nvelopment of **A**nalysis (see page 24)
DMU	**D**ecision **M**aking **U**nits (see page 24)
EBA	**E**uropean **B**anking **A**uthority (see page 12)
ECB	**E**uropean **C**entral **B**ank (see page 9)
EU28	**E**uropean **U**nion of the **28** (see page 15)
EVA	**E**conomic **V**alue **A**dded (see page 9)
GDP	**G**ross **D**omestic **P**roduct (see page 16)
GSII	**G**lobal **S**ystemically **I**mportant **I**nstitution (see page 15)
HQLA	**H**igh **Q**uality **L**iquid **A**ssets (see page 8)
LCR	**L**iquidity **C**overage **R**atio (see page 7)
LTD	**L**oan **T**o **D**eposit (see page 12)
NIM	**N**et **I**nterest **M**argin (see page 10)
NPM	**N**et **P**rofit **M**argin (see page 12)
NSFR	**N**et **S**table **F**unding **R**atio (see page 7)
OLS	**O**rdinary **L**east **S**quares (see page 22)
P/B	**P**rice to **B**ook (see page 9)

P/E	**P**rice to **E**arnings (see page 9)
ROA	**R**eturn **O**n **A**ssets (see page 9)
ROAA	**R**eturn **O**n **A**verage **A**ssets (see page 10)
ROAE	**R**eturn **O**n **A**verage **E**quity (see page 10)
ROE	**R**eturn **O**n **E**quity (see page 9)
RAROC	**R**isk **A**djusted **R**eturn **O**n **C**apital (see page 9)
RWAs	**R**isk **W**eighted **A**ssets (see page 5)
TSR	**T**otal **S**hareholder **R**eturn (see page 9)
VRS	**V**ariable **R**eturns to **S**cale (see page 26)

Chapter 1

Introduction

We discuss the Basel III regulatory framework, specifically in terms of *liquidity* and *solvency* binding conditions. We address the potential relationship between the Basel regulation and efficiency in the banking sector.

Basel III is a set of regulatory norms and guidelines issued by the Basel Committee for Banking Supervision (BCBS). It was a response to the flaws found in the second Basel Accord, many of which triggered the economic and financial crisis of 2007.

There are several implications of implementing Basel III regulation on banks. In terms of solvency restrictions, stricter capital requirements force institutions to change their capital composition. Riskier capital instruments are substituted by more secure ones to avoid breaching the regulatory norms. Also, criteria for eligible capital has become more difficult to meet. We use the Common Equity Tier 1 (CET1) ratio as a measure for capital requirements.

As for liquidity, the third Accord introduces required liquidity ratios such as the Liquidity Coverage Ratio (LCR). This ratio is designed to improve liquidity in a short-term scenario characterized by conditions of financial stress.

Many researchers and bank stakeholders argue that the impact of Basel regulation on bank efficiency is a balancing act. Some authors support the argument that these regulatory measures strengthen banks' capital position and help improving future profitability. Others claim the new measures are too rigid and ultimately put a burden on banks and their clients.

We propose two distinct methodologies to analyse the potential link between the recent regulatory measures and bank efficiency – Regression Analysis and Data Envelopment Analysis. The sample used comprises of banking institutions located across the 28 member states of the European Union, several of them being of great systemic importance. We focus on bank-level data from annual financial statements.

The study is structured as follows. Section 2 provides the context for the Basel III regulation and its relation to bank efficiency, while mentioning several authors and their respective studies. Section 3 describes the data used. Section 4 presents the methodology in detail for the Regression Analysis and Data Envelopment Analysis. Section 5 discusses the results. Section 6 refers to the conclusions while identifying limitations and recommendations for future research.

Chapter 2

Context and Literature Review

This study provides an analysis of the potential relationship between solvency and liquidity regulation issued by Basel III and several measures of efficiency.

According to BCBS (2015) each intermediation channel managed by a bank is a source of potential stress. Within those channels of stress there is a *funding* channel and a *liquidity* channel.

Stress scenarios related to *funding* are associated with risks that result from shocks on prices, maturity terms or both. On the other hand, *liquidity* consists on the bank's ability of accounting for unexpected growth shocks by efficiently managing its cash flows and running its operations. *Liquidity* challenges can arise from commitment loans, loan securitization back-ups, liquidity puts and so on.

Funding and *liquidity* are majors indicators of bank efficiency. Efficiency is one of the drivers of bank performance. [ECB (2010)] According to the European Central Bank (ECB), "it refers to the bank's ability to generate revenue from a given amount of assets and to make profit from a given source of income", while minimizing overhead costs.

Efficiency in the banking sector is affected by regulatory constraints in several ways. Regulation restrictions are often very detailed and rigid and as a consequence they can prove not to be very effective. [Chortareas, Girardone, and Ventouri (2012)]

Minimum capital requirements do not account for the risk of holding such capital levels. As a result, some banks can eventually hold an excessive amount of capital compared to their real needs which is costly for both banking institutions and its customers. On the other side of the spectrum, banks with insufficient levels of capital will most likely resort to bankruptcy. Moreover, these restrictions work as incentives for limiting risk-taking behaviour and forgoing viable investment opportunities, leading banking institutions to low efficiency and eventual failure. [Chortareas, Girardone, and Ventouri (2012)] As a consequence, banks can engage in a certain behavior path to avoid breaching the regulatory ratios imposed by supervision authorities At an extreme case, this could lead to a massive deleveraging process and asset fire sales. [BCBS (2015)]

Capital adequacy has always been the main focus point in traditional banking regulation. Basel II introduced liquidity requirements as a guide of good practices rather than actual indicators and benchmarks for liquidity measurement. This was grounded on the belief that imposing liquidity standards based on aggregate supervisory data would never be an effective way to deal with the liquidity management activities of banking institutions. Basel III takes a different approach with the imposition of minimum liquidity ratios that focus both on short-term and long-term perspectives. [Hałaj (2016)] Basel III is a comprehensive set of measures that aims to raise capital adequacy standards far above previous levels and establish global quantitative liquidity rules in the banking system.

Basel III provides a regulatory framework with the intention to strengthen the capital and liquidity of banks. However, Allen, Chan, Milne, and Thomas (2012) argue that authors and banking experts have differing views on the effects of Basel regulation. Some believe that these regulatory measures are rigid and undermine the bank's decision power over their funding and liquidity creation activities. On the other hand, there is a strain of thought which believes stricter liquidity and capital requirements promote banks' efficiency by reducing costs and seizing to obtain an excessive market share. Basel regulation can therefore limit risk-taking behaviour from the management board of a bank.

2.1 The Basel Accords

The Basel Committee for Banking Supervision (BSBS) was created in 1974 by the Central Bank governors of the G10. The reason behind the creation of the Committee was to deal with many market disruptions occurring at that time such as the collapse of Bretton Woods System.

In 1988, Basel I was created as a means to improve the knowledge and quality of supervisory measures in global terms. This Accord introduced the *minimum capital ratio* along with guidelines on capital adequacy. [Gabriel (2016)]

The *minimum capital ratio* was calculated as the ratio between Total Capital and Risk Weighted Assets (RWAs).

$$Minimum\ Capital\ Ratio = \frac{Total\ Capital}{RWAs} \tag{2.1}$$

$$Minimum\ Capital\ Ratio = \frac{Tier\ 1\ and\ Tier\ 2\ Capital}{Assets\ weighted\ by\ credit\ type + Credit\ Equivalents} \tag{2.2}$$

Total Capital comprises of Tier 1 capital and Tier 2 capital. [BIS (2011)] Tier 1 capital consists of common equity shares and retained earnings. It is the bank's core capital. Tier 2 capital is the supplementary capital and includes subordinated debt, hybrid capital instruments, loan-loss reserves and undisclosed reserves.

The minimum capital was set as a percentage of the RWAs . The minimum standard was defined according to the risk level associated with the assets of the bank. At the time, the target capital had to be at least 8% of the RWAs . The first Accord categorized credit risk into three types – on-balance sheet risk, off-balance trading risk associated to derivatives and off-balance non-trading risk. Weights were assigned to each asset according to the asset category and credit assessment.

These regulatory measures focused initially on credit risk. In 1996, market risk was added to Basel I to account for exposure to foreign exchange, traded debt securities, equities, commodities and options.

Basel II was introduced in 2004 with the intention of improving the way capital buffers reflected the underlying risks of banks. It introduced a framework that meant to reflect the idea of balancing risks faced by the bank with the adequate amount of capital that could cover their risk exposure.

The second Accord expanded the rules on capital standards. Two crucial steps to determine the minimum capital requirements were the definition of Total capital, also referred to as Regulatory capital, and the calculation of RWAs. Regulatory capital as outlined by the first Accord remained the same aside from some modifications on the eligible components of Tier 2 capital. The calculation of RWAs consisted of the sum of credit risk-weighted assets and the result of multiplying capital requirements for market risk and operational risk by 12.5 – the equivalent to a 8% minimum capital ratio. [BIS (2006)]

The main goals of this Accord were to make capital allocation more risk-sensitive and to introduce an international framework to deal with the mitigation of different types of risk. However, it had many weaknesses that amplified the financial and economic crisis. One of its major faults was the focus on the individual aspects of banks while disregarding the inter-bank risk and the feedback systemic effects between banking institutions.

In the period between 2009 and 2010, the BCBS issued the first version of the Basel III. The third Accord was a response to deficiencies detected within the financial regulation amid the financial crisis of 2007. Basel III does not substitute the first and second Accords. In fact, it is meant to complement regulation from Basel II while adding regulation on liquidity risk.

Minimum capital requirements will go from 8% to 10.50%. The implementation of Basel III requirements in European banks started in 2013 and will finish by 2019.

The main regulation being implemented and followed through in the coming years relates to the introduction of two global liquidity standards – liquidity coverage ratio (LCR) and net stable funding ratio (NSFR) – and one leverage ratio (LR), while maintaining Basel II's standards on minimum capital requirements with common equity tier 1 (CET1) ratio.

In this study the focus is on the LCR and CET1 ratios, which we now present in more detail. Unfortunately, most banks are still progressively collecting the information needed to report the NSFR and LR measures, so they had to be excluded from this analysis due to the lack of reliable information.

2.1.1 Liquidity Coverage Ratio (LCR)

LCR was created to promote short-term resilience of a bank's liquidity risk profile in the case a stress scenario might occur. The compliance of this ratio ensures banks hold enough liquid assets to bear stressful liquidity conditions under 30 calendar days.

The 30-day scenario consists of a combination of events that can trigger idiosyncratic and systemic risk such as a bank run, loss of funding and outflows of money due to credit downgrading. These shocks are meant to mimic the difficulties faced in the financial crisis of 2007. [BIS (2010)]

By managing their own liquidity resources, banking institutions will be complying with minimum regulatory requirements. Moreover, they ought to develop their own independent stress tests to meet personal liquidity needs.

LCR is calculated as the ratio between the stock of high quality liquid assets (HQLA) and net cash outflows.

$$LCR = \frac{Stock\ of\ HQLA}{Total\ Net\ Cash\ Outflows\ over\ 30\ days} > 100\% \tag{2.3}$$

The HQLA comprise of unencumbered assets that are easily converted into cash without any significant haircuts. They must be of low risk, easily valued and hold a great level of transparency in the exchange market among other criteria. Such liquid assets must also be of a sufficient amount in order to cover any unexpected cash-flow gaps. Deposits and other funding sources which may be lost in a stress scenario are perceived as cash outflows.

LCR was introduced as a quantitative rule in European banks on October 2015. This ratio is meant to surpass 100% which means the bank's most liquid assets are enough to cover all the potential outflows that could arise in a critical situation such as a bank run. The phase-in arrangements consists of an 60% compliance in 2015, a 70% compliance in 2016 and a 80% compliance in 2017.

2.1.2 Common Equity Tier 1 (CET1) ratio

Aside from the proposed liquidity regulation, Basel III includes a revision of capital rules. The fundamental reasons behind this revision were to focus more on risk coverage by reducing counterparty credit risk, eliminate procyclicality on capital measures and introduce countercyclical buffers.

The CET1 ratio is a measure of bank solvency. The best way to analyse capital strength is to measure bank solvency against the bank's assets. In Basel III, a new definition for CET1 ratio was introduced in order to strengthen the capital base of banks with more rigorous criteria of what can be classifiable as eligible capital.

$$CET1\,ratio = \frac{CET1\;Capital}{Total\;Risk\;Weighted\;Assets} \tag{2.4}$$

Capital components of common equity tier 1 (CET1) are for example common equity shares, share premium from common equity tier 1 (CET1) instruments and retained earnings. Aside from new rules for the definition of capital, two capital buffers are introduced – a Capital Conservation Buffer and a Counter-cyclical Buffer. By January 2018, these buffers will add up as further milestones to the minimum capital requirements set by target capital ratios. For the case of CET1 ratio and during the period in analysis (2014–2016), the minimum objective was to hit the 4,5%. The Conservation Buffer was applied for the first time in 2016 with additional 0,625%.

2.2 Efficiency in the Banking Sector

According to the ECB (2010), efficiency is typically referred as the ability of generating profit out of a certain level of income or a certain amount of assets.

Financial ratios are the simplest forms of assessing efficiency. These financial indicators are used by different stakeholders in order to assess the performance of a bank through different angles.

To evaluate the performance of banking institutions, the ECB classifies several measures into three groups – traditional, economic and market-based indicators. Measures are classified according to the focus given by the stakeholders when evaluating the performance of a banking institution. Traditional measures apply to most industries. Examples of traditional measures of performance are the return on equity (ROE), return on assets (ROA), cost to income (CTI) and, specifically for the banking sector, net interest margin (NIM). Economic measures of performance are associated with shareholder value creation and with analysis of the economic results of a company. Metrics like the Economic Value Added (EVA) and the Risk-Adjusted Return on Capital (RAROC) classify as economic measures. Market-based measures are based on how the market perceives the value of the company in question. These metrics compare market value with estimated or economic value. The most common ones are Total Shareholder Return (TSR), Price over Earnings Ratio (P/E), Price to Book Value (P/B) and the Credit Default Swap (CDS).

Following Gabriel (2016) and Angora and Roulet (2011), this study relies on traditional measures of performance. Economic and market-based indicators are not as easily available.

Thus, we consider the following ratios as measures of efficiency:

- Return on Average Assets (ROAA) - measures how efficient is the management of the banks' average amount of assets;
- Return on Average Equity (ROAE) - measures the amount of profit generated from the average of shareholders' equity;
- Net Interest Margin (NIM) - Performance metric that illustrates how a bank earns return from its retail and financial intermediation activities;
- Cost to Income (CTI) - Efficiency measure that entails the costs of running a bank in comparison to its operational income.

Traditional accounting ratios are still widely used by banking institutions to assess their performance. In times of prosperity, they are useful measures of bank performance. However, from ECB (2010), it is clear there are several limitations in using these ratios as proxies for bank efficiency. Firstly, these metrics evaluate institutions on an individual level. They are short-term indicators and provide a snapshot of the situation of an institution at a given point in time. Secondly, their interpretation is vague. For example, a high ROE could mean high profitability but could also mean low equity capital. Another reason why they might not be deemed fit to measure efficiency is that they are not adequate in an environment of high volatility. These ratios fail to account for banks' inter-banking relationships that trigger systemic risk and contagion effects which were key factors of the 2007 financial crisis.

In recent literature, efficiency has been estimated with frontier analysis in detriment of simple accounting ratios. See for instance Chortareas, Girardone, and Ventouri (2012).

In these methods, it is often used the concept of *economic efficiency*. Economic efficiency is related to the latter concept of efficiency. It refers to the ability of a firm to make its operations profitable. In general terms, it aims at cost minimization. A prerequisite to understand economic efficiency is *technical efficiency*.

Technical efficiency reflects the optimization process between a set of inputs and the resulting outputs. So as technical efficiency relates to the minimization of inputs to provide an output, economic efficiency is concerned with the currency value of the inputs in relation to the currency value of the output. Frontier estimation methods can be classified according to the shape of the frontier, the estimation technique used and the assumptions used to bridge the gap between observed production and optimal production.[Ouattara (2012)]

This study uses both an approach that relies on accounting ratios and a non parametric method called Data Envelopment Analysis (DEA) to measure technical efficiency. We propose an input-oriented approach based on the minimization of inputs at a given level of outputs.

2.3 Literature Review

Studying the effectiveness of regulatory binding conditions on banks' performance has been a recurring topic in recent years. Ever since its first attempt on tackling capital global standards for banks in Basel I, the BCBS has come a long way in incorporating risk-sensitive capital requirements and improving regulatory standards to fit the risk profile of banking institutions.

After the financial crisis of 2007 highlighted several drawbacks in Basel II, the BCBS decided to issue additional requirements not only focusing on capital but also on liquidity and leverage. Basel III was proposed and detailed in 2010 and the process of gradual implementation began in 2013 with a time horizon for implementation until 2019. In this section we discuss the existing literature that best relates to the effectiveness of the Basel III's new liquidity and solvency constraints and its connection to bank efficiency.

2.3.1 Regression Analysis

Gabriel (2016) studies the impact of a higher proportion of equity set by the third Accord on several measures of performance. He also tests the effects of a dividend policy based on higher dividend payouts. Banks are classified according to European Banking Authority (EBA) guidelines for Global Systemic Importance. The selected variable which represents the capital requirements is the CET1 ratio. Performance is measured using a simple set of accounting ratios used across industries (e.g. ROA, ROE) and industry-specific, such as net profit margin (NPM), loan to deposit (LTD), cost to income (CTI) and net interest margin (NIM). The author concludes CET1 has a positive and significant impact on ROE.

Other studies have focused on liquidity risk management, specifically on the determinants of the new liquidity global standards. In fact, Horváth, Seidler, and Weill (2014) argue there is a negative bi-casual relationship between liquidity creation and solvency. Angora and Roulet (2011) study the relationship between Basel's liquidity indicators, balance sheet indices and macroeconomic indicators. Cucinelli (2013) chooses two liquidity ratios (LCR and NSFR) as dependent variables for two distinct linear panel data regressions, concluding that bank size, capitalization, asset quality and specialization in lending are statistically significant determinants of liquidity risk management.

Other authors have studies on the implications of Basel regulation on the banks' probability of default. Giordana and Schumacher (2012) study the effect of recent regulatory ratios (LCR, NSFR and capital adequacy ratio – CAR) on ROA, capital levels and default. To better understand the impact of these recent regulations, the authors simulate bank behaviour in a maximization problem restricted by balance sheet constraints imposed by the Basel III. They conclude LCR has a statistically insignificant effect on banks' profitability but NSFR seems to have a positive relationship with profitability. Their results support the views of the BCBS which believe the new Basel regulation will positively reinforce capital levels and strengthen the banks' resilience during difficult times specifically those arising from a crisis of liquidity.

2.3.2 Data Envelopment Analysis

According to Cooper, Seiford, and Zhu (2011), Data Envelopment Analysis (DEA) is a data-oriented approach that measures the performance of peer entities denominated as Decision Making Units (DMUs), transforming a set of inputs into a set of outputs. It is a non parametric method which can be applied to the evaluation of banks' efficiency. It was first formally introduced by Charnes, Cooper and Rhodes (CCR) in 1978.

Ray (2014) argues the importance of this methodology dates back from the 1950s. The author mentions Koopmans who addressed the relationship between non-negative prices and quantities in a Walras-Cassel economy, in which he postulated that an increase in the net output of a good could only be considered efficient at the expense of the net output of another good. This was later coined as the Pareto–Koopmans condition for technical efficiency. Pareto, and later, Koopmans were both concerned with analysing prices and quantities to satisfy demand. Farrell, on the other hand, interpreted the Pareto-Koopmans criterion as a way of explaining the relationship between inputs and outputs. [Cooper, Seiford, and Zhu (2011)]

In 1957, Farrell proposed an empirical method to calculate efficiency, using frontier estimation. He designed a model with input and output data of a sample of firms, yielding as a result a numeric score that measures technical efficiency for each individual firm. Farrell recognised the deficiencies of an OLS regression as a production frontier since observed values fell on both sides of the regression. [Ray (2014)]

The first DEA model was introduced by Charnes, Cooper, and Rhodes (1978) (CCR), using Farrell's work as a foundation. They define DEA as a "mathematical programming model applied to observational data", providing a "new way of obtaining estimates of relations – such as production functions and/or efficient production possibility surfaces". [Cooper, Seiford, and Zhu (2011)] Charnes, Cooper, and Rhodes (1978) described the definitions of Extended Pareto-Koopmans Efficiency and Relative Efficiency which will be later discussed in Section 4 – Methodology.

In recent years, researchers have used DEA to measure the performance between a set of homogeneous entities and its connection to exogenous variables. Chortareas, Girardone, and Ventouri (2012) study the dynamics between bank regulatory measures proposed by Basel II and various aspects of banks' cost efficiency and performance. This analysis is conducted in two distinct ways – using simple accounting ratios as proxies for bank efficiency and using frontier analysis with DEA. We follow their methodology in what concerns the selection of some inputs and outputs. They consider personnel expenses, total fixed assets, and deposits and short term funding as inputs and total loans and other earning assets as outputs. The authors use an input-oriented DEA model to measure the inefficiency scores of European banking institutions, under constant returns to scale (CRS). Inefficiency is expressed as

$$Inefficiency = 1 - Efficiency \tag{2.5}$$

.

Following the estimation of inefficiency scores, they study the relationship between the efficiency measures and bank regulation and supervision variables. They opt by Papke and Wooldridge (1996)'s methodology in detriment of OLS and Tobit regressions. They conclude by proving that there is a strong connection between bank regulation and bank efficiency, indicating that strict regulation can decrease efficiency in the banking system. We choose to estimate efficiency scores and consequently use them with Tobit regressions.

Chapter 3

Data

This chapter explains in detail the data collection process and how this information is subsequently used in two different methodologies – Regression Analysis and Data Envelopment Analysis (DEA).

The focus of this study is on European banks taken from the Orbis Bank Focus, previously known as BankScope. This worldwide database gathers banks' annual reports containing detailed information on credit, risk and corporate finance indicators as well as regulatory and supervisory measures. According to Bhattacharya (2003), the database contains valuable and accurate information with little entropy regarding their primary sources.

For the selection of the sample, the following criteria are considered. Eligible banks are active and hold operations in one of the 28 members of the European Union (EU28) during the period in analysis. The period in analysis comprises of 3 years, from 2014 to 2016, coinciding with the period in which the European Banking Authority (EBA) disclosed an annual list of Global Systemically Important Institutions (GSII). A GSII is a banking institution whose failure triggers systemic ripple effects in the financial system. Furthermore, we only consider banks with available reported data on two solvency and liquidity regulatory ratios – liquidity coverage ratio (LCR) and common equity tier 1 (CET1) ratio. Following these criteria, 5415 institutions are active banks from the EU28, but only 90 banks are reporting the LCR and CET1 ratios simultaneously, during the three-year period. Data is organized by year in independent data sets.

3.1 Regression Analysis

We run simple linear regressions on cross-sectional data to analyse the relationship between the regulatory ratios and bank efficiency. For efficiency in the banking sector, we consider the four measures mentioned in the previous chapter, namely ROAA, ROAE, CTI and NIM. They are used as dependent variables in the regressions. Each dependent variable is regressed against the regulatory ratios from Basel III – LCR and CET1 ratio. Additionally, to account for country differences, the gross domestic product (GDP) annual growth rate is also included as an independent variable.

Table 3.1: Regression Analysis – Summary Statistics for a sample of 90 Banks (2016)

Variable	Observations	Mean	Standard Deviation	Minimum value	Maximum value
ROAA	90	0.58	0.64	-1.42	3.40
ROAE	90	7.17	6.31	-16.71	26.46
NIM	90	1.74	1.30	-0.099	8.23
CTI	90	67.68	22.31	12.54	144.67
LCR	90	211.72	139.37	1.78	709.00
CET1	90	19.18	19.57	7.85	168.30
GDP	90	2.06	1.03	1.10	6.10

The summary statistics for the sample of 90 banks confirms the presence of outliers in the sample. The mean of each variable is extremely high compared to what is to be expected given the nature of these metrics. For example, the LCR was designed to ensure that institutions are meeting their short-term liquidity obligations in a 30-day scenario. At the time of implementation, the ratio was set up to a minimum of 100 percent. Yet, in 2016, the mean value of our observations stands at 211.72%. Standard deviation values are also too high, indicating high dispersion relative to the mean.

The existence of outliers in our sample leads to biases in the regression parameter estimation. We decide to remove them from the sample. In order to remove the outliers from the data, cutoff values are applied to every variable showcasing extreme values. Hence, all banks with observations of the LCR above 400% and of the CET1 ratio above 50% were removed from the sample. Banks with extreme values of ROAA and CTI are also eliminated. As a result, 17 banks are removed from the sample.

Table 3.2: Regression Analysis – Summary Statistics for a sample of 73 Banks (2016)

Variable	Observations	Mean	Standard Deviation	Minimum value	Maximum value
ROAA	73	0.51	0.49	-1.42	1.61
ROAE	73	7.07	5.76	-16.71	18.72
NIM	73	1.58	0.85	-0.099	4.04
CTI	73	70.46	21.25	21.27	144.68
LCR	73	171.61	69.75	49.00	392.62
CET1	73	15.78	4.37	7.85	27.95
GDP	73	2.06	1.06	1.10	6.10

From a final sample of 73 banks, the data collected consists of a data set of 511 observations for 2015 and 2016. In 2014, we have one missing value for the variable CTI due to lack of available data in Bank Orbis Focus. Therefore, we have a total of 510 observations in this year. A substantial data sample provides more accurate estimates of the descriptive statistics tools. In addition, 27.27% are considered GSII in each year.

The summary statistics for 2014 and 2015 can be found on Tables A.4 and A.5 of the Appendix. The average value of the LCR increases over the period of 2014 to 2016. This may be justified by the fact that the implementation phase for LCR started in 2013 and the compliance ratios for each year have been increasing thus far. The CET1 ratio also grows over time but its increase is not so significant.

During the same time period, average values of ROAA and ROAE increase as well. The direction of growth for the NIM and CTI varies over the three year-period.

While comparing Table 3.1 and 3.2, the dispersion relative to the mean value of LCR and CET1 has decreased considerably. The minimum and maximum values for all variables are also far more acceptable in comparison.

In terms of correlation between variables, in 2016, the LCR is positively correlated with the ROAA, ROAE, NIM and CTI. In 2015, it has a negative correlation with CTI. In 2014, it is negatively correlated with ROAA and ROAE but positively correlated with NIM and CTI.

The CET1 and the GDP rate appear to have individually a negative relationship with CTI. NIM is only negatively correlated with CET1. Aside from LCR in 2014, ROAA and ROAE have a positive relationship with all independent variables. This analysis by itself, however, does not imply that the regulatory ratios and the GDP have any impact on the efficiency ratios.

From the graphic analysis, it is important to recognize a few things. For the variable CET1 the histogram seems to resemble a bell-shaped form in 2014 and 2016. In 2015, the histogram appears to be double peaked. Regarding the LCR, data is right skewed in the three years. From examining the scatter plots between each efficiency measure and each independent variable, most of the graphs show great variation in the sample. From the scatter diagram between CTI and CET1 and NIM and CET1 we can assume a moderate negative correlation. The scatter plots associated with GDP resemble horizontal lines. This is because more than one bank can be affected by the same GDP rate.

From analysing the boxplots over the three years, we notice a few extreme values that stand out from the data distribution. We assume all the outliers which may have been caused by data errors have been removed from the sample. We assume all the remaining outlying observations are caused by inherent variability of the data. For example, a GDP rate of 26.30% of Ireland in 2015 may be an outlier in the set of observations but it is a plausible and factual observation.

3.2 Data Envelopment Analysis

As an alternative to simple accounting ratios, we propose a methodology to compute efficiency in the banking sector based on Data Envelopment Analysis (DEA). In this methodology, efficiency is a score measured in a scale from 0 to 1. A Decision Making Unit (DMU) is deemed inefficient if the efficiency score given by the optimal value is less than 1. If it is equal to 1, the DMU is considered efficient, laying on the efficient frontier.[Cooper, Seiford, and Zhu (2011)]

As developed by Chortareas, Girardone, and Ventouri (2012), we follow the authors' methodology regarding the estimation of the efficiency scores. They propose an input-oriented DEA model under constant returns to scale to measure the efficiency of European banking institutions. Each bank is associated with an efficiency score whose value is measured by the relative distance to a best practices' efficient frontier.

For the data collection process, Chortareas, Girardone, and Ventouri (2012) consider the approach of Berger and Humphrey (1997). Banks utilize labour, fixed assets and deposits to produce loans and earning assets. In our sample we choose to simplify our model specification as to minimize two inputs in order to produce two outputs. Thus, for each year in analysis, we collect data on Personnel Expenses and Deposits and Short-term Funding that serve as inputs. For the outputs, we gather information on Gross Loans and Other Earning Assets. The descriptive statistics for 2014, 2015 and 2016 can be found on table A.20, A.21 and A.22 of the Appendix.

Chapter 4

Methodology

As a starting point for this study, two hypotheses are made on the impact of Basel III restrictions on banks' efficiency, namely:

- H1 - Liquidity and solvency constraint ratios have an impact on measures of efficiency;
- H2 - Liquidity and solvency constraints have a negative impact on measures of efficiency.

We consider two different methodologies to tackle these hypotheses:

- Multiple OLS regressions using several accounting ratios as proxies for efficiency;
- A non parametric method that relies on the estimation of an efficient frontier to compute bank efficiency scores. This is followed by a second-stage Tobit regression.

4.1 Regression Analysis

As to study the implications of Basel III regulatory constraints on the efficiency of European banks, several multiple linear regressions are used to test the existence of a relationship between liquidity and solvency ratios and several measures of performance (H1) and to verify whether this relationship is negative or otherwise (H2).

We propose a multiple regression analysis since our objective is to analyse the potential impact of two regulatory ratios on bank efficiency, while also accounting for GDP. Allowing for multiple variables to explain the independent variable y is crucial to be able to analyse the *ceteris paribus* effect of every single explanatory variable added to the model.

The generic form of a multiple linear regression model is given by:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_k x_k + u \tag{4.1}$$

The intercept parameter represents the estimated value for when all independent variables x are zero. In this case, this is rather a nonsensical scenario because regulatory ratios and the GDP rate could never be zero. Nevertheless, the intercept is essential to obtain a prediction of the independent variables. The slope parameters reflect the partial or *ceteris paribus* effect of the independent variables x included in the model. It represents the percentual change in bank efficiency given by the change in LCR, CET1 and GDP, all other factors fixed.

Following the study of Gabriel (2016), the objective is to explain bank efficiency in terms of the LCR, the CET1 and the GDP rate. For that purpose, we derive several regressions separately, which differ in the accounting measures chosen as proxies for efficiency.

$$ROAA = \beta_0 + \beta_1 LCR + \beta_2 CET1 + \beta_3 GDP + u \tag{4.2}$$

$$ROAE = \beta_0 + \beta_1 LCR + \beta_2 CET1 + \beta_3 GDP + u \tag{4.3}$$

$$NIM = \beta_0 + \beta_1 LCR + \beta_2 CET1 + \beta_3 GDP + u \tag{4.4}$$

$$CTI = \beta_0 + \beta_1 LCR + \beta_2 CET1 + \beta_3 GDP + u \tag{4.5}$$

The β_0, β_1 and β_2 are the parameters of the regression and u is the error term or disturbance. Each regression is run with data observations of three consecutive years – 2014, 2015 and 2016 which correspond to the three-period in analysis. To yield the estimates for the parameters of the model, we use the Ordinary Least Squares (OLS) regression method. In the Equation 4.6 we present the general form of a fitted OLS regression line.

$$\widehat{y_i} = \beta_0 + \widehat{\beta_j} x_i + \widehat{\epsilon_i} \quad i = 1, ..., n \quad j = 1, ..., m \tag{4.6}$$

The estimates of β_0 and β_j are the OLS estimates of the intercept and slope parameters.

In the Equation 4.6, the residual is the difference between the dependent variable $\widehat{y}$ and the set of explanatory variables $\widehat{x_i}$.

$$\widehat{\epsilon_i} = \widehat{y} - \beta_0 - \widehat{\beta_1} x_i \quad i = 1, ..., n \tag{4.7}$$

In order to obtain the optimal estimates, the OLS criterion is to choose the parameters for which the Sum of Squared Residuals (SSR) reachs a minimum. [Wooldridge (2013)] The SSR function can be expressed as:

$$\sum_{i=1}^{n} (y_i - \widehat{\beta_0} - \widehat{\beta_1} x_1 - \widehat{\beta_2} x_2 - \widehat{\beta_3} x_3) \tag{4.8}$$

For each regression specified above, we can derive mathematically the respective SSR function.

$$\sum_{i=1}^{n} (ROAA_i - \widehat{\beta_0} - \widehat{\beta_1} LCR - \widehat{\beta_2} CET1 - \widehat{\beta_3} GdP) \tag{4.9}$$

$$\sum_{i=1}^{n}(ROAE_i - \widehat{\beta}_0 - \widehat{\beta}_1 LCR - \widehat{\beta}_2 CET1 - \widehat{\beta}_3 GdP) \tag{4.10}$$

$$\sum_{i=1}^{n}(NIM_i - \widehat{\beta}_0 - \widehat{\beta}_1 LCR - \widehat{\beta}_2 CET1 - \widehat{\beta}_3 GdP) \tag{4.11}$$

$$\sum_{i=1}^{n}(CTI_i - \widehat{\beta}_0 - \widehat{\beta}_1 LCR - \widehat{\beta}_2 CET1 - \widehat{\beta}_3 GdP) \tag{4.12}$$

The equations that helps us obtain the estimates for the betas are considered the first order conditions for OLS estimation. From this point of view, OLS regression can be seen as an optimization problem. Thus, by using the method of moments and therefore match the population moments with the sample moments, we can derive the first-order conditions of a minimization problem.

Then, provided the observational values of x in the sample are not all equal, OLS leads to reliable estimates for the *betas*.

In our regression analysis, we begin by estimating the OLS regressions. We test for multicollinearity by computing the variance inflation factors (VIF). A VIF is an index that measures the variance of the estimated coefficients of a regression.

We also test for the presence of heteroskedasticity in the errors with a Breusch-Pagan/Cook-Weisberg test. In the regressions for which heteroskedasticity is present, we estimate robust versions of the regressions.

In an initial removal of banks from the sample, we deal with outlying observations whose causes may have been due to error. For the remaining outliers identified in the descriptive statistics, we use a different type of robust regression estimation which accounts for data contaminated by outliers.

Robust regression is an alternative to the Least Squares estimators, when there is no good reason to exclude the outlying observations from the sample. They provide better results in the presence of outliers since they drop observations with a Cook's distance above 1. Cook's distance is used to identify outliers based on the leverage and residuals in a regression. After detecting and dropping the outlying observations, the regressions are run based on Huber iterations in which the observations' weights are computed based on the absolute residuals of the regression. To compare both estimation methods, OLS and robust regression, we run both types of regressions for each year in analysis.

4.2 Data Envelopment Analysis

Data Envelopment Analysis (DEA) is a non parametric linear programming method used to empirically measure technical efficiency of decision making units (DMU) and to estimate production frontiers. Technical efficiency is a firm's ability of choosing the optimal set of inputs to maximize the production of outputs, provided all inputs and outputs are accurately measured. DMUs are the decision-making entities perceived as the subjects of this methodology. The initial DEA models focused on decision-making rather than profit entities which is how the term DMU was created. On subsequent years, however, the term began to be applied to the private sector as well. It has been used in recent years to evaluate efficiency of public and private sectors such as the banking sector. Banks can be treated as DMUs when they are assumed to be homogeneous units with the same or similar business objectives and activities.

Non parametric methods measure efficiency in relative terms in a scenario incorporating multiple inputs and outputs. Efficiency consists in comparing the current position of a unit to what is generally considered to be the best possible outcome. In graphical terms, this is measured as the relative distance to a best-practices efficient frontier. A DMU is considered efficient if it manages to minimize inputs given a certain output level (input-oriented approach) or to maximize the output given a certain level of inputs (output-oriented approach). We choose to focus on an input-oriented methodology.

In this case, the proxy for efficiency in the banking sector consists of DEA efficiency scores. Our sample comprises of 73 DMUs which use 2 inputs – personnel expenses and deposits and short-term funding – to produce 2 outputs – gross loans and other earning assets. The procedure that follows is to produce and interpret the DEA efficiency scores and subsequently use them as independent variables in statistical inference.

DEA has emerged as a valid alternative to regression analysis for efficiency measurement. [Ray (2014)] It does not specify any specific relationship between inputs and outputs. The production function does not rely on any explicit form, aside from convexity of the possibility set. Instead, several general assumptions are made regarding the production technology that leads to the definition of the production possibility set. Thus, a set of assumptions can be considered to support our DEA model:

- Convexity - The efficient frontier is convex towards the axis;
- Free Disposability - Banks generate the same output by wasting resources or increase the output level without increasing resources;
- Economies of Scale;
- Piece-wise linear Method - The frontier is identified and traced through a piece-wise linear function;
- Input-Orientation - Our model consists of minimizing inputs while taking in account a certain output level.

Skeptics believe there are several drawbacks on considering DEA a viable option, namely:

- The typical analysis within the scope of Economics usually involves marginal analysis, elasticities and so on which cannot be performed due to the lack of a parametric form;
- DEA employs linear programming instead of Least Squares regressions which are still far more common in Economics;
- Any deviation from the efficient frontier is deemed inefficiency. Thus, the DEA framework can be viewed as a more unstable method since it does not allow for random shocks.

Indeed, the non stochastic nature of DEA is seen as a limitation of this methodology. However, DEA is far too complex to fit its multiple inequality constraints into the stochastic properties of parametric models. [Ray (2014)] Nevertheless, recent research has been trying to converge stochastic methods with non parametric methods such as DEA but we consider them to be out of the scope of this study.

The first DEA model, denominated CCR, was pioneered by Charnes, Cooper, and Rhodes (1978) (CCR). DEA models can be classified in terms of returns to scale represented in the weight constraints added to the model. [Ji and Lee (2010)] The original model only considered technologies with constant returns to scale (CRS), in which all DMUs are operating at their optimal scale. [Ray (2014)]

$$(x, y) \in T \Rightarrow (kx, ky) \in T \ \forall \ k \leq 0 \tag{4.13}$$

This was further extended to incorporate variable returns to scale (VRS) in a study developed by Banker, Charnes, and Cooper (1984) (BCC).

Both CCR and BCC models are labeled ratio models because they define efficiency as a ratio of weighted outputs over weighted inputs.

$$Efficiency = \frac{Output_1 \times weight_1 + Output_2 \times weight_2 + ...}{Input_1 \times weight_1 + Input_2 \times weight_2 + ...} \tag{4.14}$$

Each output to input ratio of each DMU is then compared to the value of the ratio observed in other DMUs. DEA offers insight regarding the value of the weights. These reference weights are the weights necessary for the inefficient DMUs to reach Pareto-Koopmans efficiency.

$$Efficiency = \frac{Gross\ Loans \times weight_1 + Other\ Earning\ Assets \times weight_2}{Deposits \times weight_1 + Personnel\ Expenses \times weight_2} \tag{4.15}$$

In the equation above, we consider *Deposits* to be the sum of Deposits and Short-term Funding.

It is important to analyse efficiency in graphical terms since the efficiency score of each DMU is perceived as the relative distance to the efficient frontier.

In turn, inefficiency is measuring how much the inputs must contract along a ray until reaching the frontier. [Ji and Lee (2010)] When technology exhibits constant returns to scale (CRS), input and output-oriented radial measures of technical efficiency are identical. Under VRS, this equality no longer holds. We opt by an input-oriented CRS model as it is recommended by referenced authors. Productivity and technical efficiency are closely related but still different measures of performance of a firm. If we assume CRS, then they are equal.

The production possibility set of a firm producing output vectors y from input vectors x can then be described as:

$$T = \{(x, y) : x \in R_n^+; y \in R_m^+;\ y\ can\ be\ produced\ from\ x\} \tag{4.16}$$

For a input-output bundle to be considered feasible it has to belong to the opportunity set. Regarding efficient bundles, the efficient frontier can be expressed as:

$$G = \{(x, y) : (x, y) \in T; \alpha > 1 \Rightarrow (x, \alpha y) \notin T; \beta < 1 \Rightarrow (\beta x, y) \notin T\} \tag{4.17}$$

Any bundle deemed efficient should be:

$$\tau_x = \theta^* = min\theta : (\theta x, y) \in G, \quad \theta^* \leq 1 \tag{4.18}$$

Hence, for a given DMU_i, we have an envelope formulation:

$$\begin{gathered}
min\ e_j = \theta_0 \\
subject\ to \\
\theta_0 x_{ij_0} \geq \sum_{j=1}^{n} \lambda_j x_{ij}\ , i = 1, ..., m \\
y_{rj_0} \leq \sum_{j=1}^{n} \lambda_j y_{rj}\ , r = 1, ..., s \\
\lambda_j \geq 0\ , \forall j
\end{gathered}$$

There are two conditions a DMU must satisfy to be considered efficient – the DEA score must equal 1 and all *slacks* must be 0. A *slack* is the additional improvement needed for a DMU to become efficient. Thus, if the DMU meets these two conditions it is considered efficient in terms of Pareto-Koopmans efficiency. In Pareto-Koopmans efficiency or strong efficiency, a DMU needs to fully utilize its inputs to reach its full potential of production. An input-output bundle will not be considered Pareto-Koopmans efficient if it violates the following propositions:

- Increasing the amount of any output occurs at the expense of decreasing another output or increasing an input;
- Decreasing the amount of any input occurs at the expense of decreasing another input or increasing an output.

A DMU can still be called efficient in terms of *technical efficiency* if the DEA score equals 1. When only this condition is pursued, the DEA model used should be called a single-stage DEA model.

In this study, we propose an input-oriented, two-stage DEA model with constant returns to scale to tackle the two conditions and reach the Pareto-Koopmans or Strong Efficiency.

Subsequently, the efficiency scores are included as dependent variables in a second-stage regression using Tobit Regression analysis. A Tobit model is a censored regression model which means the underlying variables have a left or right censoring limit. Efficiency scores have a truncated nature since they are constrained to a [0,1] range. OLS models could never be deemed adequate because when variables are censored, OLS provides inconsistent estimates of the parameters. [McDonald (2009)]

Chapter 5

Results

This chapter is dedicated to the expression, interpretation and discussion of the results obtained in each methodology pursued. In order to study the potential relationship between the recent regulatory ratios and bank efficiency, we consider bank-level data from 73 institutions located across the EU28. Prior to conducting each analysis, the sampling data was collected from Orbis Bank Focus and then trimmed to remove several outlying observations. Data is organized in three different data sets each corresponding to a year in the three-period analysis.

5.1 Regression Analysis

For the Regression Analysis, several OLS regressions are derived with each performance ratio –ROAA, ROAE, NIM and CTI – as a dependent variable.

As previously mentioned, simple accounting ratios have vague interpretations, only consider short-term scenarios and are not very risk-sensitive. However, these traditional measures are still widely used in valuation and business decision-making and, more specifically, have been used to analyse the effects of Basel III in bank profitability.

Over the course of the three years, LCR is either positive and statistical significant or insignificant. In the first two consecutive years, the ratio presents a more significant effect in bank performance.

Minimum capital requirements are represented by CET1 ratio. In all regressions, this solvency ratio is negatively related to NIM and CTI. Regarding its relationship with ROAA and ROAE, it is only positive and statistically significant in 2014.

Effects of economic growth of the countries where banks are located in are accounted for with the inclusion of the GdP rate. Generally, this variable is not statistically significant in explaining bank efficiency during the three years in analysis. Its intepretation is ambiguous. In 2015, it is only statistically significant regarding ROAA with a positive yet minimal effect. In 2016, it is positively related with ROAA and NIM but negatively related with CTI.

Aside from statistical significance and interpretations of the regression coefficients, it is important to analyse the goodness-of-fit of the estimation of the regression model – mainly how well the regression model fits the observed data. R-squared allows us to measure the percentage of variation of the dependent variables that can be explained by the estimated model. For the most part, the estimated regressions do not have a great explaining power but it could be related to the fact that few explanatory variables are added to the regression model. It does not imply misspecification of the model since adding more variables, regardless of the relevance, would always increase the R-squared. Furthemore, it does not mean the OLS regressions do not provide reliable estimations and it only refers to the correlation between independent variables and the dependent variable y. [**?**)]. Moreover, the R-squared indicators presented in this study are in line with the literature review.

Regarding problems that usually arise in regression models, none of the regression models suffers from perfect collinearity. Heteroskedasticity is corrected with robust versions of the standard errors of the regressions.

We explain in earlier chapters that the presence of outliers is likely related to two causes – data errors and inherent variability of the data. The robust regressions based on Huber iterations are run to account for the presence of outliers. We find that in most cases the results are very similar to the ones provided by OLS regressions.

This empirical study is grounded on two hypotheses initially presented – that regulatory ratios have an impact on bank efficiency separately (H_1) and that this impact is negative (H_2). Thus, we do not account for the joint effect of these variables in the sense of the feedback effects between solvency and liquidity that could in turn have an impact on bank efficiency. We are, however, analysing the individual effect of the regulatory measures.

The Basel III liquidity requirements seem to have a positive impact on most of the efficiency ratios, aside from some exceptions. This could be because, regardless of the drawbacks of Basel III highlighted in this study, the LCR reduces banks' dependence over the liquidity inter-bank market. Concerning solvency, the CET1 ratio is mostly negatively related to efficiency measures which corroborates our view.

5.2 Data Envelopment Analysis

To surpass the limitations of traditional performance ratios, we propose a linear programming method called DEA based on an input-oriented analysis of efficiency scores under constant returns to scale.

In our results, DMUs are organized according to a rank which is assigned based on the associated efficiency score. Each score is represented by θ and consists of the optimal solution closest to the efficiency frontier. We present information regarding not only the efficiency scores but also the reference points and slacks.

Throughout the three years, we find that Bank Nederslande Gemeenten and Bank AKA Ausfuhrkredit are the most efficient banking institutions. They are also references for all the other DMUs to reach efficiency. In this sense, they are perceived as bench-marking targets. These banks have an efficiency score of 1.

The most inefficient bank is Saxo Bank, ranking last in the three years in analysis. In 2014 it has an efficiency score of 0.015, in 2015 of 0.0119 and in 2016 of 0.0066.

Our results also contain information regarding slacks and reference weights. They are important to identify the main causes of inefficiency and how it can be improved in terms of reduction of inputs or increase of outputs. As an example, in order to improve its efficiency, Saxo bank should reduce 1588.81 units of Personnel Expenses even after reducing all inputs by 98.5% (1-0.015), in the year of 2014.

Regarding limitations of the DEA computation, we find that in each year to a few institutions it has not been assigned an efficiency score. Thus, we do not present an efficiency measure for these banks.

To analyse the determinants of efficiency we propose a second-stage analysis based on Tobit regressions. Efficiency scores are right censoring or truncated data as they only go up to 1. In the three-years-period, the CET1 ratio is positively related to bank efficiency at a 5% level of significance in the first two years and at 1% level of significance in 2016. LCR is only significant in 2016, showing a negative relationship with a 5% significance level. Overall, the conclusions taken from Tobit estimation do not coincide with the argument of regulatory ratios negatively affecting efficiency in banks. The CET1 ratio has a positive albeit minimal effect in explaining banks' efficiency scores.

Chapter 6

Conclusion

In this study we propose two distinct methodologies to assess efficiency in the banking sector. We test the significance of recent Basel III regulatory ratios as determinants of bank efficiency. Our data sample consists of 73 banking institutions located across the EU28, several of them being of great systemic importance. The period in analysis is from 2014 to 2016.

Our methodologies differ in the way efficiency is perceived. In Regression analysis, we derive multiple linear regressions based on Ordinary Least Squares estimation. In our findings, the minimum capital ratio CET1 is mostly negatively related to efficiency when measured by simple accounting ratios. On the other hand, short-term liquidity requirements represented by LCR seem to have a positive effect on bank performance.The GDP rate is not very significant across the three years.

After identifying several limitations of accounting ratios, we propose a linear programming method called Data Envelopment Analysis (DEA). Under DEA, we derive efficiency scores relative to a best practices efficient frontier. These measures are then regressed against the solvency and liquidity ratios as well as the GdP rate.

Contrary to what we find in the first methodology, results obtained from DEA second-stage Tobit regressions suggest a positive but not very relevant relationship between CET1 ratio and the efficiency scores. LCR is for the most part insignificant but it is negatively related to efficiency in 2016. A common factor within both methodologies is the lack of significance of LCR in explaining efficiency.

Our initial hypotheses are not exactly corroborated through our main research findings. Indeed, there seems to exist a relationship between the Basel supervisory measures and bank efficiency but this relationship appears rather trivial or arising from random causes. Regulatory variables do not show a trend across the three years in analysis. At times, the impact of these variables is very reduced and nearly insignificant.

A major limitation of this research is the sampling data used. Many of the data observations were considered extreme and lying far outside in the data distribution. While a great part of the outlying observations were taken out from the sample, some observations remained because they seemed to be legitimate data arising from natural causes or facts.

Basel III phase-in arrangements for the compliance of regulatory ratios are still taking place and several institutions still fail to accurately report these binding conditions. LCR and CET1 ratio are still experimental ratios that are continuously suffering changes in criteria or calculation method and their full implementation will only finish by 2019. Hence, for future research, it is interesting to apply these methodologies to a future time period following the full implementation and reporting of these indicators. It can be also interesting to analyse bank efficiency with panel data to allow for dynamic relationships and to model unobserved differences across banking institutions.

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Appendix

Appendix A

Data

A.1 Regression Analysis

Table A.1: Correlation Matrix table for 73 banks (2014)

	ROAA	ROAE	NIM	CTI	LCR	CET1	GdP
ROAA	1.000						
ROAE	0.9318	1.000					
NIM	-0.2535	-0.3126	1.000				
CTI	-0.2487	-0.2990	-0.1237	1.000			
LCR	-0.2173	-0.1838	0.2973	0.0633	1.000		
CET1	0.2482	0.1829	-0.1608	-0.3273	0.1588	1.000	
GdP	0.0439	0.0505	0.0656	-0.0802	0.1071	0.0852	1.000

Table A.2: Correlation Matrix table for 73 banks (2015)

	ROAA	ROAE	NIM	CTI	LCR	CET1	GdP
ROAA	1.000						
ROAE	0.8834	1.000					
NIM	-0.0501	-0.0516	1.000				
CTI	-0.4670	-0.5782	0.0761	1.000			
LCR	0.3109	0.2581	0.1920	-0.0761	1.000		
CET1	0.0952	0.0314	-0.3040	-0.2454	0.3252	1.000	
GdP	0.1969	0.1555	0.0821	-0.1407	-0.0559	0.0266	1.000

TABLE A.3: Correlation Matrix table for 73 banks (2016)

	ROAA	ROAE	NIM	CTI	LCR	CET1	GdP
ROAA	1.000						
ROAE	0.8517	1.000					
NIM	0.3055	0.1674	1.000				
CTI	-0.6082	-0.6877	-0.1244	1.000			
LCR	0.1895	0.1491	0.1218	0.090	1.000		
CET1	0.1932	0.1317	-0.2285	-0.3252	0.2515	1.000	
GdP	0.2575	0.1539	0.1621	-0.2554	0.1399	0.2952	1.000

TABLE A.4: Summary Statistics for a sample of 73 banks (2014)

Variable	Observations	Mean	Standard Deviation	Minimum value	Maximum value
ROAA	73	0.2665	0.7523	-4.354	1.764
ROAE	73	4.3109	8.7034	-45.308	17.094
NIM	73	1.6586	0.9151	0.294	4.494
CTI	73	70.918	19.1215	33.448	132.814
LCR	73	147.1489	55.5422	62	345
CET1	73	14.2027	3.678	6.28	26.03
GdP	73	1.7658	1.6274	-1.5	8.5

TABLE A.5: Summary Statistics for a sample of 73 banks (2015)

Variable	Observations	Mean	Standard Deviation	Minimum value	Maximum value
ROAA	73	0.4412	0.5976	-1.855	1.553
ROAE	73	6.5851	6.7418	-15.793	18.667
NIM	73	1.6792	0.8901	0.2	4.306
CTI	73	68.541	18.2173	22.736	129.069
LCR	73	152.5384	51.9160	76	298
CET1	73	15.4704	4.3894	7.17	28.84
GdP	73	2.5836	4.1362	0.3	26.3

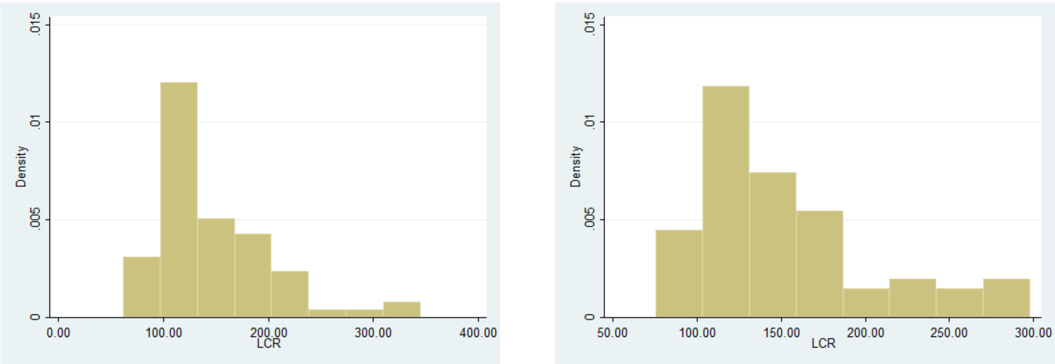

FIGURE A.1: Histogram for LCR (2014 and 2015)

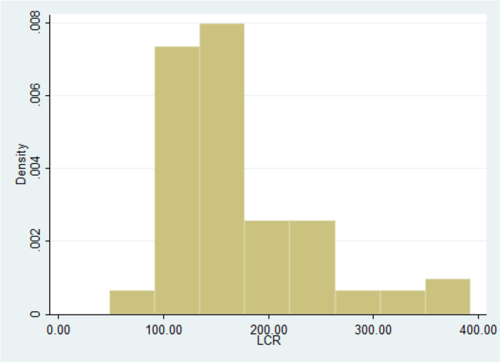

FIGURE A.2: Histogram for LCR (2016)

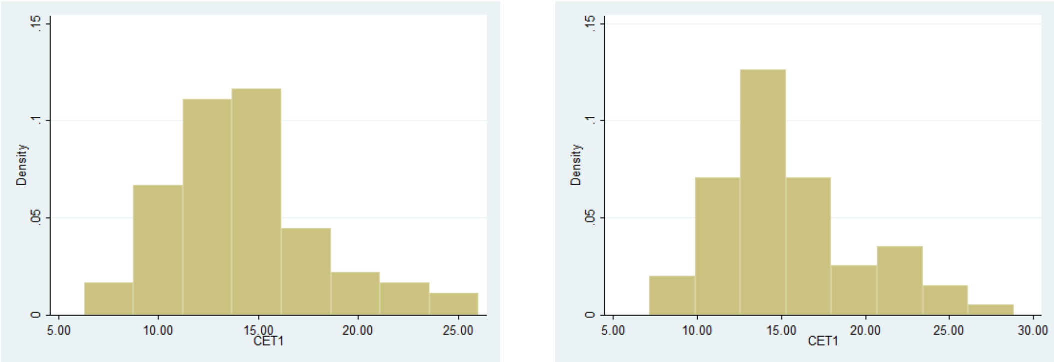

FIGURE A.3: Histogram for CET1 (2014 and 2015)

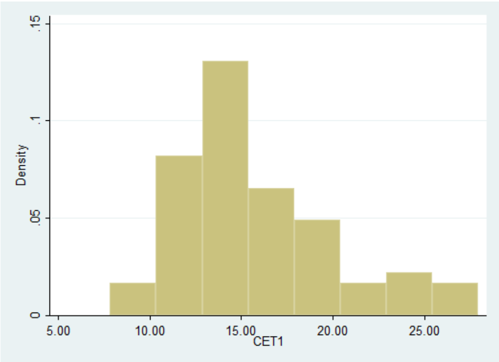

FIGURE A.4: Histogram for CET1 (2016)

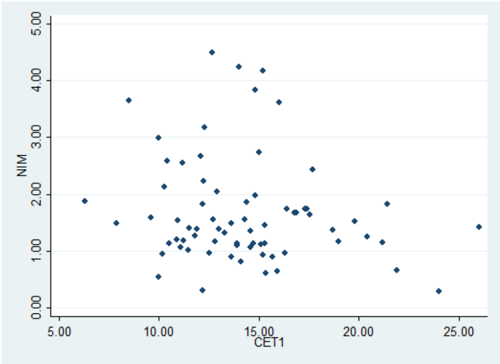

FIGURE A.5: Scatter Diagram between NIM and CET1 (2014)

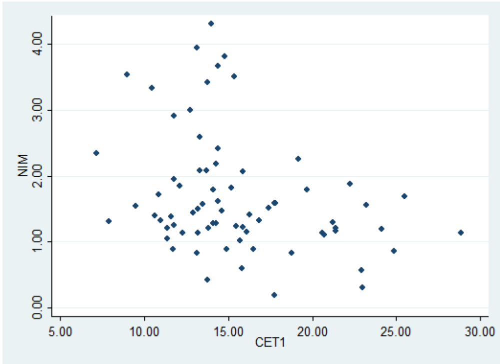

FIGURE A.6: Scatter Diagram between NIM and CET1 (2015)

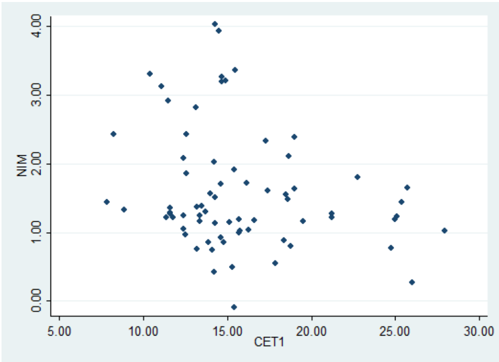

FIGURE A.7: Scatter Diagram between NIM and CET1 (2016)

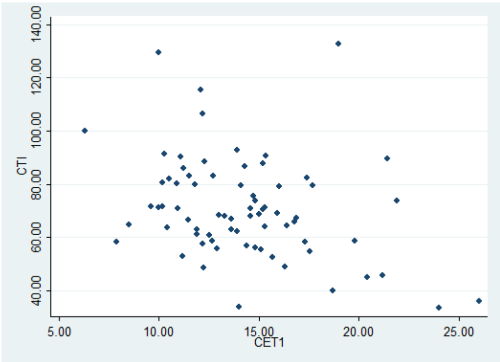

FIGURE A.8: Scatter Diagram between CTI and CET1 (2014)

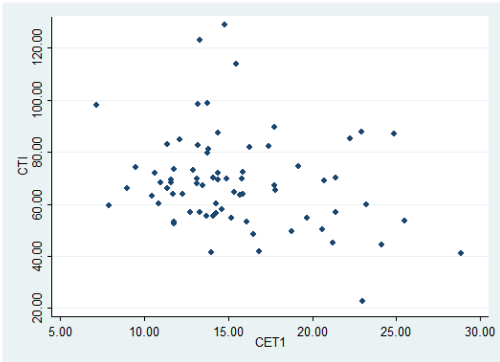

FIGURE A.9: Scatter Diagram between CTI and CET1 (2015)

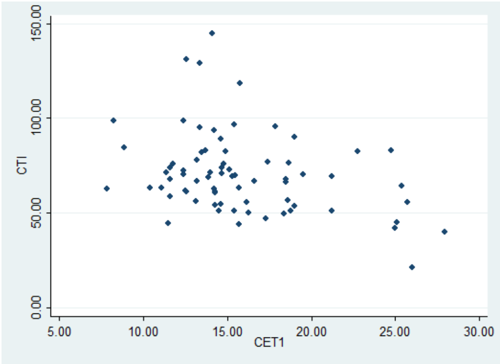

FIGURE A.10: Scatter Diagram between CTI and CET1 (2016)

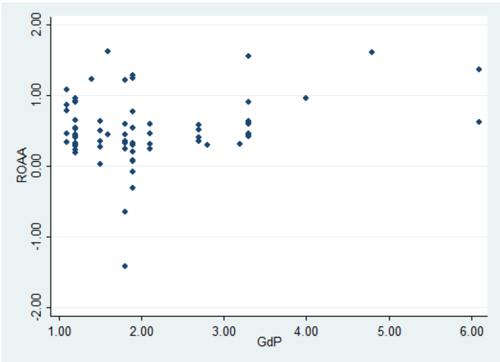

FIGURE A.11: Scatter Diagram between ROAA and GDP (2016)

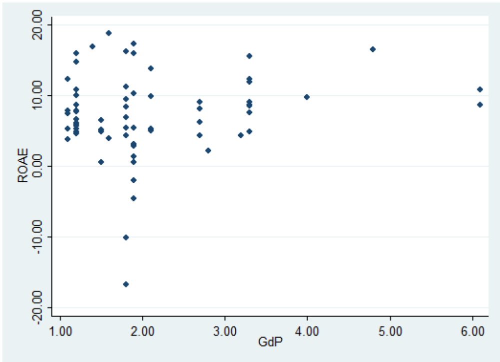

FIGURE A.12: Scatter Diagram between ROAE and GDP (2016)

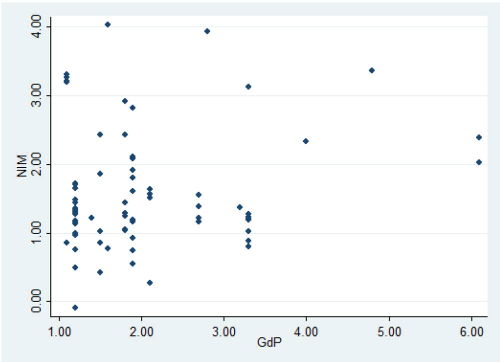

FIGURE A.13: Scatter Diagram between NIM and GDP (2016)

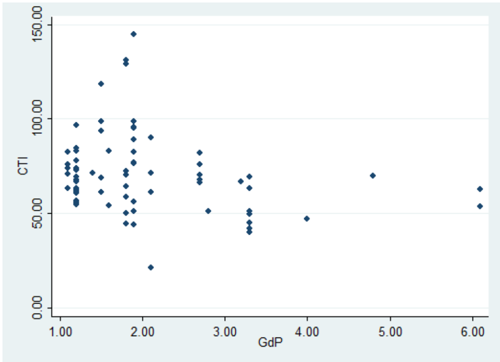

FIGURE A.14: Scatter Diagram between CTI and GDP (2016)

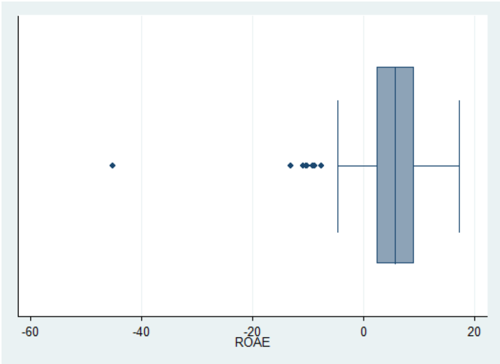

Figure A.15: Boxplot for ROAE (2014)

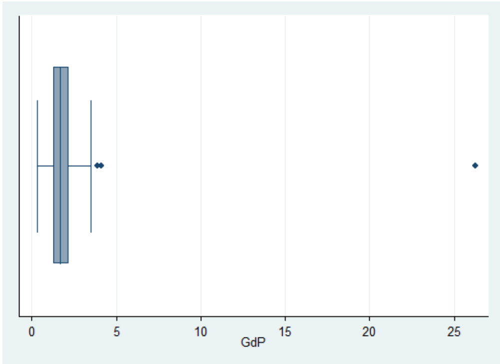

Figure A.16: Boxplot for GDP (2015)

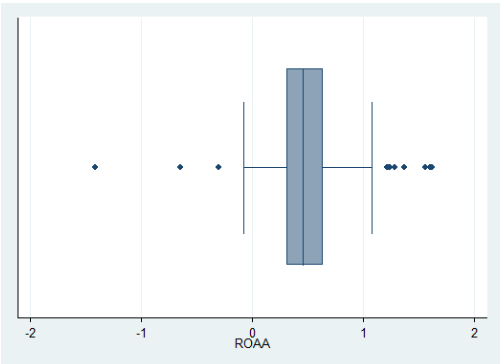

Figure A.17: Boxplot for ROAA (2016)

Table A.6: OLS Regression for ROAA (2014)

ROAA	Coefficients	Standard Errors	t-statistic	P-value
LCR	-0.0034008	0.0029756	-1.14	0.257
CET1	0.0590538	0.0220566	2.68	0.009
GdP	0.0214479	0.041232	0.52	0.605
Intercept	-0.1096328	0.3306528	-0.33	0.741
R-squared	0.1249			

Table A.7: OLS Regression for ROAE (2014)

ROAE	Coefficients	Standard Errors	t-statistic	P-value
LCR	-0.0310372	0.032826	-0.95	0.348
CET1	0.5106388	0.2512563	2.03	0.046
GdP	0.2835521	0.4583403	0.62	0.538
Intercept	1.124859	3.880833	0.29	0.773
R-squared	0.075			

Table A.8: OLS Regression for NIM (2014)

NIM	Coefficients	Standard Errors	t-statistic	P-value
LCR	0.0054488	0.0018761	2.90	0.005
CET1	-0.0535442	0.0282723	-1.89	0.062
GdP	0.0273966	0.0634188	0.43	0.667
Intercept	1.568956	0.4626466	3.39	0.001
R-squared	0.1367			

Table A.9: Illustrative Robust Regression for NIM based on Huber iterations (2014)

NIM	Coefficients	Standard Errors	t-statistic	P-value
LCR	0.0073868	0.0017431	4.24	0.000
CET1	-0.0840969	0.0205915	-4.08	0.000
GdP	0.0299444	0.0206973	1.45	0.152
Intercept	1.678293	0.3565279	4.71	0.000

Table A.10: OLS Regression for CTI (2014)

CTI	Coefficients	Standard Errors	t-statistic	P-value
LCR	0.042698	0.0396073	1.08	0.285
CET1	-1.765058	0.595261	-2.97	0.004
GdP	-0.7520482	1.334591	-0.56	0.575
Intercept	91.04286	9.784545	9.30	0.000
R-squared	0.1248			

Table A.11: OLS Regression for ROAA (2015)

ROAA	Coefficients	Standard Errors	t-statistic	P-value
LCR	0.0037823	0.0013597	2.78	0.007
CET1	-0.0023627	0.016062	-0.15	0.883
GdP	0.0311627	0.0161445	1.93	0.058
Intercept	-0.1796794	0.2781028	-0.65	0.520
R-squared	0.1430			

Table A.12: OLS Regression for ROAE (2015)

ROAE	Coefficients	Standard Errors	t-statistic	P-value
LCR	0.037618	0.0157234	2.39	0.019
CET1	-0.1035113	0.1857432	-0.56	0.579
GdP	0.2827121	0.1866974	1.51	0.135
Intercept	1.717876	3.216013	0.53	0.595
R-squared	0.0996			

Table A.13: OLS Regression for NIM (2015)

NIM	Coefficients	Standard Errors	t-statistic	P-value
LCR	0.0057137	0.0019575	2.92	0.005
CET1	-0.084231	0.0231242	-3.64	0.001
GdP	0.0240386	0.023243	1.03	0.305
Intercept	2.048609	0.4003785	5.12	0.000
R-squared	0.1994			

Table A.14: OLS Regression for CTI (2015)

CTI	Coefficients	Standard Errors	t-statistic	P-value
LCR	-0.0025956	0.0429868	-0.06	0.952
CET1	-0.9934983	0.5078113	-1.96	0.054
GdP	-0.5936495	0.5104201	-1.16	0.249
Intercept	85.84045	8.792395	9.76	0.000
R-squared	0.078			

Table A.15: OLS Regression for ROAA (2016)

ROAA	Coefficients	Standard Errors	t-statistic	P-value
LCR	0.0009114	0.0007954	1.15	0.256
CET1	0.104283	0.0131661	0.79	0.431
GdP	0.092896	0.0531116	1.75	0.085
Intercept	-0.0003745	0.2225404	-0.00	0.999
R-squared	0.095			

Table A.16: Illustrative Robust Regression for ROAA based on Huber iterations (2016)

ROAA	Coefficients	Standard Errors	t-statistic	P-value
LCR	-0.0002	0.0006	-0.39	0.697
CET1	0.0095	0.0093	1.02	0.310
GdP	0.06	0.04	1.50	0.139
Intercept	0.24	0.16	1.51	0.136

Table A.17: OLS Regression for ROAE (2016)

ROAE	Coefficients	Standard Errors	t-statistic	P-value
LCR	0.0095406	0.100673	0.95	0.347
CET1	0.0896013	0.166645	0.54	0.593
GdP	0.6408858	0.6722384	0.95	0.344
Intercept	2.696541	2.816716	0.95	0.342
R-squared	0.044			

Table A.18: OLS Regression for NIM (2016)

NIM	Coefficients	Standard Errors	t-statistic	P-value
LCR	0.0021362	0.0014163	1.51	0.136
CET1	-0.0670166	0.0234436	-2.86	0.006
GdP	0.1926731	0.0945705	2.04	0.045
Intercept	1.869761	0.3962557	4.72	0.000
R-squared	0.1383			

Table A.19: OLS Regression for CTI (2016)

CTI	Coefficients	Standard Errors	t-statistic	P-value
LCR	0.0628475	0.0330091	1.90	0.061
CET1	-1.562719	0.4998301	-3.13	0.003
GdP	-3.803642	1.250646	-3.04	0.003
Intercept	92.16109	8.475104	10.87	0.000
R-squared	0.1732			

A.2 Data Envelopment Analysis

Table A.20: DEA - Summary Statistics for a sample of 73 banks (2014)

Variable	Observations	Mean	Standard Deviation	Minimum value	Maximum value
Personnel Expenses	73	2143666	4772505	2498	25900000
Deposits & Short-term Funding	73	93100000	165000000	155302	742000000
Gross Loans	73	94600000	154000000	31903	682000000
Other Earning Assets	73	3646357	13100000	1010	107000000
LCR	73	147.1489	55.5422	62	345
CET1	73	14.2027	3.6778	6.28	26.03
GdP	73	1.7658	1.6274	-1.5	8.5

Table A.21: DEA - Summary Statistics for a sample of 73 banks (2015)

Variable	Observations	Mean	Standard Deviation	Minimum value	Maximum value
Personnel Expenses	73	2296643	5238053	2469	30600000
Deposits & Short-term Funding	73	95600000	170000000	174701	787000000
Gross Loans	73	96400000	156000000	34819	703000000
Other Earning Assets	73	3593780	12800000	1524	105000000
LCR	73	152.5384	51.9160	76	298
CET1	73	15.4704	4.3894	7.17	28.84
GdP	73	2.5837	4.1362	0.3	26.3

Table A.22: DEA – Summary Statistics for a sample of 73 Banks (2016)

Variable	Observations	Mean	Standard Deviation	Minimum value	Maximum value
Personnel Expenses	73	2142631	4725211	2804	25900000
Deposits & Short term funding	73	93900000	166000000	109058	854000000
Gross Loans	73	93300000	149000000	38148	738000000
Other Earning Assets	73	3620454	13700000	821	113000000
LCR	73	171.61	69.75	49.00	392.62
CET1	73	15.78	4.37	7.85	27.95
GDP	73	2.06	1.06	1.10	6.10

Table A.23: Tobit Regression on the DEA Efficiency Scores (2014)

theta	Coefficients	Standard Errors	t-statistic	P-value
LCR	-0.0001476	0.003376	-0.44	0.663
CET1	0.01155	0.0051029	2.26	0.027
GdP	0.018368	0.0114127	0.16	0.873
Intercept	0.1594412	0.0834027	1.91	0.060

Table A.24: Tobit Regression on the DEA Efficiency Scores (2015)

theta	Coefficients	Standard Errors	t-statistic	P-value
LCR	-0.0004569	0.0003702	-1.23	0.221
CET1	0.0104847	0.0043766	2.40	0.019
GdP	0.0006006	0.0043949	0.14	0.892
Intercept	0.1896216	0.0757325	2.50	0.015

Table A.25: Tobit Regression on the DEA Efficiency Scores (2016)

theta	Coefficients	Standard Errors	t-statistic	P-value
LCR	-0.0005193	0.0002588	-2.01	0.049
CET1	0.0121834	0.0042916	2.84	0.006
GdP	0.0045753	0.0172812	0.26	0.792
Intercept	0.134557	0.072452	1.86	0.067