

**UNIVERSITY OF VAASA**

**SCHOOL OF ACCOUNTING AND FINANCE**

Luis Bonachera López

**IMPACT OF OPERATIONAL RISK ON BANK CAPITAL  
ADEQUACY: EUROPEAN EVIDENCE**

Master's Degree Programme in  
Finance

**VAASA 2020**



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**UNIVERSITY OF VAASA****School of Accounting and Finance**

<b>Author:</b>	Luis Bonachera López		
<b>Topic of the thesis:</b>	Impact of operational risk in bank capital adequacy: European evidence		
<b>Degree:</b>	Master of Science in Economics and Business Administration		
<b>Master's Programme:</b>	Master's Degree program in Finance		
<b>Supervisor:</b>	Denis Davydov		
<b>Year of entering the University:</b>	2018		
<b>Year of completing the thesis:</b>	2020	<b>Pages:</b>	64

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**ABSTRACT:**

The purpose of this thesis is to study the effect of European banks' operational risk on their capital adequacy. Thesis distinguishes between observed data published by the European Banking Authority and adverse economic conditions compiled in their Stress tests.

Thesis utilizes a panel dataset of 666 operational losses reported from 21 European countries between years 2013 and 2018 with a series of explanatory variables to control for events in the economy and financial indicators. Countries are grouped into regions of the European Union to control for different characteristics in the European banking system. Additional tests use econometric techniques and tests for changes in the qualitative insights during the time period chosen.

Results conclude that there is not a significant relationship between the level of operational losses and the capital adequacy reported by European banks; heterogeneity of results is also evident among different regions within European banking system. Rather than external risks to bank's operations, financial indicators such as solvency and liquidity play an important role in the final capital adequacy ratio reported by European banks. Similarly, operational risk is not found to be driving lower capital adequacy ratio under financial distress or worst-case economic conditions. By employing robustness tests and alternative models, these findings are reinforced. Additionally, other risks such as market and credit have more potential to determine capital adequacy systemic shock.

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**KEYWORDS: Capital adequacy, Operational risk, stress test, systemic risk**



## 1. INTRODUCTION

Banking sector has evaluated different types of risk since its existence for the purpose of assuring financial stability. As financial institutions, banks have a determinant implication on the whole economic sustainability and welfare, thus their due diligence regarding risk management becomes essential. Referring to drivers of financial institutions sustainability, capital adequacy requirements settled by Public Central Financial Bodies represent the most valuable tool for assessing financial sustainability. With this aim, regulatory institutions both locally and internationally have set the path towards the control of risks in the financial sector, and applicable to this research, the Basel Committee on Banking Supervision and the European Banking Authority are the main ones, and more specifically, the focus is based on the operational risk component that financial institutions face towards the accomplishment of capital adequacy.

Barakat & Hussainey (2013) concisely explain the most important points of the Basel II accord that was introduced in 2004, differentiating three pillars in terms of operational risk which correspond to the bank's capital adequacy and internal regulation, minimum capital requirements in order to face arising financial distress and the proper disclosure of the financial ratios and expenditure regarding risk. Consecutively, in 2006 the stated points were implemented by the Capital Requirements Directive (CRD) and most European banks followed the recommendations but, as a drawback pointed out by the authors, Pillar 3 measures according to Basel Committee were quite general and there were no strict paths to follow, leading to a misrepresentation of what the purpose of the Pillar 3 was.

Following these points already put into practice by the Basel II accord, financial crisis had an impact on the way regulation had to be settled. This was motivated by a set of failures and problems within the banking sector and the economy. Financial measures had to be taken into account and, according to Liikanen et al. (2011), banking sector had to be restructured to meet the needs of de-risking and deleveraging; the obligations met by state aids to support sector failures and ongoing regulatory reforms regarding capital and liquidity requirements. At this point these authors proposed five main reforms that had to be implemented in order to improve the quality of the previous regulations. They concerned the way banks need to report and transparently show their measures in terms of risk, trading activity and recovery solutions in the event of financial distress.

After previous Basel II regulatory framework and the financial crisis effects, Basel Committee (2018) had also to perform and develop a new framework meeting all the requirements of the economy and the banking sector. In 2010 Basel III was finally proposed to be applied for the correction of the abovementioned financial needs both for banks and society. It has been an ongoing process that has been revised all along the period comprising 2012-2019, but monitoring was already implemented in 2012 for the member countries. Among their main points to be supervised, minimum leverage and liquidity ratios, stricter requirements in common equity measures or a countercyclical capital buffer avoiding the anomalies of credit busts or booms. This new framework tried to test the ability of banks to overcome the past financial crisis and how resilient they could be if applying those measures to their operations. In order to measure this, EBA (European Banking Authority) launched the stress-testing practices to account for the possible adverse scenario in the event of financial crisis, as a means of avoiding potential losses and shocks on the banking sector.

This paper provides meaningful conclusions about the impact of this kind of risk on the capital adequacy of the European Union banks, analysis that is extended with respect to adverse economic scenarios tests of the European Union. In other words, this thesis tests if the European banking system is influenced by the degree of operational exposure; moreover, it is also examined its ability to impact the Eurozone banking system in a systemic way. This thesis contributes to the existing literature by testing purely European sample, as a whole and among regions, including the analysis of operational risk influence into EBA stress tests results. At the time of writing this thesis, there were very few previous empirical researches investigating the impact of operational risk on capital adequacy, and no previous literature was implemented in the case of capital adequacy forecasted by stress tests. Thus, this paper is an initial path to assess the influence of such a non-observed risk factor as operational risk is both at stable and critical economic conditions.

### **1.1. Purpose of the study**

The purpose of this study is to examine the possible impact of operational risk on the capital adequacy requirements of European Union banks. Operational risk is the expected operational loss of a bank within the period from 2013 to 2018; it is regressed with respect



to the Common Equity Tier 1 published by main economic repository databases and the EBA, representing the main capital adequacy indicator. According to operational risk disclosure, there is a set of categories within operational risk itself such as human behavior, information and technology equipment use or the presence of financial crime activities within the bank. On the one hand, it would be more accurate to include these measures separately in order to get more in depth results and comparing the weight of each category in the results; on the other hand, due to lack of resources and for the purpose of simplification, it is more practical to include all these categories into a single variable, then making more global assumptions of what operational risk encompasses. Once this step has been fully completed, the second test of this paper is the assessment of the operational risk loss implication on the event of adverse economic scenarios. The point of this experiment is to argue if operational risk has real effects on the Common Equity Tier of the European Banking sector in the adverse scenario implemented by the EBA stress tests.

In the case of the first test, I explain if the operational risk is an important component of the European Financial Institutions' capital adequacy. With the aim of having a meaningful and comparable pattern in the dataset, I classify the results of this study for the whole sample of banks available and the defined geographic European regions since the beginning of the sample period; that is, since their inclusion in the transparency documents from where I am collecting the data. By means of this distinction, followed by robustness checks, I discuss if operational risk loss is homogeneously affecting the European banks' capital adequacy among regions or, on the contrary, it depends on different countries and not representative of the Eurozone as a whole. Before writing this thesis, there was previous research focusing on more specific regions or countries, but with this new research I am seeking to provide a more global and consistent approach of the Eurozone, so as to influence financial institutions awareness of the importance of this issue.

## **1.2. Structure of the Thesis**

This thesis has been planned to explain fluently the intended hypothesis or research question. First, I explain in depth all the theoretical concepts applied in this research's methods: how operational risk is divided and the characteristics and peculiarities of each group. They represent the main independent variable of the regression model, and the

main point from where the rest of independent variables give an answer to the capital adequacy of European banks. Secondly, main ratios and types of risk to be studied are explained as well so that concepts are well defined and accordingly related to my research goal. In a second part, previous empirical evidence is considered for the purpose of having a real background from which subtracting meaningful conclusions. Then, results of the regression analysis are represented: first, regression results of banks' capital adequacy, for the whole set and grouped into European regions; secondly, stress tests' regression model for the whole sample divided into two periods. Finally, robustness checks are implemented for the consistency of the models. Last part summarizes the main findings and conclusions to be discussed implying suggestions for future research.

## 2. OPERATIONAL RISK AND CAPITAL ADEQUACY

As I previously mentioned, this thesis is based firstly on the measure of operational risk component within a bank core financial data. Because of further simplified analysis and limitations in data gathering, the operational risk measure is defined as a whole variable which is regressed with the rest of financial ratios to address in this paper. However, it is essential to explain and divide in a more theoretical and readable way what operational risk is depending on their subsequent components.

Operational risk encompasses a set of factors that are present in every business activity and organization. According to Coleman and previously settled by the Basel II Committee in 2001, “Operational risk is the business risk of loss resulting from inadequate or failed internal processes, people, systems, or from external events” (2010). It refers to the degree at which a company can control and prevent a loss in their most basic and bottom-level activity which remains in the utilization and performance of the main services a company offers. Another important point to mention is that the author effectively assigns this type of risk to any organization or industry, but even in any other activity apart from the business spot (distinguishing that losses could be also made of intangible assets and value).

Nevertheless, in the specific case of banking, other authors like Abdullah, Shahimi and Ghafar Ismail defined Operational risk as “a residual risk given the fact that any risk faced by a bank that is not market risk or credit risk falls under this category” (2011: 131-151). Banking is composed of three different types of risk and it has the obligation of mitigating the total amount of loss arising from these misbehaviors or failures within the core business activity. That is why all the operations carried out for the purpose of absorbing this loss will have a wealth protection component rather than a profit generation aspect. With these previous operational risk definitions, I study in depth which are the type of events encompassing operational risk. I ensure that the different components of operational risk would add up to a single measure that is, at the same time, comparable to the other types of risk faced by financial institutions that, at the end of the day, play an important role in the whole risk valuation of a bank’s activities.

## **2.1. Operational risk and its components**

### **2.1.1. Human factor**

Starting the distinction between the existing components within operational risk, the human factor could be thought to be the most evident and simple to understand. In any industry, the human component represents both first-line service employees to top management activities and decisions concerning the enterprise. What does it happen when employees do not perform with due diligence in their job position? It goes beyond the transaction itself as, mentioning Coleman's paper (2010); it has a repercussion on the brand image and reputation of the bank. This represents a potential loss as well for the bank, measured within the operational risk as previously pointed out.

Little due diligence as it has been pointed out is the main reason why human factor occurs, and Coleman stated a classification of mistakes according to "fatigue, incompetence, lack of management supervision, and inadequate staffing levels". This is one of the main points of the research paper of Harris (2006) and its application of operational efficiency within the airline sector. According to this author, efficiency is meant to be the general purpose of the whole business activity; on the contrary efficiency is not made by a solely established component as human factor could be. The paper finds key to improve the whole organization as a sole body where human factor is in a close relationship with the rest of components of the business activity. When performing a specific task, the proper functioning of both human and machines and processes becomes the only purpose from the organization perspective. Consequently, the quality of the operating system has to be appreciated by the final consumer and this economic agent is indeed the true evaluator of the efficiency in the service line.

### **2.1.2. System equipment**

Secondly, I classify operational risk based on the level of technology systems failure or diseases. A good implementation of data processing elements in a business line plays an important role on the final service quality. Citing again previous research paper of Harris (2006), it was pointed out that technology rather than human factors were the main drivers of operational efficiency. Considering this statement and its application on the banking industry, an effective electronical payment method to allow transfers among customers could be a potential risk of loss for the bank if this service is not well designed and

implemented. In addition to this main issue, “programming errors, errors in data management, insufficient processing capacity” comprise other failures included in this category, where not only it is mentioned technological implementation but information processing or storage. It should be highlighted that the banking industry must strictly accomplish regulation for contracts signatures and compliance matters, so paperwork or, in a more developed technological age, virtual agreements, represent the principal issue to respect. Therefore, the truthful and proper treatment of documents becomes again a potential threat for the loss of a bank direct revenue generation but also prestige or reputation among its customers.

### **2.1.3. Fraudulent activity: Financial crime**

Once it has been analyzed both system and human failures within the operational risk of a firm, the following component may be the most relevant one or maybe the one with higher attributed relationship within the total amount of this variable. As a primary step, Gottschalk (2010) defined financial crime as “crime against property, involving the unlawful conversion of property belonging to another to one’s own personal use and benefit”. At the same time, he stated that financial crime has linked the concept of fraud, misbehavior in the way to treat property and trying to find legal holes to perform without being detected or sanctioned. It can be represented in many ways, according to this same author like corporate fraud, bank account fraud, payment (point of sale) fraud, currency fraud, and implying more common practices like tax violations, money laundering or in more recent technological banking system, cyber-attacks.

In a deeper meaning of what financial crime is, it has been already thought to be structured and organized in more complex and systematic procedure. In this case the term evolves to the concept of Corruption, which would be defined by this same researcher as “the giving, requesting, receiving, or accepting of an improper advantage related to a position, office, or assignment”. It may involve politic parties or companies when accomplishing their obligations towards the public entities. A good example on this matter would be the research carried out by Purcell (2006) where Australian local government was studied from a behavioral finance perspective. At some point governments and individuals were found to have several reasons why they act in such a way, and potential interests like decision making, power and self-interest or even risk-taking desire.

For a better understanding of the corruption issue, Sampford et al. (2006, p. 1) stated that within a society, corruption represents the most inherent component for not assuring a solid and stable society and the wealth derived from this. This idea is a general and common approach when talking about profitability and reputation correlation, which is applied to every kind of business activity and organization. Actually, Purcell points out that the misbehavior of an individual could anyways influence the misconduct of more complex structures and groups, finally involving political parties or, in some very famous cases, top index companies (Enron's case). Unfortunately, this same author was not able to give a clear explanation of why these practices are motivated for, so corruption motives are still on the spot of further research. Following reputational effects, Micocci (2009) discovered that there exists obvious reputational effect regarding internal fraud practices. This author analyzed cumulative abnormal returns in a window event which showed sharp negative impact on its values.

As an opposite phenomenon of this current and existing problem, it is well known that private corporations are implementing new policies to ensure the proper functioning of its economic structure and, at the same time, preventing the existence of shady activities within it. Gilsinan et al. (2008) argued that policies carried out to control financial crime or abuse can be made in many different ways, but in any case the implementation would be based on the correlation between the degree of privatization of the company and the incentives for the private corporation. As a result, they showed that, in most cases, it was quite difficult to find real incentives when complying with governmental framework, that is, the high cost of the policies demanded were one of the most important constraints to the establishment of an effective and efficient strategy from the point of view of the private corporation.

Another issue derived from this paper was the real application of sanctioning policies regarding a legal approach. Papers like the one carried out by De Koker (2007) pointed out that countries can be well structured in terms of Legal Frameworks (the example of South Africa was shown), but the point is to enforce the financial investment on this structures to ensure their real application. Related to this investment it is included working conditions like salaries and, in general, an improvement of the availability of resources to allow these practices. Unfortunately, referring to Ponsaers (2002), this task is becoming even more complex as legislation worsens rather than clarifies distinctions among types of crimes in the business field.

Following the idea introduced by Gilsinan et al., Harvey (2018) also addressed the issue of the behavior of Legal institutions towards the abolishment of financial crime. The main point this author focuses on is that, based on previous research and findings, regulatory frameworks may have been settled but there was a clear evidence of inconsistency in the application of those. The result of such a non-valid application would be the rise of vulnerabilities in the whole financial system, flows of money and shady activities that could be out of the regulators' eyes or control. The author ends up recognizing that the existence of financial crime is unavoidable, and its control resides on the fact that "it is perfectly acceptable for some fish to swim through the net".

In relation to this last idea, I should also remark that financial crime potential has increased exponentially in the last decades through the increase and development of virtual and technological networks which allow transactions and virtual money to be hidden. A notably recent paper addressing this topic was the one of Didimo et al. (2014), where authors have developed an operative system with the aim of detecting the with the highest possible accuracy the path followed by, mainly, money launderers and fraud seekers. They highlighted the importance for finding patterns and identifying the economic agents behind encrypted data. The massive volume of data composing these financial networks is the biggest challenge to face when creating a more reliable and effective detection system.

In line with financial networks, banks have promoted the presence of electronic payments through their online systems. Armev et al. (2014) developed a meaningful paper to explain the key insights about this kind of transactions and channels. They studied the possible correlation between the access to electronic financial payments and the propensity to observe economic crime, and their results suggested the negative and significant correlation of the statement "higher access ends up in lower incidence". Moreover, they also experienced this relationship as a good reason for development in poorer countries, by means of strengthened supervision for further economic activities. Hence, they indicate there is a promoting attitude from the point of view of financial institutions to implement in the present and near future the consolidation of this type of payments. It would not only mean an easier business activity for customers but also a growing wealth for defined economies.

## **2.2. Main Capital Adequacy indicators**

The second phase of this thesis' theoretical part is dedicated to the definition and understanding of the main Capital Adequacy indicators to be used in the research, which correspond, in the case of the Common Equity Tier 1, to the dependent variable of the regression model, and to the control variables in the case of both liquidity and solvency ratios. The ratios are analyzed and defined according to previous research and official Financial Institutions guidelines as the BIS (Bank of International Settlements – Basel III Committee) to give consistency and transparency.

### **2.2.1. Common Equity Tier I**

This value is assessed in order to know if it is affected by the operational loss of European Banks. According to Basel Committee (2019), the Common Equity Tier 1 (abbreviated as CET1) is defined as the “highest quality of regulatory capital, as it absorbs losses immediately when they occur.” This final report in 2019 summarizes the target that European Banks should accomplish by this year, being 4.5% the final target. Among its components, it is included the sum of common shares together with stock surplus value, retained earnings, minority interests and other comprehensive income, in addition to regulatory adjustments. It is chosen for this research as the core of the regulatory capital banks in the Eurozone (and worldwide) should respect, without taking into consideration less strict components as AT1 & AT2 would be (additional Tier 1 and 2).

### **2.2.2. Solvency Ratios and Liquidity Ratios**

The first variable is considered as a control one for the purpose of the research hypothesis. It is important to notice the typology of the Solvency ratio, the most accepted definition and the one introduced by the Basel Committee (2014) in the Basel III accords, as it should not be equally treated. In the case of the former, solvency ratio is meant to assess the ability of a company or bank to pay its long-term liabilities (Ucal & Oksay, 2011). It can be based on the computation of short and long-term debt by the amount of total assets. This is the ratio to be used in our regression model as accurate and more data has been found with respect to the latter in the case of the first regression; Basel III Leverage will be included in the second regression model to account for robustness in the EBA stress' tests.



From a regulatory perspective, the Basel III leverage ratio settlement is motivated by the creation of excessive leverage on the banking system that was accounted and not accounted on balance sheets of European banks. As a rule, it is designed as a “simple, transparent, non-risk-based leverage ratio” constituted as a complement to the already existing risk-based capital requirements. By means of a credible leverage ratio, the Basel Committee tries to account for the effects of both on and off- balance sheet declaration of leverage. Then, Basel III leverage ratio is composed by the capital measure (the numerator) divided by the exposure measure (the denominator), with this ratio expressed as a percentage:

$$(a) \text{ Basel III Leverage ratio} = \frac{\text{Capital Measure}}{\text{Exposure measure}}$$

The Institution objective at the settlement date was to test a minimum requirement of 3% for the leverage ratio within the period from 1 January 2013 to 1 January 2017.

In addition, Liquidity is employed simultaneously to the abovementioned control variable. At the same time as Leverage ratio was settled, Basel Committee (2014) also created the Basel III Liquidity coverage ratio as a reaction to problems in the easiness of converting assets (so-called HQLA or High Quality Liquid Asset ) into liquid instruments (cash) on a 30-days calendar period (so-called Total Net Cash Outflows). This time frame was thought to be appropriate for institutions to take corrective actions. The fraction would be as follows:

$$(b) \text{ Basel III LCR} = (\text{Stock of HQLA}) / (\text{Total Net Cash Outflows in a 30-days calendar period}) \geq 100\%$$

This ratio is therefore a more specific measure of short-term resilience of European banks under stress-tests with adverse economic scenarios. In the case of this thesis, a more broadly accepted liquidity ratio, measuring as well the ability of commercial banks to meet liabilities when they are due and its incurred cash (Alshatti, 2014), is employed based on the Net Loans divided by Total assets of the bank. It represents the amount of loans outstanding with respect to total assets. If it is high, the liquidity of a bank tends to be lower. As mentioned in the previous subsection, higher availability of data with respect to the regulatory Basel III ratio is preferred for the purpose of this thesis’ model.

### 2.3 Systemic Risk

To finish the theoretical framework of the thesis, it is essential to explain the implications of the interest in predicting Systemic Risk for the whole of the European Union banks. As a result of the linkage between the previous control variables explained and the systemic risk component, its understanding represents a main objective of this research. Recent authors have addressed the importance of determining systemic risk and its definition.

Acharya et al. (2010) initially reflected that systemic risk analysis seems to be able to forecast the financial firms that contributed in a more harmful way previous systemic crisis. Regarding this assumption, systemic risk is a reliable tool to control financial firms that are potentially dangerous to the economic environment. The latent need for definition and purpose of stress-tests was officially set by the European Banking Authority (2011) as a tool “to assess the resilience of the EU banking system, and the specific solvency of individual institutions assessed, to hypothetical stress events under certain restrictive conditions.” Deeper specifications were made by Acharya, Engle & Richardson (2012) by defining stress tests as a “standard device used to determine the capital that an institution will need to raise if there is a financial crisis”. According to them, systemic risk is based on the capital shortfall under the economic crisis scenario for a specific firm  $i$ . This can be represented by the expression:

$$(c) \text{ SRISK } i,t = E_{t-1} (\text{Capital Shortfall } i \mid \text{Crisis})$$

A more accurate definition of stress tests tools was set by Oura (2012) as “Stress tests are forward-looking tools to assess financial institutions’ solvency and liquidity and the resilience of the entire financial system under possible adverse scenarios”. However, they also specified that this assumption is made taking into consideration as well that stress tests do not measure the probability of those economic scenarios occurring. That is the reason why further research should be implemented. Supporting the need of systemic risk definition and awareness, later Derbali & Hallara (2016) found that systemic events occur principally after the outbreak of financial crisis which resulted after the 2007 great financial crisis and 2010 sovereign debt crisis in Europe. Furthermore, they also agree that the European Banks are the most important source of contribution to the systemic risk of their economies, what is in line with the purpose of this thesis.

However, previous literature does not agree on which is the most effective measure on the Systemic risk estimation. At a first attempt of determining reliable measures of systemic risk, Rodríguez-Moreno and Peña (2013) found CDS and bonds much more determinant to predict financial stress than measures based on stock market, arguing that the main reason would be a more direct relationship to the concepts of default risk and financial stress-tests. Pederzoli and Torricelli (2017), using the current thesis EBA stress-tests exercise results, show that it is not possible to relate MES (Marginal Expected Shortfall) to them; either CoVar is reliable to predict the specific institution's systemic risk potential – this last finding goes on the opposite direction as the paper of Adrian and Brunnermeier (2011) which establishes wider risk management measurements that can be applicable to systemic risk estimation - . This thesis as well contributes to expand the range of possible measures of systemic risk with the adverse scenario results of CET1 in the Eurozone.

### 3. PREVIOUS EMPIRICAL EVIDENCE

As an initial point, it is relevant to know if Operational Risk disclosure is important to the Banking system relying on previous literature. According to previous research, operational risk disclosure and its correlation with banking performance has been met by other authors such as Linsley, Shrivies and Crumpton (2006) where they did not find a positive association between these two measures. Others like Bischoff (2009) supported the idea that implementation of regulation frameworks implied a higher level of risk disclosure in banks that would be in line with the Basel Committee premises and goals. Barakat and Hussaney (2013) as well proposed that operational risk disclosure quality has a positive outcome on stakeholders when outside monitors or supervisors are implicated – by means of independence and power supply -.

On the contrary, other authors like Ford et al. (2009) argued that practically half of a sample of 65 international active financial institutions were effectively accomplishing minimum requirements of the regulatory frameworks. Following this last premise of effective implementation in the real world, Brown et al.(2008) found that, even though operational risk disclosure has been promoted in a business extent and may avoid losses with respect to it, this kind of information is not valuable in case investors do not react and employ it in their analysis. This last idea is held by Acharya, Engle and Pierret (2014): if we were interested in controlling for operational losses, it is not found regulatory risk to have a significant weight on the realized risk of a bank in the event of a financial crisis. Up to this point the need of reporting operational risk may seem unclear to have a positive impact.

Next phase focuses on how the measure of operational risk has been made previously. In line with the measure of potential risk, authors like Dutta and Babel (2014) tried to evaluate how big would be the loss from the existence of operational risk in business activity. They pointed out that previously this kind of risk was measured as a residual component for banks apart from market and credit risk. Hence from this statement they concluded that operational risk was not being addressed as it should, what would be in detrimental of banks and financial institutions interests. Parallel to this study Chernobai, Jorion and Yu (2011) discover a set of determinants in an internal level that they thought

to be understated, considered as independent events which could be improved by internal controls and management.

Other source of debate is the distinction between quantitative and qualitative approaches. Jobst (2007) guesses that consistent risk estimates are dependent on the reporting of operational risk losses and the model sensitivity of quantitative methods – and maybe a qualitative model complements and improves data robustness -. In the case of Bardoscia (2012) he proposed an abstract dynamic model from the LDA comprising both accidental generation of losses and losses events caused by interactions between different processes – with remarkable explanatory power – in a bank internal level.

Extensive literature has made efforts on assessing Operational Risk using a Loss Distribution Approach. Introduction to it was made by Frachot, Georges and Roncalli (2001), by computing the capital charge of operational risk as a means of strong risk quantitative methods in the banking sector. Followers of LDA as Jimenez-Rodríguez (2009) argued LDA model presents much more innovative conclusions than non-advanced approaches proposed by the Committee like the Basic Indicator Approach or the Standardized Method. One year later Shevchenko (2010) replied that Bayesian Methods were more suitable as, by nature, assessing the dependencies of operational risks is much more complex than previously thought.

Furthermore, there is a common point on the assessment of operational loss and bank's performance regarding event studies. One of the main concerns has been the market value of banks and its potential stock value loss from operational losses. Cummins, Lewis and Wei (2006) addressed this problem by evaluating stock value response to operational losses events. Both in the banking and insurance industry in the U.S., it was found that generally stock value responded negatively to operational loss events (higher than \$10 million), within a (-5,-1) trading days event window period: operational loss has an immediate negative impact on stock value even prior to the operational loss announcement. Consequently, Cummins, Wei and Xie (2007) extended this discussion by distinguishing the effect of operational losses on announcing and non-announcing firms, within and across the financial industry (commercial, investment banks and insurance companies). They also found significant the negative abnormal return on stock value, specifically to non-announcing firms both at intra-inter industry level.

Additional papers such as Gillet, Hübner and Plunus (2010) agree on the capability of operational losses to explain stock market value decrease, introducing the concept of reputation damage. This research goes beyond stock value loss and relates it to firm reputation; cumulative abnormal return is found to be negative when operational losses are recognized, and returns are worsened when they are found to be caused by fraud, which indeed turn into reputational damage. Reputation in this case is linked to firm's value, potentially threatened by the type of operational loss incurred. Same argument is also followed by Sturm (2013) to support this association, where operational loss events determine the loss of stock market value of financial firms (measured with respect to cumulative abnormal stock returns around the date operational loss was firstly noticed in the press); further conclusions are derived from this study as reputation damage is independent from the event type, size or growth indicators of financial firms.

From these articles, the bank performance is understood and measured according to stock market value and revenue from a shareholder's point of view. Opposite to this approach, the interest of this thesis relies on the measurement of banks' performance according to regulatory requirements under a regression model; in this sense, the capital adequacy ratio has not been broadly evaluated across literature. Limited papers considered capital adequacy as a representative performance indicator, in very different economic and banking systems with respect to the European Union. Recent papers such as Aspal and Nazneen (2014) examined capital adequacy ratios with respect to other bank's performance characteristics including credit, liquidity, sensitivity and operational efficiency indicators. According to the last one, named as "Management Efficiency" variable, they found a positive significant relationship with capital adequacy; the increase in the net income generated with respect to expenditures from bank operations influences the better capital adequacy ratio. This is the opposite concept as this thesis means by "operational risk", as according to them less loss resulting from banks operations represent better capital adequacy ratio (it is presumed but not confirmed the opposite effect).

The definition of "Operational Efficiency" instead of operational risk or loss has been repeated across previous literature; an example of this is the paper of Abusharba et al. (2013), where the criteria is to measure the operating expenses to the operating income. These authors also represent this ratio as a management quality property of banks, and they found it to be insignificant to impact the final capital adequacy ratio of Islamic banks.

This opposite conclusion from the one given by Aspal and Nazneen provides non-homogeneity of results across banking systems; moreover, they introduce that the objective of the research was to find significance without interpreting if positive or negative. After this statement, it is still a question to be explored among countries, the kind of impact of operational efficiency in capital adequacy ratios, even more when this thesis provides a different approach of operational performance assessment, in a negative instead of positive way.

Moving to the systemic risk evaluation, it has also predominated the use of event study models. Another type of event study considered along operational risk measures has been the tail event. It is the case of Curti and Migueis (2016) who evaluated the risk tailed distributions on operational risk losses; it was proven that, despite measuring future operational losses based on past losses was reliable, all those large operational risk losses based on more rudimentary LDA approaches were not predicting future expected operational losses as simpler average frequency metrics did. Further research has been implemented, and a very relevant paper in which I recall along this thesis is the one from Berger et al. (2018) as it also applies the application of tail events into the measurement of operational risk as a source of systemic risk (arguing indeed it has a more systemic nature, in addition to the fact that systemic risk is influenced by high-severity risk tail events, also relevant for our research hypothesis).

Following risk tail event approaches and, specifically to this thesis, to systemic risk events, a more accurate and detailed analysis of bank's operational losses and its impact on systemic risk was implemented by Abdymomunov, Curti and Milhov (2015). The operational risk loss was divided into potential loss categories events: mainly "Clients, products and Business practices" and "Execution, delivery and Product Management", accounting for a 90% of the total banking industry loss, were found to be negatively correlated with the variable of interest, "Macroeconomic Growth". It indicates that the operational risk affects notoriously the global economic performance, measured by the increase in productivity among industries; it tends to explain periods of economic downturn, motivated principally by operations and transactions with direct clients. Later in 2017, Abdymomunov and Ergen added to previous literature that as a result of tail losses dependence across large banks, it is possible to confirm a potential systemic risk that is common to a large sample of banks, occurring in a simultaneous way.

A subsequent debate is the fact that systemic risk and operational risk are correlated as a cyclical phenomenon. Related papers like Allen and Saunders (2004), (previously mentioning that, at that point, no extensive literature was available for the measurement of macroeconomic and risk factors cyclicity) found market and credit risk to be much more pro-cyclical whereas operational risk was uncovered to be counter-cyclical. The meaning of this statement is that market and credit risk would move according to the conditions of the economy while operational risk would be thus moving in the opposite direction. By contrast, this same last author together with other (Allen and Bali (2007)) showed that operational risk represents 18% of total equity returns for financial institutions when financial catastrophe is experienced. Hence, they give an opposite statement which assumes procyclicality in operational risk measures. Besides, Eckert and Gatzert (2019) duly argue that significant losses are experienced in a set of financial firms because of spillover effects from large operational losses. Jiřina (2012) as well supports the fact that both high operational losses and its exponential trend are significant for the stability of the economy (while this paper assures there is no visible trend on operational losses).

Systemic risk can be motivated by several economic factors. Silva, Kimura and Sobreiro (2017) argued that the financial sector is negatively impacted by the rise in macroeconomic and financial stress. This fact, according to them, was due to regulatory aspects. This last issue was also addressed by Köster and Pelster (2018), who associated financial penalties and systemic risk to be correlated (while banks were not the main contributor). Simultaneously, financial penalties would also make banks more vulnerable when systemic risk events were observed. Under the premise of financial distress, Kaspereit (2017) found that operational losses are experienced in periods of abnormal negatives stock returns while they explain contagion around the European financial industry.

Others like Acharya et al. (2010) found that the most harmful component of financial crisis in determining the likelihood of systemic risk was the short-term debt. Another focus was business size. Already Amran, Manaf Rosli Bin and Che Haat Mohd Hassan (2008) explained that business size is relevant for the risk management disclosures. Therefore, more research was implemented to see a pattern in size and loss associations. Moosa and Li (2013) already mentioned the ability of bank size to be driving market value loss derived from operational losses, instead of leverage or others; abovementioned



paper from Abdymomunov, Curti and Milhov (2015) also agreed that size was driving potential operational loss. Laeven, Ratnovski and Tong (2016) as they proved bank size to be strongly affecting the rise of systemic events – large banks have such an influence that it was not clear how to control their impact, so they proposed capital tightening requirements that could be parallel to this thesis proposal - .

Nevertheless, previous literature addressing systemic risk has also discussed the non-contagion ability of operational losses. Elsinger, Lehar and Summer (2006) refused this idea and did not provide great importance of contagion probability of default in a banking system regarding interbank connections. Generally, risk of contagion among banks has been modeled by analyzing the probability of default of a bank considering other banks balance sheets fixed; this criticism is said not to be correctly assessing the ability of contagion of a whole banking system, otherwise it is suitable for conditions where a banking system is proved to be idiosyncratic. This discussion is extended in Elsinger, Lehar and Summer (2013), as idiosyncratic bank failures are characterized by operational losses, generally affecting a small portion of banks within an integrated system. Hence, from an interconnected banking system, specific and idiosyncratic events are not the drivers of insolvency in a whole banking system, mainly since the quantification of adverse scenarios leading to contagion is indeed very difficult.

The findings derived from this set of studies have a common feature, that is, there is no consensus in the ability of operational losses : firstly, to explain bank's performance; secondly, to measure its probability of contagion within banking systems , featured by periods of financial crisis. It relates to the method and data gathered to establish the connection between both which makes the gap between results and conclusions.

When it is referred to operational loss and bank's performance, the definition of the last one has been commonly referred to market value while recent papers have moved to bank's strength to meet capital requirements. This is the reason why, at the same time, it is complex to give a solid and homogeneous answer to problems coming from different concepts and approaches. It has been reflected that there is extensive literature assessing bank's market value by means of operational loss events; meanwhile, regression models have recently linked capital adequacy with operational efficiency instead of operational loss. Conversely, the relationship has not been yet confirmed to be significant, either positive or negative. It is also argued that, in case of finding impact of economic factors,

others have more significance than operational losses do. This is also mainly due to the availability of data regarding operational risk by banks as appointed by Ford et al. (2009), what has been translated into different scopes and methods to quantify it.

Systemic risk has also been debated to be explained by operational loss as a contagion phenomenon: conclusions are also dependent on the type of model used, as event or tail loss studies are inclined to prove the rise of operational losses simultaneously to economic downturn. Again, literature has not been found regarding regression predictive models, where capital adequacy was meant to represent bank performance, operational loss accounting for non-idiosyncratic banking systems either. The contagion effect of operational loss is now reviewed as a linear relationship instead of accidental loss events, in other words, the aim is to find common patterns along time rather than analyzing cause-effect relationships.

This thesis incorporates new perspectives to the measurement of capital adequacy and financial crisis events motivated by operational risk: it applies purely official information about bank's risks disclosure, both for stable and under adverse economic conditions, by the European Banking Authority, from a wide range of banks and countries within the European Union. In contrast to other papers focusing on a single country as it has been found on previous empirical evidence, the heterogeneity of banks in our sample makes challenging the finding of answers to the research question. European Union has very specific features as a global banking system, and its heterogeneity is evaluated to know if previous results can be applied to it. Consequently, it is discussed if the operational risk variable significance depends on European regions or if it has a standardized pattern and its importance with respect to other economic indicators. Nevertheless, the difficulty itself of quantifying operational risk by individual banks also has implications on the data collected by the EBA, something to discuss within the robustness checks of our results.

#### 4. RESEARCH HYPOTHESIS

The hypothesis of this study involves the issue of how operational risk of European banks has an impact on the capital adequacy of the European Union. Given the data of operational risk values across banks in different countries of the European Union and its corresponding capital adequacy ratios, I create two hypotheses: firstly, regarding the operational risk effect on capital adequacy ratios of banks across Europe. The hypothesis formulation would be as follows:

*H<sub>0</sub> : Operational Risk value of banks does not affect the EU capital adequacy*

*H<sub>1</sub> : Operational Risk value of banks affects the EU capital adequacy*

In this first regression model, it is tested if the capital adequacy is affected by the extent of operational losses incurred within the chosen period. The significance or not of this variable has been under discussion previously, and different results have been found. In the event of proving operational risk to be significant, it is expected to find inverse (negative) relationship as generally higher operational losses were found to reduce capital adequacy ratio (on the contrary, operational efficiency has contributed to better capital adequacy ratios).

Another supplementary hypothesis is tested to gather more meaningful information about the relationship of the two measures, in this case regarding the systemic risk of European Union banks. Consequently, if operational risk is able or not to explain significant relationship with the capital adequacy of the EU banking system, I would be interested in knowing if operational risk is also implying that the banking sector systemic risk is influenced as well, represented by the results of the EBA stress tests. For this reason, the second main hypothesis of this research is:

*H<sub>0</sub>: Operational Risk does not explain systemic risk of the EU Banking sector*

*H<sub>1</sub>: Operational risk explains systemic risk of the EU Banking sector*

As formulated in the previous hypothesis, it is reviewed the ability of operational loss to influence banking systemic risk. In case of finding significance, positive relationship is expected from previous evidence given that a higher systemic risk would be motivated by operational losses incurred by banks within the banking system. On the contrary to papers focusing on single countries, European Union systemic risk is under evaluation.

Once set these hypotheses out, it can be argued that there is more significant impact on the capital adequacy of the whole EU banking system of other variables that are included in the regression. They would be called control variables and they relate to different ratios influencing banking performance of the banks included in the sample: on the one hand, I include those related to features that are determinant for the bank's performance of EU banks (size or business volume of the bank, book to market value and return on assets, or the net income of each bank); on the other hand, I set control variables related to other risks apart from operational risk that are also determinant for banks' capital adequacy and systemic risk ( financial, credit, liquidity, market and sovereign risk).

## 5. DATA AND METHODOLOGY

The purpose of this study is to assess the possible impact of operational risk exposure number of banks on the European Union bank's capital adequacy, that is, the Common Equity Tier indicator observed within the period 2013-2018. Consecutively, it is assessed, in line with the results of the first step regression, if the adverse scenario Common Equity Tier published from subsamples 2013-2016 & 2015-2018 are affected as well by operational risk.

### 5.1 Data

Tables 1 and 2 correspond to the supervised financial institutions included in the transparency exercises of the European Banking Authority, which publishes yearly the financial institutions' reports in terms of transparency and detailed bank-by-bank data regarding asset quality, capital positions and risk exposure amounts. These tables are shown with all the countries analyzed year by year (from 2013 to 2018). From the two tables, countries with less than two supervised banks during more than 4 periods were excluded from the final sample of this research with the aim of eliminating non-drivers of the results (Bulgaria, Estonia, Latvia, Romania and Other Banks).

[Table 1 here]

[Table 2 here]

Mentioned figures are materialized into a total panel data sample accounting for regression analysis of 666 bank observations for each variable, together with the control variables that I explain later. After controlling for outliers with respect to Common Equity Tier 1 in our sample, a final version of 525 observations is analyzed, classified by bank cross-sectional data and year period data. At the same time, sample is divided into regions according to the geographical situation of countries in our sample, distinguishing between Southern, Western-Central and Northern Europe (Avdeev et al., 2011). For the purpose of ensuring homogeneous sample among regions, United Kingdom and Ireland are included in the Northern region. The countries are divided after accounting for outliers' detection. The purpose is to compare results between the whole sample and regions to give consistency to the conclusions and, at the same time, to find new insights about European banking sector patterns. A detailed list of banks included in the sample is shown.

[Table 3 here]

Conversely, scenario for 2013-2016 and 2015-2018 results of the EBA stress' tests publications are included. They represent the 2013(2015) initial or actual result for each of the variables. Again, outliers' detection process and homogeneity of both periods' sample was considered, resulting in a total number of 189 and 177 observations, respectively. In this case the results are based on European Union banks supervised without grouping as, because of data size, we would not get reliable conclusions. A detailed list of banks assessed in our study is described in table 4.

[Table 4 here]

[Table 5 here]

Table 5 shows descriptive statistics for the sample of European banks (differentiating among all banks, Northern banks, Western-Central banks and Southern banks) included in our first regression model. Referring to the main variables of interest, CET1 and Operational risk, we can obtain some preliminary conclusions: the Operational risk exposure on average is around 18.5 million euros for the global European Union; meanwhile, this figure varies among regions depending and, at the same time, in relation to the total size of the banking sector in each region. This is why if Southern banks are compared to Northern or West-Central ones, the operational risk is consequently much lower; on the other hand, it is possible to assume that the Western-Central region, is presumably a more concentrated banking system as Northern region in terms of total operational risk and size in million euros.

Secondly, Common Equity Tier 1 along the sample period for European Banks was 14.17% ; the minimum one that has been settled for the 2019 year is 10.6% according to the ECB (European Central Bank), this means that our sample of banks within the European Union, in a year frame of 5 years, would have widely accomplished current capital adequacy requirement. However, this is neither a real measure of each country solvency nor of each bank. This mean is empowered by top performer countries or banks, which have a higher weight on the statistics. Simultaneously, this is proved by looking at each region: Southern banks had lower capital adequacy than Northern or Western banks, a trend that has been typically associated to consequences from past financial crisis.

Northern countries, composed by the Nordics and British islands had the best adequacy, with a lower size and concentration as Western banks had.

[Table 6 here]

In addition, descriptive data corresponding to the adverse scenario from 2013 to 2018 is displayed in table 4. Note that, with the aim of having a reliable regression study of these indicators, I divided the sample into two subsamples corresponding to the stress-tests scenarios published by the European Banking Authority. Stress tests are performed based on prediction of a 4-year time frame: firstly 2013(to 2015) observed data; secondly, worst-case economic conditions determine the forecasted indicators in year 2016 (to 2018). For this reason, data should not be combined or mixed as new factors have been considered for the second stress-test or even macroeconomic conditions have varied from one period to another.

To proceed with the analysis of stress' tests, we now focus more on the standard deviation and minimums of each period. It is possible to appreciate that the effect of adverse economic scenarios reduce drastically, compared to the first regression model, the figures of net income: means are negative in both periods, and if minimums are observed, net losses even reach the amount of 622 million euros in 2013-2016 stress tests. Compared to the 2015-2018 period, economic indicators can harm banks in a much higher extent. This is also reflected in the standard deviation of period 13-16 reaching 45.27. On the other hand, it is also interesting that average CET1 is reduced in 3-5 % with respect to the average CET1 of the first regression model; proof that stress tests estimate a significant decrease on general banking sector downturn.

With the purpose of giving consistency to the results of the regression analysis, a group of variables referring to the characteristics of the banks of the sample have been included. Following Berger et al. (2018), these refer to the business volume of the bank, measured by total assets (called "size"); the market to book value so as to account for the real value of the firm at that time; the return on assets (RoA); and Net Income in the case of the second regression.

Once I included the main bank's features that are also significant for the systemic risk of the banking system, there are also other types of risk that I should add to the regression equation: financial, liquidity, credit, market and sovereign risk. With respect to the last

three, Duffie and Singleton (2012) explained that credit risk is the “risk of changes in value associated with unexpected changes in credit quality “. Then it is said to be any probability for a bank to see its credit rating to be reduced and, thus, affecting the final value of the credit activity. These authors also reflect that credit risk can be forecasted based on the probability of default of a third party and the amount of loss given default. Thus, this measure is also considered since it is such a determinant risk component on the bank’s activity and, applicable to this research purpose, to the systemic risk of the whole banking system.

Remarkable components on the risk management of banks are also the sovereign and market risk. According to Beirne and Fratzscher (2013) sovereign risk is a result of the own country’s economic fundamentals especially during the rise of financial crises periods, a measure of financial contagion indeed. Enria, Farkas and Overby (2016) even insist on the need of including this risk assessment onto the balance sheets of financial institutions. Furthermore, they also found that “the decrease in market liquidity during the European debt crisis can be attributed mainly to those banks that did not maintain frequently updated disclosure on sovereign risk”. According to the second term, market risk is defined as “the risk to an institution’s financial condition resulting from adverse movements in the level or volatility of market prices” (Frain & Meegan, 1996). It has always been featured by its difficulty to be measured, as it incorporates different ways to be assessed, and at the same time the sum of assets and derivatives of varied nature. Generally measured by Value at Risk, the EBA tests compute it from the average net trading income volatility with respect to adverse market risk conditions (EBA, 2014).

## **5.2 Methodology**

The analysis of the abovementioned variables is held as follows. An Ordinary Least Squares regression method is implemented in order to obtain meaningful conclusions about the impact of the operational risk exposure to the Capital Adequacy of the European Union banks, both in a global and regional scale, within the period 2013 to 2018. The structure of the hypothesis formulation follows a similar pattern to the ones proposed by Berger et al. (2018). The final sample of this study is structured into a panel data set from a bank-level perspective for European Union and subregions in this first regression model; the second one is based on the stress tests results.



The impact of European Banks' operational risk exposure to their Common Equity Tier 1 is assessed with the following panel setting:

$$(1) CET1_{i,t} = c + \beta_1 Op.Risk_{i,t} + \beta_2 Size_{i,t} + \beta_3 Market-to-Book_{i,t} + \beta_4 RoA_{i,t} \\ + \beta_5 Liquidity_{i,t} + \beta_6 Solvency_{i,t} + \beta_7 Credit Risk_{i,t} + \beta_8 Sovereign Risk_{i,t}$$

The dependent variable  $CET1_{i,t}$  is the Common Equity Tier 1 for bank  $i$  in year  $t$ . The main explanatory variables are *operational risk* exposure (loss) at the end of year  $t$ , measured in million euros. Same way is computed the business volume (*Size*) of the bank  $i$  at year  $t$ ; *Market-to-Book* represents the Market to Book value or accounting profitability of bank  $i$  at time  $t$ ; *RoA* represents the return on assets of bank  $i$  at time  $t$ ; *Solvency* is the solvency ratio of bank  $i$  at time  $t$ ; *Liquidity* represents the liquidity ratio of bank  $i$  at time  $t$ ; *Credit Risk* is the ratio computed by Non-Performing Loans divided by Total Loans of bank  $i$  at time  $t$ ; finally, *Sovereign Risk* is the sum of all local country's sovereign impact published by the EBA of bank  $i$  at time  $t$ . Note that raw data has been directly subtracted from the Data Repositories belonging to EBA (in the case of Operational Risk, CET1, Net Income and Market/ Sovereign Risk) and both FitchConnect and Orbis databases (in the case of Size, M-to-B, RoA, Solvency, Liquidity and Credit Risk for first regression model).

In a second regression model, I used the Operational Risk losses and the rest of control variables in order to measure the impact of them to the CET1 in the case of adverse scenarios, published by the stress-tests of 2014 and 2016 by the EBA. The equation model would be as follows:

$$(2) CET1\ adverse_{i,t} = c + \beta_1 Ln(Op.loss)_{i,t} + \beta_2 Net\ Income_{i,t} + \beta_3 Market\ Risk_{i,t} \\ + \beta_4 Credit\ Risk_{i,t} (+ \beta_5 Leverage_{i,t})$$

Where *CET1 adverse* represents the Common Equity Tier 1 under adverse economic conditions of the Eurozone banks in this second regression sample, divided into

subsamples of 2013 to 2016 and from 2015 to 2018; *Net income* represents the net profit or loss of Bank  $i$  in year  $t$ ; *Market Risk* represents the total amount of market risk exposure; *Credit Risk* is the amount published by EBA stress tests; ; for robustness tests, and due to the unavailability of this variable in the 2013-16 period, the variable *Leverage* is added in the second period to represent the Basel III Leverage Ratio used by the EBA. Accordingly, to the previous explanations of reliability of results, subsamples have been set to eliminate mixed CET1 ratios. Rest of control variables are used in the same manner than in the first regression model.

As a preliminary check, it should be explained that results are provided according to the initial discussion of including or not fixed effects. This is explained in depth in the last section for robustness checks: the equation models are tested regarding a choice of Fixed or Random effects, implemented to see the fit of the sample to each of the effect-testing models. This choice is based on the Hausman Test that tries to set the rule for selecting the appropriate model. Furthermore, a comparison between the outcomes of the proper model and the alternative one is also provided to show possible insights. After the analysis of regression models, multicollinearity checks (Variance Inflation Factor is used to account for multicollinearity between variables) are also tested to ensure the validity of variables within the model and supporting the conclusions obtained.

These robustness checks arise from the interest on the possibility of finding specific characteristics of the European Banking system among regions; moreover, the nature and periodicity of the data represents a concern for reliable analysis as, given the novelty of EBA and Basel Accord transparency reporting requirements, dataset only corresponds to this last 5-year period. Tables report the outcomes of the regression analysis and impact of each variable on the CET1 both for stable and under adverse economic conditions while assuming cross-section and time period fixed effects, or bank random effects in the case of the robustness check to give consistency to results. Outcomes are compared and the explanatory power of each circumstance is argued between regions and models.

## **6. EMPIRICAL RESULTS**

The results of the abovementioned methods and empirical research are now presented in this section. First, CET1 regression model results will be presented after Hausman Test checking. Same procedure is applied in the case of the Stress tests' regression model. Finally, regression models are tested for alternative models and multicollinearity of variables and, in the case again of Stress tests, additional factors are added.

### **6.1 Regression models: CET1 and Stress Tests' results**

Before the analysis of the proposed regression models and results, a preliminary check for choosing between Fixed or Random effects is employed. This test is needed to provide more effective conclusions of the analysis of variables in the model to impact the dependent variable. The use of random effects should be made in case that omitted variables and their unobservable effect is not correlated with the set of independent variables. This argument (Wooldridge, 2009) implies that independent variables would be capable of explaining, at most, the possible variation in the dependent variable. The nature of the independent variables taken into account for this thesis' regression models can have several reasons why random effects can or cannot be applied: for instance, different types of risk are not related or, in other words, pertain to different measures as capital adequacy do (ratios measuring leverage or liquidity may have stronger relation and, then, the fit of the model may indicate using fixed effects).

This is also something to consider as the dataset, instead of having a larger time period, has a large amount of cross sections (that is, the number of banks used in this Thesis' regression models). This is motivated by the fact that banks are clustered into regions, what Bell, Fairbrother & Jones (2018) argue that it would be reasonable to check if a variable of interest can vary among these groups or clusters. In line with this heterogeneity of data, random effects can be suitable when researchers focus on the role of the context of data, separating the within and between components in a model (Bell & Jones, 2015). The type of data gathered in this thesis could be a match to these assumptions, worth to test.

Thus, testing for both the CET1 regression model and the stress tests are explored, consequently results are discussed following the model properly chosen from the Hausman test. The choice between random and fixed effects (Hausman, 1978) is based

on the comparison between the standard error of random and fixed effects estimation by evaluating the variance of the independent variables, again from random and fixed model results. Therefore, the objective of this test is to accept the Null hypothesis, which is the employment of random effects, otherwise rejecting the null hypothesis results in using fixed effects for the model. It is also tested for individual variables, which is also interesting for robustness tests conclusions and findings. Equation 3 shows the illustration of this test where  $\beta_{FE} / \beta_{RE}$  is the output coefficients of fixed and random effects estimated whereas the difference in the variances of those coefficients is shown in the denominator:

$$(3) \text{ Hausman test} = (\beta_{FE} - \beta_{RE})^2 / \text{Var}(\beta_{FE} - \beta_{RE})$$

[Table 7 here]

[Table 8 here]

According to the first table, it is possible to appreciate differences among the regions of the sample. If the top section of the table is observed, which corresponds to the p-values of each model as a whole by region, EU, Northern and Western-Central countries are found to be assessed using fixed effects ( p-value < 0.05 or 5% significance level ); meanwhile, Southern countries have larger p-value of 0.44, indicating the random effects would be more appropriate. Therefore, these considerations are taken into account for the regression model shown in our empirical evidence section; however, the bottom section of table 7 shows p-values for individual variables of interest. Some variables show a different p-value from what the model is predicting, then additional arguments can be derived for the robustness checks, where some variables have a better fit with random effects implementation. That is the case of Operational Risk, which is observed for all categories to be a better fit of random effects; others such as liquidity are also observed to be broadly appropriate for random effects, so the comparison between both models is discussed in the robustness checks to see if the conclusions significantly vary or not.

After this regression model, the focus is on the Stress tests' Hausman results. Similar to the outcomes of the first regression model, Stress tests are also found to be appropriately measured by fixed effects rather than random effects. P-values for both subperiods do not reach the threshold of 5 % significance. As previously mentioned, the analysis is also compared to random effects in the robustness check section, in addition to other adjusted models.

Once Hausman-tests have been implemented, the results of our regression analysis are shown. This is the case of the CET1 regression model, corresponding to Table 9. The dependent variable in this model is CET1 or Capital adequacy ratio of each bank from year 2013 to 2018; this is available and recorded data after the closure of each accounting year, published by EBA and other data repositories the following year. Same type of data corresponds to the set of explanatory variables, from Operational Risk to Sovereign Risk. The analysis is divided into the regions of the sample, pertaining to European Union banks, Northern, West-Central and Southern countries, from column 1 to column 5, ordered from left to right. In the case of Southern Countries, both fixed and random effects are shown to provide an easier and uniform analysis.

[Table 9 here]

This research focuses the analysis on the European Union banks, what is shown in column 1. Regarding the results of this first column, Operational Risk is not significant: the set of banks analyzed in this Thesis sample do not show an impact on the Capital Adequacy of European banks. This is the answer to the first hypothesis of this paper; in fact, further assumption is robust when other regions such as the Northern and Southern countries either show significance on operational risk. Conversely, it is found an interesting outcome in the case of the Western-Central countries: for them, a positive and significant relationship exists between operational risk and capital adequacy ratio.

This implies that, for this group of banks, a higher amount of operational losses for banks is showing a better capital adequacy ratio for their banks. This figure, which is marginally significant (0.081, 10% level significance) is compared to alternative random effects where operational risk was found to be suitable. In any case, the model is shown to be sufficiently significant for the EU case (83% adjusted R-squared – low Standard Error of 1.18), Northern as well, showing that little potential variance and high explanatory power is found.

On the other hand, this is a path to further research, following previous insights about operational risk disclosure and potential impact on capital adequacy: it follows previous conclusions such as Linsley, Shrivs and Crumpton (2006) where there was not relationship between banking performance (CET1) and operational risk disclosure; in the case of Western banks, it is in line with Bischoff (2009) where higher operational risk

disclosure led to better regulatory implementation, which indeed can improve bank's regulatory capacity and performance; in addition, it also applies to the finding of Eckert and Gatzert (2019) who agreed that overall financial firms' losses can be motivated by operational ones.

Other insights can also be derived regarding the rest of variables included: model shows that the real drivers of the capital adequacy behavior are both liquidity and solvency indicators. This is the case of the latter for all samples analyzed, and all except from Northern countries in the case of the former. Therefore, a higher degree of solvency of banks is extremely associated to a better capital adequacy (for the European level, a single unit change in solvency ratio corresponds to a 39% change in capital adequacy ratio, and over 100% change in Northern and Western countries). In the case of liquidity, coefficient terms indicate a negative relationship with capital adequacy ratio (ranging from a 6 to 8% change), which implies that banks in a European level should incur in less short-term debt to improve the future capital adequacy requirement. It is a pattern in all subsamples analyzed, giving consistency to this practice in all levels of the banking sector: long-term prevails over short-term capability to repay a bank's liabilities.

Finally, other control variables have been significant at any point of the subsamples. Bank size, specifically, is a negative influence on the capital adequacy ratio: following Moosa and Li (2013) findings, the size of banks can drive market loss of banks and, in this thesis, the capital adequacy ratio. It implies then that the European Union suffers from a Too-Big-to-Fail pattern, as bigger banks will have more impact on it than lower size banks. On Furthermore, together with operational risk, other types of risk included in our model were not significant in a general basis; neither credit nor sovereign risk are found to be impacting capital adequacy, only in the case of credit risk it represents a slightly important factor for Northern countries, where less credit risk would improve the capital adequacy ratio.

A qualitative argument is derived at the same time for this set of results: it is obvious that the banking sector and its indicators are idiosyncratic. Significance that is found on different variables like RoA or Credit Risk depending on the subsample analyzed is obviously leading to this conclusion. Cerasi, Chizzolini and Ivaldi (2002) found this statement to be true due to deregulation: idiosyncrasies are generally found for the purpose of competition among banks in different country levels, that is, obvious existence

of differences across banking industries. Therefore, along this paper analysis of results, differences can be found depending on the subsample analyzed, however that is the proper way to approach conclusions: comparing results among regions to better give conclusions on the European Union extent.

After the analysis of the first regression model, stress test regression model is assessed with the aim of finding either supportive or opposite conclusions to the effect of operational risk on capital adequacy. In this case, the capital adequacy is measured in worst-case scenarios showing that (as previously done on the descriptive statistics analysis) the average capital adequacy ratio was significantly reduced. Because of this event, is the operational risk leading to this change? This is the hypothesis formulated in layman's terms of this second regression model.

Regression model for stress test and results are shown in table 10. Dependent variable CET1 corresponds to the variable recorded along the years from 2013 to 2016, in the first column, and from 2015 to 2018 in the second one. Distinction between the two subperiods is made following the publication of the stress tests' forecasts: EBA studies the change in CET1 and rest of variables (mainly the other two types of risks are included such as credit and market risk, in addition to Net Income) from an initial base year (2013 and 2015) to the following three years. It is important to analyze each period separately for the purpose of correct interpretation of data and non-duplication. Each period considers economic indicators (these can range from volatility indexes, oil prices...) that affect differently the initial base year – thus, the outcome and prediction of the following years is also dependent on the scenario taken into account - . Before the start of this research, EBA 2014 and 2016 publications were available, and with the aim of aligning findings with respect to the time period chosen for the first regression model, same period from 2013 to 2018 is implemented.

[Table 10 here]

Referring to the results of the second regression under fixed effects, operational risk is not found to be significant in the event of adverse economic situation; capital adequacy is not impacted by a possible increase or change in the operational risk loss for the forecasted years, neither in the first nor the second period of the stress tests publications. Besides, the rest of variables are not significant either, even though the explanatory power of the model is high (82 and 91%) and the standard error very low (0.96 and 0.92).

The null hypothesis is accepted and the operational risk does not relate to systemic risk in the European Union banking sector and, according to all the variables available in the EBA stress tests' reports, other risks and performance indicators (similar to the first regression model findings) do not influence the capital adequacy under financial crisis.

## **6.2 Robustness tests**

Previous regression models' analysis is now tested for robustness by applying multicollinearity checks and comparison between the alternative random or fixed effects, depending on the choice made regarding Hausman test. First, the alternative models are shown in order to contrast and to support the conclusions derived from the chosen regression models. It can also be added that an alternative model of the regressions was considered for lagging values of the explanatory variables. Previous research showed event studies where the impact of operational losses was materialized into market value loss immediately (Cummins, Lewis and Wei (2006) found a great significance on -5/+5 trading days' event window) so this was the first choice to report results. After a second trial of regression models with one-year lagged values, operational risk results did not vary, neither under stable nor adverse economic scenarios; thus, results for lagged-model are not reported.

Concerning the CET1 first regression model, Table 11 shows in this case the opposite selection of fixed-random effects model (random effects for the European, Northern and Western-Central countries; fixed effects for the Southern countries). Results show that most of our previous statements are held as well in this second check of the regression model. For instance, and referring to the variable of interest, operational risk is found to be still insignificant for the European Union as a whole and the regions analyzed except from the Western-Central group of countries.

Consequently, it is possible to say that, even though alternative models present much lower predictive explanatory power (only in the case of Southern countries was found a higher explanatory power than its respective fixed effect), results are almost repeated: mainly solvency ratio is again a very significant value; liquidity in two of the regions (while coefficients change signs); other variables can even become significant in some of the regions. Facts such as the operational risk significance or the solvency and liquidity ratios support the theories and the answer to the original research question. On the



contrary, the selection of these models has been proved to be non-optimal, leading to results like the change of signs in the case of Western-Central liquidity.

The selection, then, between fixed and random effects' models is efficient, meanwhile having close or similar results from the use of one model to another means that the difference between both was very narrow. It can be observed, as the Table 7 shows, that individual variables can be significant to be proven in a random effect model or vice versa, and then the difference between coefficients from one model to another becomes much lower. Despite this tight difference, the value to consider is the one applied by the Hausman Test, which gives the overall model selection.

Next, regression model for the stress tests is compared following the same procedure as the CET1 regression did. Now the alternative model for both period 2013-16 and 2015-18 is the random effects model, given that we found high significance (p-value lower than 0.05) in the Hausman Test. This time, the results are shown in columns a) and b) for the 2013-16 and 2015-18 period, respectively. According to results, the significance completely changes from one model to another: now for the operational risk, the first period shows a 2.8% significance when under fixed effects did not; same case is applied for the net income variable in period 15-18. Its positive relationship would imply that a lower net income would impact negatively the final capital adequacy ratio during that period; on the contrary, risks variables have opposite direction than performance variables do: higher operational risk, which is meant to be losses, would be explaining lower capital adequacy ratio, but it is the opposite way according to this model, as the coefficient sign is positive. This now seems to go in a different direction to what it is supposed.

[Table 12 here]

A different outcome is obtained from the other two types of risk included in the stress tests: with respect to the credit and market risk, coefficient signs are negative, hence inversely impacting the capital adequacy ratio under adverse economic scenarios. In the case of the market risk, it is also shown to be significant; this implies that the market risk's increase under financial distress would impact negatively the capital adequacy ratio of the European union banks (ranging from 5 to 10% change). This conclusion seems to be worth as it is observed, in table 13 for individual variables in Hausman Tests, that the market risk variable is meant to be assessed in both subperiods under a random effects model. This may have a consistent conclusion (in spite of the fact that adjusted R-squared

for both subperiods are extremely lower than the ones predicted under fixed effects) that is in line with previous findings such as Allen and Saunders (2004) where they stated that, instead of operational risk, other significant risks as credit or market risk could be are indeed cyclical, that is, related to systemic failures in the economy.

[Table 13 here]

As a consequence of this last argument in the stress tests' robustness check, the inclusion of a leverage variable was thought to be convenient, thus, to provide more alternative models to the preliminary one. The leverage ratio used is the Basel III leverage ratio published in the 2015-18 stress-tests: given the data constraint, it is only analyzed in the case of the second subperiod as EBA stress tests did not provide data for more variables in preceding tests. Moreover, the leverage ratio is interesting to be included as, in the first regression model, was proved to be significant and explaining capital adequacy behavior (in that case "Solvency" variable or the ability of banks to repay their long-term liabilities). Previous tables 12 and 13 add a third column named c) to show results both for the regression analysis results and Hausman tests in the case of Leverage adjusted model.

Regarding the Hausman Test choice between fixed or random effects, the p-value obtained is equal to 0, then null hypothesis is accepted, and fixed effects should be applied for this model. More specifically, in the case of this adjusted model, all variables are properly assessed using the fixed effect models (even market and credit risk have lower than 5 and 10% level significance, respectively). In addition to this, this adjusted model has a much higher explanatory power with respect to the previous ones, of 96%, which implies that results for this one are meant to be conclusive.

Moving to the regression analysis, now high significance is found in the included variable, Leverage, confirming the findings of the first regression model under "stable" economic conditions: with a very big coefficient term (178% change), leverage is meant to be driving the capital adequacy ratio, as the positive sign represents. Leverage in the European Union becomes a very important financial instrument for macroeconomic policies and, relating to banks, a preferred tool if the purpose is to improve their capital adequacy; opposite conclusion can also be derived as a lower leverage ratio will incur in a worse capital adequacy. In spite of the fact that this variable, towards systemic risk, cannot be compared to liquidity as it was in the first regression model, it is presumed that

the behavior is potentially the same given the explanatory power of the model – consequently, banks are found to be more leveraged if capital adequacy ratio was higher and vice versa - .

A second variable is also significant, the credit risk: opposite to the other two types of risk, credit risk is impacting the capital adequacy under financial distress by 1.3% per unit change (at a 6.2% significance level). Again, risks other than operational risk are more important and explanatory for the bank’s capital adequacy requirements, following findings from previous authors and this paper itself, within a model with higher explanatory power.

Once the alternative models have been evaluated, multicollinearity checks are provided to reinforce the validity of the chosen models. Collinearity is the problem that arises from the possible linear relationship existing between two or more variables within a regression model, which has been broadly solved with the implementation of Variance Inflation Factor (VIF) (Salmerón Gómez et al., 2016); in this estimation, it is assessed the collinearity of variable  $X_i$ ,  $i=1, \dots, p$ , with the rest of the independent variables, defined by the following :

$$(4) \text{VIF}(i) = 1 / (1 - R^2_i), i = 1, \dots, p,$$

where  $R^2_i$  is the coefficient of determination of  $X_i$  on the rest of independent variables.

The value obtained from the computation of VIFs is then compared to general rule of thumbs, set by the maximum inflated coefficient a variable can reach. As discussed by O’Brien (2007), despite improvements that are still needed to be done, the general rule has been set to a maximum coefficient of 10. Hence, this is the value that is being considered in this paper for the multicollinearity check of the regression models. Following tables 14 and 15 show the centered VIFs of the variables present in each of the regression models; firstly table 14 presents VIFs for the CET1 regression under proper Hausman Test model selection ; table 15 those belonging to Stress tests regression, both under proper and alternative Hausman Test models.

[Table 14 here]

[Table 15 here]

As it is observed, both for the first and second regression models, in all the possible fixed and random effects regression models, VIFs are proved to be under the threshold of 10 previously indicated. Table 14 divides VIFs into regions and European Union, where all of them showed a very low coefficient (only two of them exceeded the coefficient of 2). It means that the first section of this thesis accomplishes the multicollinearity checks and requirements from this VIFs. Similarly, the Stress Tests meet the threshold of 10 in all of its forms, but significant changes are appreciated when random effects were introduced; from fixed effects around 1.5 on average, operational risk or credit risk reached the 8 and 7 coefficients under random effects, close to the maximum requirement and, then being potentially multicollinear with respect to capital adequacy. These coefficients again are reduced to lower levels when Leverage is adjusted to the model.

## 7. CONCLUSIONS

This thesis studies the effect that operational risk has on the capital adequacy of European Union banks and the implication of operational risk in the systemic risk of European banks by examining 21 countries and 119 banks from 2013 to 2018. The research is conducted by assessing annual ratios and amounts for banks or regions with a panel of controlling variables under fixed or random effect estimation models. The main results are analyzed considering robustness checks ranging from econometric techniques and alternative variables and models.

According to previous empirical evidence, the role of operational risk in the banking industry had diverse interpretations and effects. Many different approaches about the measure and model adopted to explain the relationship between operational risk and bank's performance have been adopted, thus without having a consensus and homogeneity on the procedures. An example of this limitation is discussed by Abdymomunov and Ergen (2017) where tail loss reporting weakens the measurement of aggregated operational risk, which is translated into inaccurate risk modelling. Similarly, it has not been broadly proved that operational risk is determinant to the banks' losses, either under systemic risk; meanwhile other variables have shown higher level of significance, that is, explaining in a more accurate way patterns within the banking system.

Based on results of this thesis, supported by previous literature within banking industry in different geographic groups, it is possible to conclude that the operational risk does not have an impact on the capital adequacy of European banks under stable and adverse economic conditions. This type of risk is not driving the overall ability of European banks to accomplish minimum regulatory requirements, which determine their financial strength. This finding supports the conclusion of Linsley, Shrives and Crumpton (2006), that can also be extensive to other literature in a regulatory field. Nevertheless, the case of Western-Central banks in Europe shows little significance which can be explored and, then, argued for future research. The fact that banking industry is idiosyncratic as Cerasi, Chizzolini and Ivaldi (2002) discussed, provides the possibility to further investigate uniform patterns among banking sectors with different typology and commercial strategies.

Further insights are obtained from regression models. Both Long-term and Short-term ability to repay debt are the real drivers of the capital adequacy of European banks, with much more preference for long-term debt. Long-run indebtedness is a common financial instrument for European banks which results in better performance and ability to meet regulatory requirements. Once said this, this thesis does not investigate the level of debt that is potentially beneficial or harmful for the economy, which has been a point of debate through financial literature. Robustness checks also give similar results to original regression model, indicating that the financial strength is still measured by the long and short run liability repayment instead of external risks to the banking business processes. This leads to the conclusion that the banking sector is dependent on their internal financial instruments and commercial strategies to improve or to meet regulatory requirements imposed by central banks.

Additionally, systemic risk in the form of worse-case economic conditions are not found to be influenced by the rise of operational losses. Regression model for the stress tests of the European Banking Authority are not demonstrating relationship between operational risk and the capital adequacy observed in the event of financial distress. This first model is tested, in the Robustness check section, under alternative random effects where market risk shows impact for the periods analyzed in this thesis. Likewise, the preliminary model is improved by the inclusion of the Leverage ratio also published by the EBA, where this indicator together with credit risk are proved to be impacting the capital adequacy ratio. Therefore, results support previous findings from Allen and Saunders (2004) stating that other types of risk rather than operational risk have a procyclical pattern with adverse economic conditions.

Findings of this study reflect the absence of homogeneous practices within European banks from different regions. This heterogeneity is also motivated by the availability of data from a very recent period, since 2013, given the fact that regulatory reporting and stress tests publication have started at that time, motivated by Basel III new regulations imposed to banks. Further and accurate research can be driven with the aim of gathering larger time-series data, eliminating biases within short time frames. Operational risk disclosure, already indicated by Bischoff (2009) can lead to the reinforcement in the operational regulatory practices for central public banks, which in turn will lead individual banks to report accurately and timely the set of other risks incurred.

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## APPENDIX

**Table 1.** Total Number of Supervised Financial Institutions by EBA

<u>YEAR</u>	<u>2013</u>	<u>2014</u>	<u>2015</u>	<u>2016</u>	<u>2017</u>	<u>2018</u>
<u>N°COUNTRIES</u>	21	24	24	24	25	25
<u>N°BANKS</u>	105	131	131	131	132	130

**Table 2.** Number of Supervised Financial Institutions by EBA per country and year

<u>COUNTRY/YEAR</u>	<u>2013*</u>	<u>2014</u>	<u>2015</u>	<u>2016</u>	<u>2017</u>	<u>2018*</u>
<u>AUSTRIA</u>	2	5	8	8	6	6
<u>BELGIUM</u>	1	5	6	6	6	6
<u>BULGARIA</u>	-	-	1	1	1	1
<u>CYPRUS</u>	1	3	4	4	3	3
<u>DENMARK</u>	4	4	4	4	4	4
<u>ESTONIA</u>	-	-	-	1	1	1
<u>FINLAND</u>	1	1	2	2	2	2
<u>FRANCE</u>	4	10	12	11	11	11
<u>GERMANY</u>	12	20	19	19	20	20
<u>GREECE</u>	4	-	4	4	4	4
<u>HUNGARY</u>	1	1	1	1	1	1
<u>ICELAND</u>	-	-	-	-	3	3
<u>IRELAND</u>	3	3	4	5	4	4
<u>ITALY</u>	6	14	15	11	11	11
<u>LATVIA</u>	-	1	1	1	-	-
<u>LUXEMBOURG</u>	1	2	5	5	5	5
<u>MALTA</u>	1	1	3	3	3	3
<u>NETHERLANDS</u>	4	6	6	6	6	6
<u>NORWAY</u>	1	1	2	3	3	3
<u>POLAND</u>	1	1	1	2	2	2
<u>PORTUGAL</u>	4	3	6	5	5	5
<u>ROMANIA</u>	-	-	1	1	1	1
<u>SLOVENIA</u>	2	2	2	3	3	3
<u>SPAIN</u>	4	14	14	13	12	12
<u>SWEDEN</u>	4	4	6	7	7	7
<u>UNITED KINGDOM</u>	4	4	4	6	6	6
<u>OTHER BANKS</u>	-	-	-	1	1	1

\*data as of 30th June

**Table 3.** List of banks included in the final sample for CET1 regression model

REGION	COUNTRY	BANK	
NORTHERN	DENMARK	Danske Bank	
	DENMARK	Jyske Bank	
	DENMARK	Sydbank	
	FINLAND	OP-POHJOLA GROUP	
	ICELAND	Íslandsbanki hf.	
	ICELAND	Landsbankinn	
	IRELAND	Allied Irish Banks, Plc	
	IRELAND	Bank of Ireland Group plc	
	IRELAND	Citibank Holdings Ireland Limited	
	IRELAND	DEPFA BANK Plc	
	IRELAND	Permanent TSB Group Holdings Plc	
	NORWAY	DNB BANK ASA	
	SWEDEN	Länsförsäkringar Bank AB - group	
	SWEDEN	NORDEA BANK AB (PUBL)	
	SWEDEN	SBAB Bank AB - group	
	SWEDEN	SKANDINAVISKA ENSKILDA BANKEN AB (PUBL) (SEB)	
	SWEDEN	SVENSKA HANDELSBANKEN AB (PUBL)	
	SWEDEN	SWEDBANK AB (PUBL)	
	UNITED KINGDOM	BARCLAYS plc	
	UNITED KINGDOM	HSBC HOLDINGS plc	
	UNITED KINGDOM	LLOYDS BANKING GROUP plc	
	UNITED KINGDOM	Nationwide Building Society	
	UNITED KINGDOM	ROYAL BANK OF SCOTLAND GROUP plc	
	UNITED KINGDOM	Standard Chartered Plc	
	SOUTHERN	CYPRUS	Bank of Cyprus Public Company Limited
		CYPRUS	Co -operative Central Bank Ltd
CYPRUS		Hellenic Bank Public Company Ltd	
CYPRUS		RCB Bank Ltd	
GREECE		Alpha Bank AE	
GREECE		Eurobank Ergasias SA	
GREECE		National Bank of Greece SA	
GREECE		Piraeus Bank SA	
ITALY		Banca Carige SpA - Cassa di Risparmio di Genova e Imperia	
ITALY		Banca Monte dei Paschi di Siena SpA	
ITALY		Banca popolare dell'Emilia Romagna SC	
ITALY		Banca Popolare di Milano Scarl	
ITALY		Banca Popolare di Sondrio	
ITALY		Banca Popolare di Vicenza SCpA	
ITALY		Banco Popolare Società Cooperativa	
ITALY		Credito Emiliano Holding SpA	
ITALY		Credito Valtellinese	
ITALY		ICCREA Holding	
ITALY		Intesa Sanpaolo SpA	



	ITALY	Mediobanca - Banca di Credito Finanziario SpA
	ITALY	UniCredit SpA
	ITALY	Unione di Banche Italiane SCpA
	ITALY	Veneto Banca SCpA
	MALTA	BANK OF VALLETTA (BOV)
	MALTA	MDB Group Limited
	PORTUGAL	BANCO BPI, SA
	PORTUGAL	Banco Comercial Português SA
	PORTUGAL	Caixa Central de Crédito Agrícola Mútuo, CRL
	PORTUGAL	Caixa Económica Montepio Geral
	PORTUGAL	Caixa Geral de Depósitos SA
	PORTUGAL	ESPIRITO SANTO FINANCIAL GROUP, SA (ESFG)
	PORTUGAL	Novo Banco
	SLOVENIA	Abanka d.d.
	SLOVENIA	NOVA KREDITNA BANKA MARIBOR D.D.
	SLOVENIA	NOVA LJUBLJANSKA BANKA D.D. (NLB d.d.)
	SPAIN	Abanca Holding Hispania
	SPAIN	Banco Bilbao Vizcaya Argentaria, S.A.
	SPAIN	Banco de Crédito Social Cooperativo SA
	SPAIN	Banco de Sabadell, S.A.
	SPAIN	Banco Mare Nostrum
	SPAIN	Bankinter SA
	SPAIN	BFA Tenedora de Acciones
	SPAIN	CaixaBank, S.A
	SPAIN	Ibercaja Banco, S.A.
	SPAIN	Kutxabank, S.A.
	SPAIN	Liberbank, S.A.
	SPAIN	Unicaja Banco S.A.
WEST-CENTRAL	AUSTRIA	Aareal Bank AG
	AUSTRIA	BAWAG Group AG
	AUSTRIA	Erste Group Bank AG
	AUSTRIA	Raiffeisen Bank International AG
	AUSTRIA	Raiffeisen-Holding Niederösterreich-Wien Registrierte
	AUSTRIA	Raiffeisen-Landesbanken-Holding GmbH
	AUSTRIA	Volksbanken Verbund
	AUSTRIA	VTB Bank (Austria) AG
	BELGIUM	AXA Bank Belgium SA
	BELGIUM	Belfius Banque SA
	BELGIUM	DEXIA SA
	BELGIUM	Investar
	BELGIUM	KBC Group NV
	FRANCE	BNP Paribas SA
	FRANCE	Crédit Agricole Group
	FRANCE	Crédit Mutuel Group
	FRANCE	CRH (Caisse de Refinancement de l'Habitat)
	FRANCE	Groupe BPCE

FRANCE	La Banque Postale
FRANCE	RCI banque (Renault Crédit International Banque)
FRANCE	Société Générale SA
GERMANY	Bayerische Landesbank
GERMANY	Commerzbank AG
GERMANY	DekaBank Deutsche Girozentrale
GERMANY	Deutsche Apotheker- und Ärztebank eG
GERMANY	Deutsche Bank AG
GERMANY	Deutsche Pfandbriefbank AG
GERMANY	Deutsche Zentral-Genossenschaftsbank AG
GERMANY	Erwerbsgesellschaft der S-Finanzgruppe mbH & Co. KG
GERMANY	HASPA Finanzholding
GERMANY	HSH Nordbank AG
GERMANY	Landesbank Baden-Württemberg
GERMANY	Landesbank Hessen-Thüringen Girozentrale
GERMANY	Landeskreditbank Baden-Württemberg-Förderbank
GERMANY	Münchener Hypothekenbank eG
GERMANY	NORD/LB Norddeutsche Landesbank Girozentrale
GERMANY	SPAREBANK 1 SMN
GERMANY	SR-bank
GERMANY	VW Financial Services AG
LUXEMBOURG	Banque et Caisse d'Épargne de l'État, Luxembourg
LUXEMBOURG	Precision Capital S.A.
NETHERLANDS	ABN AMRO BANK NV
NETHERLANDS	Coöperatieve Rabobank U.A.
NETHERLANDS	ING Groep N.V.
NETHERLANDS	N.V. Bank Nederlandse Gemeenten
NETHERLANDS	SNS BANK NV
POLAND	Powszechna Kasa Oszczędności Bank Polski SA
POLAND	Bank Polska Kasa Opieki SA

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**Table 4.** List of banks included in the final sample for stress-test regression model

<b>BANK</b>	<b>COUNTRY</b>
ERSTE GROUP BANK AG	AUSTRIA
RAIFFEISEN ZENTRALBANK OSTERREICH AG	AUSTRIA
KBC BANK	BELGIUM
BANK OF CYPRUS PUBLIC CO LTD	CYPRUS
DANSKE BANK	DENMARK
JYSKE BANK	DENMARK
NYKREDIT	DENMARK
OP-POHJOLA GROUP	FINLAND
BNP PARIBAS	FRANCE
BPCE	FRANCE
CREDIT AGRICOLE	FRANCE
SOCIETE GENERALE	FRANCE
Crédit Mutuel Group	FRANCE
La Banque Postale	FRANCE
BAYERISCHE LANDESBANK	GERMANY
COMMERZBANK AG	GERMANY
DEKABANK DEUTSCHE GIROZENTRALE, FRANKFURT	GERMANY
DEUTSCHE BANK AG	GERMANY
DZ BANK AG DT. ZENTRAL-GENOSSENSCHAFTSBANK	GERMANY
HSH NORDBANK AG, HAMBURG	GERMANY
LANDESBANK BADEN-WURTTENBERG	GERMANY
LANDESBANK HESSEN-THURINGEN GZ, FRANKFURT	GERMANY
NORDDEUTSCHE LANDESBANK -GZ-	GERMANY
VW Financial Services AG	GERMANY
ALPHA BANK	GREECE
EFG EUROBANK ERGASIAS S.A.	GREECE
NATIONAL BANK OF GREECE	GREECE
PIRAEUS BANK GROUP	GREECE
ALLIED IRISH BANKS PLC	IRELAND
BANK OF IRELAND	IRELAND
PERMANENT TSB	IRELAND
BANCA MONTE DEI PASCHI DI SIENA S.p.A	ITALY
INTESA SANPAOLO S.p.A	ITALY
UNICREDIT S.p.A	ITALY
UNIONE DI BANCHE ITALIANE SCPA (UBI BANCA)	ITALY
BANQUE ET CAISSE D'EPARGNE DE L'ETAT	LUXEMBOURG
BANK OF VALLETTA (BOV)	MALTA
ABN AMRO BANK NV	NETHERLANDS
ING BANK NV	NETHERLANDS
RABOBANK NEDERLAND	NETHERLANDS
N.V. Bank Nederlandse Gemeenten	NETHERLANDS
DNB BANK ASA	NORWAY
POWSZECHNA KASA OSZCZEDNOSCI BANK POLSKI S.A.	POLAND

BANCO COMERCIAL PORTUGUES, SA	PORTUGAL
CAIXA GERAL DE DEPOSITOS, SA	PORTUGAL
NOVA LJUBLJANSKA BANKA D.D. (NLB d.d.)	SLOVENIA
BANCO BILBAO VIZCAYA ARGENTARIA S.A. (BBVA)	SPAIN
BANCO SANTANDER S.A.	SPAIN
CAIXABANK	SPAIN
BFA Tenedora de Acciones	SPAIN
NORDEA BANK AB (PUBL)	SWEDEN
SKANDINAVISKA ENSKILDA BANKEN AB (PUBL) (SEB)	SWEDEN
BARCLAYS plc	UNITED KINGDOM
HSBC HOLDINGS plc	UNITED KINGDOM
LLOYDS BANKING GROUP plc	UNITED KINGDOM
ROYAL BANK OF SCOTLAND GROUP plc	UNITED KINGDOM

**Table 5.** Descriptive statistics for CET1 regression model

<b>EU</b>	Mean	St.Dev.	Maximum	Minimum	Observations
CET 1	14.17	2.90	24.60	8.15	259
OP.RISK*	18.59	24.17	105.96	0.38	259
SIZE*	488.03	619.16	2671.32	6.85	259
<b>NORTHERN</b>	Mean	St.Dev.	Maximum	Minimum	Observations
CET 1	16.05	3.30	24.60	9.10	69
OP.RISK*	22.15	27.82	105.96	0.39	69
SIZE*	621.21	713.49	2671.32	8.75	69
<b>WEST-CENTRAL</b>	Mean	St.Dev.	Maximum	Minimum	Observations
CET 1	14.22	2.42	20.50	9.70	77
OP.RISK*	26.95	26.77	93.49	0.48	77
SIZE*	725.78	710.25	2077.76	15.20	77
<b>SOUTHERN</b>	Mean	St.Dev.	Maximum	Minimum	Observations
CET 1	12.76	1.93	17.40	8.15	111
OP.RISK*	11.22	16.74	72.76	0.38	111
SIZE*	256.00	360.11	1459.27	6.85	111

\*Data in million euros

**Table 6.** Descriptive statistics for stress' tests regression model

<b>13-16</b>	Mean	St.Dev.	Maximum	Minimum	Observations
CET 1	9.82	2.31	15.34	4.12	189
OP.RISK*	18.75	21.10	86.44	0.38	189
Net Income*	-3.68	45.27	12.54	-622.00	189
<b>15-18</b>	Mean	St.Dev.	Maximum	Minimum	Observations
CET 1	11.57	3.13	20.01	3.40	177
OP.RISK*	21.84	25.34	105.96	0.76	177
Net Income*	-0.03	2.35	12.80	-16.67	177

\*Data in million euros

**Table 7.** Hausman test for CET1 regression model**Hausman Test - Cross Section Random**

	EU	Northern	West-Central	Southern
P-value	0.00	0.01	0.00	0.44

**Hausman Test - Cross Section Random**

P-value	EU	Northern	West-Central	Southern
Op.Risk	0.88	0.90	0.10	0.74
Size	0.03	0.78	0.09	0.39
Market-to-Book ratio	0.95	0.03	0.00	0.33
RoA	0.00	0.07	0.03	0.52
Liquidity	0.58	0.31	0.00	0.29
Solvency	0.00	0.01	0.00	0.29
Credit Risk	0.00	0.51	0.95	0.26
Sovereign Risk	0.86	0.03	0.00	0.57

**Table 8.** Hausman test for Stress test regression model**Hausman Test - Fixed/Random Effect Criteria**

	(1)	(2)
P-value	0.022	0.000

(1) 2013-2016 stress test – model

(2) 2015-2018 stress test – model

**Table 9.** OLS regression for Operational Risk Exposure on CET 1. Columns from 1 to 5 show results of the regression model according to European Union banks, Northern, West-Central and Southern countries, using bank fixed/random effects. First figures represent coefficient terms, p-values are shown in parenthesis. Statistical significance of the explanatory variable indicated with an asterix: \* 10%, \*\* 5% and \*\*\*1% level of confidence. Sample data range from year 2013 to 2018.

	EU	Northern	West-Central	Southern	Southern
Constant	15.6630 <b>(0.000)***</b>	14.4154 <b>(0.007)***</b>	7.3597 <b>(0.098)*</b>	17.0495 <b>(0.000)***</b>	13.0483 <b>(0.000)***</b>
Operational Risk	0.0047 (0.806)	-0.0488 (0.340)	0.0450 <b>(0.087)*</b>	-0.0272 (0.657)	-0.0495 (0.164)
Size	-0.0033 <b>(0.015)**</b>	0.0002 (0.923)	-0.0003 (0.893)	-0.0095 (0.118)	0.0024 (0.367)
Market-to-Book ratio	0.1666 (0.216)	-0.2550 (0.785)	-0.4148 (0.716)	0.0796 (0.587)	0.2027 (0.137)
RoA	0.0128 (0.459)	0.7857 (0.584)	2.6113 <b>(0.071)*</b>	0.0026 (0.888)	0.0025 (0.886)
Liquidity	-0.0478 <b>(0.045)**</b>	-0.0617 (0.233)	-0.0879 <b>(0.055)*</b>	-0.0750 <b>(0.063)*</b>	-0.0668 <b>(0.001)***</b>
Solvency	0.3974 <b>(0.001)***</b>	1.0486 <b>(0.013)**</b>	1.5153 <b>(0.000)***</b>	0.3184 <b>(0.034)**</b>	0.4638 <b>(0.000)***</b>
Credit Risk	0.0001 (0.809)	-0.3610 <b>(0.066)*</b>	0.0000 (0.789)	-0.0090 (0.793)	0.0137 (0.339)
Sovereign Risk	-0.0045 (0.318)	-0.0063 (0.371)	-0.0059 (0.454)	0.0167 (0.450)	-0.0080 (0.528)
Bank fixed effect	Yes	Yes	Yes	Yes	No
Bank Random effect	No	No	No	No	Yes
Time fixed effect	Yes	Yes	Yes	Yes	No
Observations	525	107	214	191	191
Adjusted <i>R</i> -squared	0.83	0.84	0.90	0.63	0.36
<i>S.E. of regression</i>	1.18	1.33	0.76	1.20	1.26

**Table 10.** OLS regression for Operational Risk Exposure on adverse scenario CET 1. Columns from 1 to 2 show results of the regression model according to 2013-2016 and 2015-2018 periods, respectively. First figures represent coefficient terms, p-values are shown in parenthesis. Statistical significance of the explanatory variable indicated with an asterix: \* 10%, \*\* 5% and \*\*\*1% level of confidence.

	(1)	(2)
Constant	8.688 <b>(0.016)**</b>	13.868 <b>(0.000)***</b>
Operational Risk	0.029 (0.885)	-0.038 (0.523)
Net Income	-0.009 (0.853)	-0.012 (0.777)
Market Risk	0.016 (0.587)	-0.006 (0.921)
Credit Risk	0.002 (0.813)	-0.008 (0.445)
Bank fixed effect	Yes	Yes
Bank Random effect	No	No
Time fixed effect	Yes	Yes
Observations	189	177
Adjusted <i>R</i> -squared	0.828	0.914
<i>S.E. of regression</i>	0.96	0.92

**Table 11.** OLS regression for Operational Risk Exposure on CET 1: alternative models. Columns from 1 to 5 show results of the regression model according to European Union banks, Northern, West-Central and Southern countries, using bank fixed/random effects. First figures represent coefficient terms, p-values are shown in parenthesis. Statistical significance of the explanatory variable indicated with an asterix: \* 10%, \*\* 5% and \*\*\*1% level of confidence. Sample data range from year 2013 to 2018.

	EU	Northern	West-Central	Southern	Southern
Constant	11.7966 <b>(0.000)***</b>	11.5863 <b>(0.000)***</b>	9.4281 <b>(0.000)***</b>	13.0483 <b>(0.000)***</b>	17.0495 <b>(0.000)***</b>
Operational Risk	-0.0010 (0.956)	-0.0446 (0.273)	0.0454 <b>(0.013)**</b>	-0.0495 (0.164)	-0.0272 (0.657)
Size	-0.0014 (0.139)	-0.0009 (0.587)	-0.0025 <b>(0.027)**</b>	0.0024 (0.367)	-0.0095 (0.118)
Market-to-Book ratio	0.2158 (0.131)	-1.1602 (0.144)	-1.1158 (0.247)	0.2027 (0.137)	0.0796 (0.587)
RoA	0.0032 (0.868)	2.5250 <b>(0.009)***</b>	0.5011 (0.607)	0.0025 (0.886)	0.0026 (0.888)
Liquidity	-0.0157 (0.429)	0.0087 (0.790)	0.0686 <b>(0.026)**</b>	-0.0668 <b>(0.001)***</b>	-0.0750 <b>(0.063)*</b>
Solvency	0.5124 <b>(0.000)***</b>	0.7141 <b>(0.000)***</b>	0.2459 (0.178)	0.4638 <b>(0.000)***</b>	0.3184 <b>(0.034)**</b>
Credit Risk	-0.0001 (0.775)	-0.3665 <b>(0.000)***</b>	0.0000 (0.877)	0.0137 (0.339)	-0.0090 (0.793)
Sovereign Risk	0.0028 (0.538)	-0.0003 (0.956)	0.0096 (0.137)	-0.0080 (0.528)	0.0167 (0.450)
Bank fixed effect	No	No	No	No	Yes
Bank Random effect	Yes	Yes	Yes	Yes	No
Time fixed effect	No	No	No	No	Yes
Observations	525	107	214	191	191
Adjusted <i>R</i> -squared	0.14	0.44	0.19	0.36	0.63
<i>S.E. of regression</i>	1.43	1.45	1.14	1.26	1.20



**Table 12.** OLS regression for Operational Risk Exposure on CET 1 under stress tests: alternative models. Columns from a) to c) show results of the regression model according to random effects in period 13-16, random effects in period 15-18 and fixed effects with leverage included in period 15-18. First figures represent coefficient terms, p-values are shown in parenthesis. Statistical significance of the explanatory variable indicated with an asterix: \* 10%, \*\* 5% and \*\*\*1% level of confidence.

	( a )	( b )	( c )
Constant	10.213 <b>(0.000)***</b>	12.582 <b>(0.000)***</b>	6.303 <b>(0.000)***</b>
Operational Risk	0.079 <b>(0.028)**</b>	0.047 (0.235)	-0.051 (0.179)
Net Income	0.005 (0.209)	0.226 <b>(0.000)***</b>	-0.038 (0.169)
Market Risk	-0.055 <b>(0.007)***</b>	-0.103 <b>(0.021)**</b>	0.019 (0.614)
Credit Risk	-0.006 (0.142)	-0.005 (0.171)	-0.013 <b>(0.062)*</b>
Basel III Leverage			1.718 <b>(0.000)***</b>
Bank fixed effect	No	No	Yes
Bank Random effect	Yes	Yes	No
Time fixed effect	No	No	Yes
Observations	189	177	177
Adjusted <i>R</i> -squared	0.058	0.149	0.965
<i>S.E. of regression</i>	1.604	1.78	0.6

**Table 13.** Hausman test for Stress test regression model: alternative models

**Hausman Test -  
Fixed/Random Effect  
Criteria**

	( a )	( b )	( c )
P-value			0.000
<b>Hausman Test - Cross section Random Effect</b>			
Op.Risk	0.729	0.002	0.000
Net Income	0.568	0.000	0.000
Market Risk	0.183	0.778	0.037
Credit Risk	0.522	0.010	0.070
Basel III Leverage			0.000

**Table 14.** Multicollinearity Test: VIFs for CET1 regression model

<b>Variance Inflation Factor - Centered</b>				
	EU	Northern	West-Central	Southern
Op.Risk	1.07	1.52	1.61	1.16
Size	1.08	1.33	1.92	2.53
Market-to-Book ratio	1.12	1.24	1.85	1.13
RoA	1.13	1.57	1.83	1.14
Liquidity	1.03	1.15	1.06	1.09
Solvency	1.08	1.19	1.48	1.30
Credit Risk	1.05	1.29	1.50	1.16
Sovereign Risk	1.07	1.24	1.64	2.46

**Table 15.** Multicollinearity Test: VIFs for Stress Tests regression models

<b>Variance Inflation Factor - Centered</b>					
	(1)	(2)	( a )	( b )	( c )
Op.Risk	1.123	1.235	8.358	8.929	4.721
Net Income	1.219	1.098	1.006	1.105	1.203
Market Risk	1.788	2.275	3.636	5.202	3.393
Credit Risk	2.193	2.062	7.758	4.247	3.478
Basel III Leverage					1.155

1) Fixed effects 13-16

2) Fixed effects 15-18

a) random effects 13-16

b) random effects 15-18

c) fixed effects 15-18: leverage adjusted