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Mestrado em Estatística e Gestão de Informação

Master Program in Statistics and Information Management

The Impact on Operational Risk: An Analysis on Macroeconomic, Governance and Firm-Level Determinants

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Dissertation presented as partial requirement for obtaining the Master's degree in Statistics and Information Management

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by

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Dissertation report presented as partial requirement for obtaining the Master's degree in Statistics and Information Management, with a specialization in Risk Analysis and Management

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November 2021

ACKNOWLEDGEMENTS

I would like to begin by expressing my gratitude to all those who helped me throughout this incredible challenge.

On the academic front, I wish to express my deepest appreciation to my advisors, Professor Rui Gonçalves and Professor Bruno Damásio for their guidance, patient assistance and all the knowledge shared during my research. Their advice, dedication and expertise were fundamental to deliver the best work possible.

I would like to acknowledge my co-workers at BNP Paribas, who have supported me and had to put up with my stress for the last months.

Some special words of gratitude go to my friends, with whom I have shared moments of deep anxiety but also of big excitement.

On a more personal note, I would like to thank my amazing partner, Gonçalo Prates, for never letting me doubt myself and for giving me the strength I needed to conclude this chapter of my life. Finally, I would like to thank all my family for the love and support, specially to my parents and brother, for helping me get through the stressful periods, for continually encouraging me and for never letting me give up. Without their massive support, this dissertation would have never been concluded.

Thank you all.

ABSTRACT

Financial institutions and organizations in general face risks every day that threat the stability of the business. An effective Operational Risk management is essential to mitigate, monitor and manage any negative effect or significant impact that can cause uncertainty in financial markets. Among the various risks financial institutions face, most top managers argue that Credit Risk has more impact on an organization, however Operational Risk is also considered the most important type of risk because they can lead to the destruction of a business and is present in every organization.

The purpose of this dissertation is to investigate, assess and analyse firm and country specific factors as determinants of operational loss severity. The goal is to increase knowledge regarding Operational Risk, investigate the determinants that explain differences in Operational Risk losses and simultaneously test and validate some of the key findings of previous research.

The study deals with 2306 operational loss events from SAS OpRisk database. Events occurred between 2000 and 2020 in European financial firms. The empirical research was conducted by using panel data regression analysis which includes truncation and two-ways fixed effects. The results of this study suggest that operational loss events tend to be more severe during economic downturn, which predominate the high unemployment rate, inflation and interest rate. The results indicate that operational losses are linked with governance indicates, being positively related with rule of law and negatively related with regulatory quality. The findings also found firm specific variables to be insignificantly linked with operational risk losses, with the exception of the size of the firm. We find evidence of significant correlation between Internal Fraud and inflation rate. External Fraud losses show a significant relation with regulatory quality, return on equity and assets. Execution, Delivery and Product Management events indicate a strong relationship with the size of the firm. It is also shown that Clients, Products and Business Practices and Employment Practices and Workplace Safety events are sensitive to macroeconomic and governance indicators.

KEYWORDS

Operational Risk; Panel Data; Macroeconomic Impact, Governance and Firm Determinants

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1. INTRODUCTION

1.1. BACKGROUND

The working definition of Operational Risk among financial institutions is “the risk of loss from inadequate or failed internal processes, people, and systems or from external events”. Operational Risk come in many forms and can cause losses of almost any size. As cited by Robertson (2016), “the losses can be insignificantly small or large enough to destroy an institution almost overnight”.

In the last decades, Operational Risk has been receiving attention from researchers, regulators, and practitioners, because of the many severe incidents which have underlined the dangerousness of Operational Risk. Several losses derive from misconduct, rogue trading, computer hacking, inadequate procedures and many more. The reason for this attention is due to the development of “information technology, new and changing fields of business, growing globalization and automation as well as the emergence of increasingly complex products” (Power, 2005). Other reasons attributed to this are the impact from the increasing size, complexity of financial institution and the changing in operational environment. Furthermore, the importance of Operational Risk was recognized by the introduction of the Basel II accord. In 2004, the Basel Committee released its definitive Basel II Accord with the establishment of new capital charge rules for Operational Risk (Micocci, Masala, & Flore, 2009). The Basel II Accord helps financial institutions to pay more attention to qualitative and quantitative aspects of their risk exposure (BCBS, 2006) by developing models for quantifying the capital requirement for Operational Risk rather than only credit and market risk. There is a need for an effective Operational Risk management and measurement system due to the increased sophistication and complexity of the banking sector. Since the financial crisis in 2008, many inadequacies in the regulatory capital calculation have been exposed. Therefore, in December 2017, the Basel Committee issued the Basel III framework which includes a number of improvements, mainly the introduction of the Standardized Approach framework to calculate minimum Operational Risk capital requirements that replaces the three calculation methods of Basel II (one of these being the Advanced Measurement Approach) (BCBS, 2017).

Operational Risk has been around since the 1990s, contributing to every financial catastrophic event that occurred ever since. (Allen & Bali, 2004) consider that Operational Risk losses are an indication of future larger losses that can be disastrous, which have an impact on the market value of a firm. Likewise, one example of the dangerousness of Operational Risk is the US subprime mortgage crisis of 2007/2008. During this time, mortgage fraud became a serious matter as a result of “negligent lending practices by banks, low, protracted global interest rates, high oil prices, historically low world-wide inflation, environment and inappropriate assumptions made for the assignment of financial derivative credit ratings” (Jongh et al., 2013). Many borrowers took on mortgages they could not afford by exaggerating their income or assets (Dilley, 2012). Numerous deficiencies were exposed during this crisis, including negligent managerial oversight and monitor internal control policies (Hess, 2011). One of the most notorious catastrophic events is the collapse of the Barings Bank, where "a loss of US$1 billion resulted from rogue trading activities by Nick Leeson in February 1995" (Jongh et al., 2013). We can also mention Daiwa Bank and Sumitomo Corporation which lost $1.1 billion and $2.6 billion, respectively, due to unauthorised trading activity.

Operational Risk attracts a lot of attention thanks to the exceptional and fatal nature of it. Although rare, extreme events constitute "threats rather risks, which are hard to measure and even more difficult (or impossible) to predict, because they have never occurred" (Jobst, 2007). Extreme Operational Risk events usually occur rarely but can be catastrophic and lead to the failure of an institution's activity. A bank, or any other financial institution, must take into consideration the probability of their occurrence and "develop and use better risk management techniques in monitoring and managing their risks" (BCBS, 2004). For the purpose of estimating possible future losses, a bank needs to understand its past operational loss experience. Therefore, it is important to study whether Operational Risk losses were caused by macroeconomic, macroenvironmental or firm-specific factors.

The study of the determinants of Operational Risk has been receiving some attention in the past few years and has enriched. Previous literature has investigated the correlation between the size of operational losses and the size of the institutions (Shih et al., 2000 ; Na et al., 2006; Wei, 2006; Cope & Labbi, 2008; Dahen & Dionne, 2010; Prokop & Pakhchanyan, 2013). Chernobai et al., 2011 and Cipriano et al., 2018 present evidence on strong links between Operational Risk and firm specific factors.

The empirical literature on the macroeconomic factors of Operational Risk has increased in the last years. Allen & Bali (2007), Hess (2011) and Hambuckers et al. (2018) focus on the pro-cyclical nature of operational losses. Prokop & Pakhchanyan (2013) present evidence that market-related factors play a significant part in operational loss formation. In particular, they show a positive relationship between operational losses and GDP growth rate. These results are corroborated by Abdymomunov (2014) and Abdymomunov et al. (2017).

Cope et al. (2012) find significant relationship between operational losses and governance and macroeconomic indicators. Moosa & Li (2015) have also studied the connection between Operational Risk and country specific governance factors, such as rule of law, control of corruption, voice and accountability, political stability, and absence of violence/ terrorism.

Many studies have explored the determinants of Operational Risk, however few investigations focused on Europe. The focus on European countries will ensure homogeneity in the dataset.

1.2. OBJECTIVES

The existing research has focused on modelling the frequency and severity of Operational Risk, analysing them both or separately. Some examples can be found on (Chernobai et al., 2011), (Cope et al., 2012) and (Li & Moosa, 2015). This thesis will focus on the severity of operational loss events.

The general objective of this research consists of examining the causes and consequences of Operational Risk by identifying firm-specific, macroeconomic and governance determinants among financial institutions that explain the level of operational losses, as well as test and possibly validate some key findings of the previous research.

Most of the studies conducted on the key determinants of operational losses are focused on firm-specific factors and macroeconomic covariates, for example (Alifano et al., 2019) and (Chernobai et al., 2011).

Therefore, we aim to examine the key research questions for this study which are presented as follows:

- As done by Chernobai et al. (2008), Prokop & Pakhchanyan (2013) and Hambuckers et al. (2018), we aim to answer to the question "Which firm-specific factors have a significant impact on the magnitude of operational loss events?"
- As similar studied by Cope et al. (2012), Chernobai et al. (2011) and Hambuckers et al. (2018), we intend to answer to the question "Which macroeconomic factors have a significant impact on the magnitude of operational loss events?"
- Such as studied by Cope et al. (2012), Moosa & Li (2015) and Alifano et al. (2019), we expect to answer to the question "What are the governance indicators that have more impact on Operational Risk levels?"

1.3. RELEVANCE AND IMPORTANCE

Operational Risk has become one of the main focus in the banking sector due to the massive losses that have been occurring in the past decades. This study contributes to this literature in several dimensions. Our empirical results complement those available in the literature because we include a large set of variables. This study emphasizes the significant association between operational losses in the banking industry and macroeconomic and macroenvironmental conditions, extending the literature on Operational Risk at financial institutions.

The results could help improve risk management practices by increasing the internal processes and control which aims at reducing the occurrence of operational losses. According to Auer et al. (2015), the benefits of an efficient Operational Risk management are freeing up capital, better decision making, lower cost of funds, lower operating costs, less profit and loss volatility, increased customer and staff satisfaction and better regulatory compliance.

1.4. STRUCTURE

This thesis is organized as follows:

Chapter 2 introduces Operational Risk with a theoretical overview of its definition, classification, characteristics, measuring and modelling of Operational Risk. We also present an overview of the explanatory variables that will be used in the research. Chapter 3 we discuss the methodological approach to be employed and the methods to be used to collect data for the research. Chapter 4 the results are presented from the quantitative model. Chapter 5 we discuss the findings of the research in line with the aims and objectives defined for the study. In this chapter the conclusions are drawn over the results presented in the previous section. Chapter 6 the limitations and recommendations for future works are presented.

2. LITERATURE REVIEW

2.1. OPERATIONAL RISK CONCEPT

Operational risk has always been present, however with the rapid changes and the complexity in the financial environment, a widespread concern has grown (Basak & Buffa, 2019). Operational Risk had already been officially coined in 1991 (COSO, 1991), but it was not until the early 1990s that the term Operational Risk was first defined (Moosa, 2007b). Power (2005) argues that the rogue trader attributed with the destruction of Barings Bank is “the true author and unwitting inventor of Operational Risk, since most discussions of the topic refer to this case as a defining moment”.

The Group of Thirty (1993) first defined Operational Risk as “uncertainty related to losses resulting from inadequate systems or controls, human error or management”. The British Bankers' Association (1997) specified Operational Risk with a possible cause as:

- The risk associated with human error, inadequate procedures and control, fraudulent and criminal activities; the risks caused by technological shortcomings, system breakdowns
- All risks which are not “banking” and arising from business decisions as competitive action, pricing, etc
- Legal risk and risk to business relationship, failure to meet regulatory requirements or an adverse impact on the bank’s reputation
- External factors include natural disasters, terrorist attacks and fraudulent activity.

According to The Commonwealth Bank of Australia (1999), Operational Risk is “all risks other than credit and market risk, which could cause volatility of revenues, expenses and the value of the Bank’s business”. Shepheard-Walwyn & Litterman (1998) defined it as “a general term that applies to all the risk failures that influence the volatility of the firm’s cost structure as opposed to its revenue structure”. For Kingsley et al. (1998) Operational Risk is “the risk of loss caused by failures in operational processes or the systems that support them, including those adversely affecting reputation, legal enforcement of contracts and claims.” Of course, Operational Risk is not easy to define because of its diversity and that’s why Crouchy (2001) argues that Operational Risk is a “fuzzy concept” because it is hard to distinguish Operational Risk from normal uncertainties and hazards faced by companies on its day-to-day business activities.

While there is an agreement on the current concept of Operational Risk, diversity on definitions continues to exist. There are several definitions for Operational Risk, ranging from narrow to broad classifications (Pakhchanyan, 2016). First definitions were mostly based on an exclusion principle. Rao & Dev (2006) argue that five years ago it was not unusual to consider Operational Risk as a residual and that 'everything other than credit risk or market risk was, by default, Operational Risk’. According to Doerig (2000), “defining Operational Risk in such an exclusionary way - "total risk - credit risk - market risk" - prevents from identifying a structured way of managing it". Financial institutions are faced with several risks, which includes Credit, Market and Operational Risk. Credit risk is defined as "the risk of losses due to borrowers' defaults or deterioration of credit standing" (Bessis, 2010). Market risk is "the risk of losses due to adverse movements of the value of financial instruments because of market movements for an horizon that depends on the required time to liquidate them, thereby avoiding further losses" (Bessis, 2010). When compared to market and credit risk, Operational Risk has some peculiarities – it is a natural consequence that is originated from within the financial institution (except external events) (Sironi & Resti, 2007) , whereas credit and market risk originate from outside the bank. Medova & Kyriacou (2001) and Chapelle (2019) state that, for some practitioners, Operational Risk definition as 'everything not covered by exposure to credit and market risk' still remains.

The most common definition of Operational Risk, adopted by The Basel Committee, first appeared in Robert Morris Associates et al. (1999) as "the direct or indirect loss resulting from inadequate or failed internal processes, people and systems, or from external events." The Basel Committee adopted this definition but excluded systemic risk, strategic and reputational risks as well as indirect losses since these losses are difficult to measure. This concept reflects a long process of discussion, debate, and disagreement where there was no consensus in the banking industry. For Turing (2003), the definition is quite useless due to its broad description while Herring (2002) criticizes this definition as it is disregarding business risk. The current definition of Operational Risk proposed by the Basel Committee on Banking Supervision (BCBS), and the one accepted in this study, is "the risk of loss resulting from inadequate or failed internal processes, people and systems or from external events". This definition, according to (Alifano et al., 2019), recognizes different probable causes of operational losses which includes "bank specific features and processes, and those related to the external legal, regulatory and economic environment".

Defining Operational Risk is "more than a simple matter of labelling and is a meeting point for different interests and ambitions" (Power, 2005). According to Power (2005), the central part of the logic of any practice is to define key concepts and that "without a system of concepts and taxonomies, any practice of intervention is blind, disorganised and of questionable legitimacy". Defining it is very important for risk awareness at the management level and for the calculation of regulatory capital (Buchelt & Unteregger, 2003) – which is not possible with definitions and frameworks not settled.

2.2. IMPORTANCE OF OPERATIONAL RISK

Ever since the beginning of the corporate world, financial institutions and businesses in general have been experiencing hazards attributed to the development in information technology, business disruption and the increasing complexity of financial instruments and trading procedures, "leaving the corporate world more exposed to Operational Risk than ever before" (Moosa, 2007a). The profession of 'Operational Risk' appeared, roles such as

‘Operational Risk manager’ were being created and books were being published (Power, 2005). What was a question mark in the early 1990s, became a topic everyone talked about by the end of that decade.

Moosa (2007) assigned the importance of Operational Risk to the recent development of “e-commerce, mergers and consolidations, the use of automated technology, the growing use of outsourcing arrangements, and the increasing complexity of financial assets and trading procedures”. According to Buchelt & Unteregger (2003)**,** the significance of Operational Risk is due to the increasing “complexity of the banking business, information technology, new and changing fields of business, growing globalization and automation as well as the emergence of increasingly complex products”. All these factors contributed to the changing risk profile of the financial services sector, which led to a greater interest of the regulators (Moosa, 2007b)**.**

Buchelt & Unteregger (2003) argue that the risk of fraud and external events have been around ever since the beginning of banking, but what really hoisted the concept of Operational Risk is probably the collapse of large corporations such as Barings Banks, LTCM and Eron due to the materialisation of operational loss events. Operational events have contributed to extremely large losses since 1990, including the global financial crises of 2007/2008 (Jongh et al., 2013)**.** During that time, several operational loss events materialised including British Airways, MacDonald’s, Société Générale, Lehman Brothers, Microsoft and MF Global (Moosa, 2008)**.**

Catastrophic and extremely large events have been receiving attention from media, regulators, and business executives as they are related with huge failures. As cited by Robertson (2016), “the losses can be insignificantly small or large enough to destroy an institution almost overnight”. Cummins et al. (2006) published a study supporting the theory that the announcement of large loss events has impact on the market value of a firm and that most of the stock price reaction occurs in the days surrounding the announcement date. Operational Risk started being defined in an exclusionary way and treated as a residual, but according to BCBS (1999) Operational Risk is “sufficiently important for banks to devote the necessary resources to quantify the level of such risks”. Regulators, therefore, realized that credit, and market risk management was not enough to prevent from those events, there was indeed a need to manage Operational Risk. Consequently, firms and supervisors have a common interest in identifying, monitoring, and controlling Operational Risk.

2.3. EXTREME OPERATIONAL LOSS EVENTS - EXAMPLES

Operational Risk events can negatively impact the operations of a financial institution, incurring in losses that can lead to their collapse. Since the 1990’s, many institutions experienced extremely large losses due fraud, theft, hacking, lawsuits, terrorism, vandalism and natural disasters. In the past decades we have seen several scandals involving institutional and retail corporations. Some examples are presented by Moosa (2007b), in Table 1.

Table 1 – Historical operational losses (Source: Moosa (2007b))

Firm Name	Year	Description
Barings Bank	1995	Nick Leeson, the rogue trader, lost $1.2 billion in unauthorized speculation in futures contracts and other trades. This isolated incident was catastrophic and led to Barings' bankruptcy.
Prudential Insurance Company of America	1990	$2 billion loss due to fraudulent sales practices over 13 years.
Orange County	1994	$1.7 billion loss due to unauthorized trading activity that led to bankruptcy.
Daiwa Bank	1995	$1.1 billion loss due to illegal and unauthorized trading by an employee in attempt to recoup the losses.
Banco Nacional	1995	$9 billion loss due to credit fraud
Sumimoto Corporation	1996	$2.6 billion loss due to unauthorized trading activity
Allied Irish Bank	2002	$750 million loss of due to rogue trading. A trader tried to cover his huge losses for 5 years through foreign-exchange trades.
Lehman Brothers	2008	During the subprime crisis, the institution filed for bankruptcy after huge losses. The bank presented losses of $3.9 billion in the third trimester of 2008.
Société Générale	2008	In January 2008, all the unauthorized trades done by Jerôme Kerviel were discovered. In three days, the bank undid all the operations that led to €4.9 million in losses.

Furthermore, besides the events mentioned above, Operational Risk also covers external events such as the terrorist attacks of 9/11 in New York (that caused substantial amounts of property damage, human and economic costs) and natural disasters, such as Hurricane Katrine, which damaged the premises of most financial and non-financial institutions.

2.4. CLASSIFICATION OF OPERATIONAL RISK

The classification of Operational Risk is a valuable starting point for Operational Risk management. It is important to classify and categorize it in a way that is relevant to the company's needs as "disaggregation empowers and encourages the functions to monitor and manage risk on a structural basis" (Moosa, 2007b).

According to Chernobai et al. (2007), Operational Risk can be classified in several ways:

- Nature: Operational Risk sources can be internal or external to the business. Internal Operational Risk is a consequence of errors, such as human failure and rogue trading, that can be managed and mitigated. As for external sources, which include earthquakes or terrorist attacks (Aloqab et al., 2018), their management is much more complicated due to its unpredictability.
- Impact of the loss: Losses can be directly associated with financial losses, whereas indirect losses are often related with opportunity costs, near misses, latent losses, and contingent losses (BCBS, 2001b)**.**
- Degree of expectancy: events that occur frequently can be expected, such as employee errors in processing payments, internal and external fraud, or equipment failure. Unexpected events, such as a terrorist attack, are referred to as "black sawn events" which are rare events that can lead to extremely large losses (Jongh et al., 2013).
- Risk type, event type and loss type: It is essential for banks to separate operational events data according to the event type, loss type and the appropriate risk type when recording it.
- Severity and Frequency of loss: Operational Risk events can be divided into high-frequency; low-severity events and low frequency; high severity events. The frequency is the number of loss events and the severity is the total loss amount incurred in a loss event (Moosa, 2007b).

Moreover, Operational Risk can be classified on whether the action is intentional or unintentional (Robertson, 2016). Marshall (2001) argues that Operational Risk can also be distinguished by its control. If there is the possibility to prevent loss events and mitigate the risks, at that point, the Operational Risk is controllable, else it is uncontrollable.

According to Moosa (2007b)**,** Operational Risk should be classified based on the cause, the event, and the effect of an incident. However, the turmoil among causes and effects of Operational Risk losses still exists. The cause corresponds to the fact that generated the event, and the effect is typically the consequence in financial terms.

Event type is another criterion for classifying Operational Risk based on the cause. The Basel Committee on Banking Supervision has determined an alternative to the cause of the incidents which is the use of event types (Robertson, 2016). Therefore, the Basel Committee established seven event types:

- Internal Fraud
- External Fraud
- Employment Practices and Workplace Safety
- Clients, Products and Business Practices
- Damage to Physical Assets
- Business Disruption and System Failure

- Execution, Delivery and Process Management

Table 2 – Event Type Definitions

Event Type Level 1	Definition	Categories (Level 2)	Activity (Level 3)
Internal Fraud	Losses due to acts of a type intended to defraud, misappropriate property, or circumvent regulations, the law or company policy, excluding diversity/discrimination events, which involves at least one internal party	Unauthorized activity	Transactions not reported; Transaction type unauthorized; Mismarking of position
		Theft and fraud	Fraud / credit fraud / worthless deposits; Theft / extortion / embezzlement / robbery; Misappropriation of assets; Malicious destruction of assets; Forgery; Check kitting; Smuggling; Account takeover / impersonation; Tax non-compliance / evasion; Bribes / kickbacks; Inside trading
External fraud	Loss resulting from an act by a third party of a type intended to defraud, misappropriate property, or circumvent the law	Theft and fraud	Theft / robbery; Forgery; Check kiting
		System security	Hacking damage; Theft of information (with monetary loss)
Employment practices and workplace safety	Losses resulting from an act inconsistent with employment, health, or safety laws or agreements, from payments of personal injury claims, or payments arising from diversity and discrimination type events	Employee relations	Compensation, benefit, termination issues; Organized labour activity
		Safe environment	General liability; Employee health and safety rules events; Workers compensation
		Diversity and discrimination	All discrimination types
Clients, products, and business practices	Losses arising from an unintentional or negligent failure to meet a professional obligation to specific clients, or from the nature or design of a product	Suitability, disclosure, and fiduciary	Fiduciary breaches / guideline violations; Suitability / disclosure issues; Retail customer disclosure violations; Breach of privacy; Aggressive sales; Account churning; Misuse of confidential information; Lender liability
		Improper business or market practices	Antitrust; Improper trade; Market manipulation; Inside trading; Unlicensed activity; Money laundering
		Product flaws	Product defects; Model errors
		Selection, sponsorship, and exposure	Failure to investigate client per guidelines; Exceeding client exposure limits
		Advisory activities	Disputes over performance of advisory activities
Damage to physical assets	Losses arising from loss or damage to physical assets from natural disaster or other events	Disasters and other events	Natural disaster losses; Human losses from external sources
Business Disruption and System failures	Losses arising from disruption of business or system failures	Systems	Hardware; software; Telecommunications; Utility outage / disruptions
Execution, delivery, and process management	Losses from failed transaction processing or process management, from relations with trade counterparties and vendors	Transaction capture, execution, and maintenance	Miscommunication; Data entry, maintenance, or loading error; Missed deadline or responsibility; Model / system misoperation; Accounting error / entity attribution error; Delivery failure; Collateral management failure; Reference data maintenance

Monitoring and reporting	Failed mandatory reporting obligation; Inaccurate external report
Customer intake and documentation	Client permissions / disclaimers missing; Legal documents missing / incomplete
Customer / client account management	Unapproved access given to accounts; Incorrect client records; Negligent loss or damage of client assets
Trade counterparties	Non-client counterparty misperformance; Miscellaneous non-client counterparty dispute
Vendors and suppliers	Outsourcing; Vendor disputes

Source: Basel Committee on Banking Supervision (2017b). *OPE25 Standardised Approach* (pp. 1–17)

According to McConnell (2006), several large operational loss events do not "fit easily into the very broad *one size fits all* Basel II event type classification". Certain events may overlap more than one event type (Robertson, 2016).

Peccia (2003) notes that classifying operational losses based on causes is prone to errors and misunderstandings. However, this classification in fact facilitates the distinction between credit and market risk, as opposed to classifying events by consequence, and "makes Operational Risk manager's task easier, as losses can be considered to materialize in an event" (Moosa, 2007b).

2.5. CHARACTERISTICS OF OPERATIONAL RISK

Operational Risk has several characteristics that distinguish it from other types of risk. For Doerig (2000), Operational Risks are "primarily institutional, bank made, internal, context dependent, incredibly multifaceted, often judgemental, interdependent, often not clearly discernible vis à vis e.g. market and credit risks and not diversifiable."

Although some characteristics might be accepted by the overall community, for example the diversity of Operational Risk, others are still controversial such as the fact of being one-sided and idiosyncratic (Moosa, 2007a; Pakhchanyan, 2016).

The diversity of Operational Risk is a feature that makes it distinguishable from market and credit risk. The Economist (2003) describes Operational Risk as "the risk of all manner of mishaps and foul-ups, from a lost document to a bomb blast". With numerous different origins, Operational Risk is an exceptionally diverse and interrelated set of risks Buchelt & Unteregger (2003). As Operational Risk is incredibly multifaceted, "bending it into one simple figure requires making a significant amount of unstable assumptions" (Doerig, 2000). Therefore, quantifying and identifying Operational Risk is much more difficult than market and credit risk.

For Lewis & Lantsman (2005)**,** the one-sided feature of Operational Risk is explained by the fact that an institution has a probability of incurring in a loss or no loss. This feature is also supported by Birindelli & Ferretti (2017), who pointed out that operational risk is transversal to the whole banking activity, not being easily transferred and/or hedged and it is not correlated with the firms size and/or its volume of business. However, Moosa (2007b) argues that Operational Risk is not one-sided as there is a risk-return trade-off in the sense that, when increasing their daily operations, companies will be exposed to Operational Risk with the expectation of potential return.

Likewise, it is argued that Operational Risk might be idiosyncratic, in the sense that when a firm is affected, others will not be impacted. However, this argument is debatable. When a firm is affected, other firms might be affected as well. This does not mean that when a bank goes bankrupt other banks will too, but they will be affected in some way (Moosa, 2007b). One example that supports the argument that Operational Risk is not idiosyncratic is the financial crisis of 2007-2008, where the failure of a large financial firms created systemic risk which impacted the overall economy.

Furthermore, McConnell (2006) suggests four characteristics of extreme Operational Risk events: a perfect storm, an ethical meltdown, an infrastructure disaster, and a learning curve. A ‘perfect storm’ is a term that means the combination of several harmful factors that “in a largely unforeseen scenario, precipitate a very large loss” McConnell (2006). Example of a catastrophic loss is the Barings case. An ‘Ethical Meltdown’ is “a widespread failure of ethical values across the industry”, which include improper and illegal activities such as inappropriate pricing or spinning (the act of offering preferred allocations of shares in an initial public offering by a brokerage firm or underwriter). The ‘Infrastructure disaster’ encompasses natural disasters and terrorist attacks which result on losses due to the disruption of vital services (e.g., damage to premises and technology infrastructure). Lastly, the ‘learning curve’ is a well-known phenomenon in the engineering field and is related to losses that occur due to new financial products and the development in information technology.

Apart from the characteristics mentioned above, some would argue that Operational Risk losses are influenced by cyclical factors such as macroeconomic and environmental fluctuations (Allen & Bali, 2004).

2.6. MEASURING AND MODELLING OPERATIONAL RISK

The interest in measuring and managing Operational Risk has been increasing because of the immense changes in environment in which banks operate, “when it appeared clear that this kind of risk would attract a specific capital requirement in the new prudential regulation” (Mignola & Ugoccioni, 2006). What increased the ability to measure, monitor and manage risk was the development of new quantitative techniques and computational resources (Fontnouvelle et al., 2003).

Although risk cannot be completely removed, it can be mitigated with the appropriate risk management practices (Moosa, 2007b). According to Bocker & Kluppelberg (2005), identifying and minimizing the risk by developing quantification techniques is the most feasible approach to manage Operational Risk.

Moosa (2007b) defines Operational Risk modelling as the "exercise that is conducted with the objective of arriving at the best-fit distribution for potential operational losses over a given period of time". Likewise, Operational Risk measurement is "arriving at a single figure that tells us how much the underlying firm is likely to lose within a certain probability, so that a correspondingly adequate amount of capital is held for the purpose of protecting the firm from insolvency." Modelling Operational Risk helps risk managers anticipate operational events (Chalupka & Teplý, 2008) as well as making better decisions about the level of risk an organization is willing to tolerate (also called risk appetite or risk tolerance) (Moosa, 2007b). One advantage of Operational Risk modelling is that the quantification of Operational Risk is a regulatory requirement needed for the formulation of economic capital framework, which allows the firm to meet the regulatory requirements (Fujii, 2005). Furthermore, Holmes (2003) argues that Operational Risk modelling may force institutions to allocate more economic capital to protect against unexpected losses, despite the reliability of the scientific nature of it.

Of all types of risk, Operational Risk is the most difficult one to measure and model. As cited by (Sheedy, 1999), "quantifying risks that are not suitable for precise measurement can create further moral hazard; the process of quantification can create a false sense of precision and a false impression that measurement has by necessity resulted in management. Managers, wrongly thinking that Operational Risk has been addressed, may reduce their vigilance in this area, creating an environment where losses are more likely to occur." To start with, one issue with modelling Operational Risk is the difficulty of finding an appropriate and definitive definition for Operational Risk. The second issue is the limited data availability (Dutta & Perry, 2007). Other concern arises with the cyclicality of Operational Risk events. Allen & Bali (2004) argue that "macroeconomic, systematic and environmental factors" have an impact in Operational Risk losses and that those factors, if neglected, can result in flawed models. Besides these issues, another problem is the assumption that operational loss events are correlated. When calculating the regulatory capital requirement including correlations, the calculation can have an effect. However, Frachot et al. (2004) argue this assumption is dubious and not supported by empirical evidence.

2.7. BASEL COMMITTEE ON BANKING SUPERVISION

2.7.1. The Basel Committee and the Original Basel Accord

In 1974, as a result of the financial market turmoil that followed the failure of Bankhaus Herstatt in West Germany, the central bank Governors of the Group of Ten (G10) created the Committee on Banking Regulations and Supervisory Practices, which was later after renamed to The Basel Committee on Banking Supervision (Aloqab et al., 2018; BCBS, 2004) . Committee reports to the Group of Central Bank Governors and Heads of Supervision. The Committee was “designed as a forum for regular cooperation between its member countries on banking supervisory matters“ (BCBS, 2014) and its main objective has been “to improve supervisory understanding and the quality of banking supervision worldwide” (BCBS, 2001). The Committee seeks to achieve its goals by sharing supervisory issues, approaches and techniques, by exchanging information on national supervisory arrangements and by setting minimum supervisory standards. The Basel Committee does not have any formal supernational supervisory authority with respect to banking supervision, and its recommendations and set standards do not to have legal force. In this sense, individual national authorities are responsible to implement its standards and guidelines and recommendations (BCBS, 2014).

A first step in this direction was the paper issued in 1975 that came to be known as the ‟Concordat”. In May 1983, the Committee revised it as the "Principles for the Supervision of Banks' Foreign Establishments" which set down the principles for sharing supervisory responsibility for banks' foreign branches, subsidiaries and joint ventures between host and parent (or home) supervisory authorities (BCBS, 2014).

In the late 1970s, the Basel Committee became increasingly concerned about the losses incurred by some large international banks from Third World loans which could cause the failure of one or more banks, and the serious adverse effects that such failure could have on the international financial system. Fearing cross-border contagion, and insufficient capital held by large banks in relation to the risks they were assuming, the BCBS began to focus on the development of international regulation, with the objective of establishing and implementing higher and more uniform capital standards for banks across countries (Moosa, 2007b). Therefore, the members of the Basel Committee, supported by the Group of Ten, decided to work towards greater convergence in the measurement of capital adequacy (BCBS, 2001)

In May 1983, a revised version of the Concordat was published. After that, in December 1987, The Basel I Accord was approved by the Group of Ten Governors. Finally, in July 1988, The Basel I Accord was released to banks. After the introduction of the Basel I Accord, several amendments were made and, in January 1996, it was incorporated the market risks arising from open positions in foreign exchange, traded debt securities, equities, commodities, and options (Moosa, 2007b). With this amendment banks are allowed, although subject to strict quantitative and qualitative standards, to use their own internal models for measuring their market risk capital requirements (BCBS, 2014). According to Herring (2002), these internal models approach have several benefits such as to “(I) reduce or eliminate incentives for regulatory arbitrage since the capital charge would reflect the bank’s own estimate of risk, (II) deal more flexibly with financial innovations, incorporating them in the regulatory framework as soon as they were incorporated in the bank’s own risk management models, (III) provide banks with an incentive to improve their risk management processes and procedures in order to qualify for the internal model's approach and (IV) compliance cost would be reduced to the extent that the business was regulated in the same way that it was managed."

Following the criticism of the Basel I Accord, the Basel Committee decided to issue a new capital Accord. In June 1999, the Committee issued a first-round proposal for a new accord to replace the 1988 Accord. After refining the 1999 proposals over many years, the new Accord was released as the Revised Capital Framework in June 2004, also known as "Basel II Accord" (Moosa, 2007b). The new framework was designed to enhance the soundness and stability of the international banking system without introducing competitive inequality among international banks and had the objective of narrowing the gap between regulatory capital requirements and the economic capital produced by the banks' own internal models (Moosa, 2007b).

The Basel Committee defined in 1998, for the first time, Operational Risk as the risk of everything other than credit and market risk. In 2001, the BCBS has started to focus on Operational Risk and refined its approach to set minimum capital requirements, but the year which Operational Risk has received more attention among researchers and practitioners was in 2006, when the new guidelines for international Convergence of Capital Measurement and Capital Standards, also known as the Basel II Accord, was published in June 2006 (Herring, 2002). By introducing the obligation to calculate the capital requirement also for Operational Risk, the new accord made Operational Risk practically an essential features of financial institutions risk management among other factors such as credit and market risk (Jobst, 2007). The introduction of capital requirement for Operational Risk in Basel II Accord will also "lead institutions to enhance the measurement and management of Operational Risk" (Herring, 2002).

2.7.2. Basel II and its pillars

Unlike Basel I Accord, which had one Pillar, the new framework of Basel II consists of three pillars, (I) minimum capital requirements, which seeks to develop and expand the standardised rules set out in the 1988 Accord, (II) Supervisory Review of Capital Adequacy, which is designed to ensure the framework is effective in the identification, assessment, monitorization and controlling of risks and (III) Market discipline through disclosure requirements, which requires public disclosure of relevant market information and management methods (Embrechts et al., 2003)

As for the Pillar I, minimum capital requirements, the Basel Committee identified three approaches to set capital charges for Operational Risk. The Basic Indicator Approach is the most straightforward approach and requires banks to hold capital for Operational Risk as a fixed percentage of a financial indicator, such as gross income (Frachot et al., 2001). The Standardized Approach requires that the institution holds capital for Operational Risk, but at a more granular level. This approach divides the banks' operations into eight different business lines and then the capital charge is estimated as an exposure indicator for each line of business multiplied by a coefficient. The overall capital charge is then the sum of the Operational Risk capital charge over the eight business lines (Herring, 2002). The Advanced Measurement Approach allows calculating the minimum Operational Risk capital requirements by developing internal models incorporating internal operational losses, external operational losses, scenario analysis and business environment and internal control factors. (Robertson, 2016).

2.7.3. From Basel II to Basel III

According to (Aloqab et al., 2018), "many attributed the 2008 financial crisis due to the inability of financial risks to manage operational risks". As a response to the global financial crisis in 2008, the need to strengthen the Basel II Accord emerged (BCBS, 2017). The financial crisis has left the banking sector with too much leverage, inadequate liquidity buffers and poor governance and risk management. As a response to these factors, that combined could lead to the mispricing of credits as well as liquidity risk, BCBS issued *Principles for sound liquidity risk management and supervision* in the same month that Lehman Brothers failed (BCBS, 2014).

Consequently, the Basel Committee issued the Basel III framework which addresses shortcomings in the pre-crisis regulatory framework by providing a resilient foundation for the banking system. This reform introduced, in December 2017, the Standardized Approach for measuring minimum Operational Risk capital requirements that replaces the Advanced Measurement Approach (AMA) already existing in The Basel II Accord (BCBS, 2017). As stated by (O'Reilly, Idnani, Davis, & Bhatti, 2018), this new approach seeks to restore credibility in the calculation of risk-weighted assets and improve the comparability of bank's capital ratios.

Under the new Standardized Approach, Operational Risk capital is calculated by multiplying the business indicator component (BIC) by the internal loss multiplier (ILM). The BIC is calculated by multiplying the business indicator (BI) by a set of regulatory-determined marginal coefficients (α). The internal loss multiplier is a scaling factor that is based on a bank's average historical losses and the BIC (BCBS, 2017).

The revised framework was scheduled to be implemented by January 1, 2022 to give banks time for the transition into the new approach and improve their processes for collecting, managing, and analysing internal loss data (O'Reilly et al., 2018). However, due to the impact of Covid-19 on the global banking system, the implementation of the Basel III standards has been deferred by one year to January 1, 2023 (BCBS, 2020).

2.7.4. Sound Practices for the Management and Supervision of Operational Risk

In 2003, the BCBS published the paper "Sound Practices for the Management and Supervision of Operational Risk" (BCBS, 2003) which outlines a set of principles that provide a framework for the effective management and supervision of Operational Risk. Due to the new requirements of the Basel II Accord, the Basel Committee has naturally acknowledged the need for an appropriate management of Operational Risk and decided to supplement the regulations with new guidelines regarding the risk culture and corporate governance through the publication of the document "Principles for the Sound Management of Operational Risk" (BCBS, 2011).

Some of the principles are presented as follow (BCBS, 2011):

- The Board of Directors should ensure the implementation of a robust risk management culture, appropriate risk management framework, risk appetite and tolerance.
- Senior management is responsible for developing an effective and robust governance structure.
- Senior management should ensure the identification and assessment of the Operational Risk inherent in all material products, activities, processes, and systems to make sure the inherent risks and incentives are well understood.
- Senior management is responsible for the implementation of processes to monitor Operational Risk profiles and material exposures to losses.
- Banks should have a strong control environment, internal control, risk mitigation and risk transfer strategies.
- Banks should have business resiliency and continuity plans in place to mitigate against unexpected and unforeseen contingencies.
- A bank's public disclosures and exposures should allow stakeholders to assess its approach to Operational Risk management.

2.8. DETERMINANTS OF OPERATIONAL RISK

Although interactions between Operational Risk and the macroeconomic environment is still not a topic well-studied, the interest and the attention towards the determinants of Operational Risk has been growing over the recent decades. (Prokop & Pakhchanyan, 2013) state that little empirical research has been done on the determinants of Operational Risk which, as an important topic, would deserve more attention. Operational losses are often an early warning of future larger, sometimes catastrophic losses (Allen & Bali, 2007) and they have reputational effects which can lead to market value loss (Cummins et al., 2006). Hence, it is important to disentangle whether losses have been caused by internal, institutional, or macroeconomic factors.

Previous investigations focused on the determinants of Operational Risk have been derived from firm-specific characteristics. Among these, Shih et al. (2000) , Na et al. (2006), Wei (2007), Cope & Labbi (2008), Dahen & Dionne (2010) and Alifano et al. (2019) study the correlation between the size of losses and the size of the banks. Wang & Hsu (2013) examine the relationship between board composition and Operational Risk events at financial institutions, where their findings indicate that both board size and age heterogeneity contribute to the soundness of Operational Risk management. Furthermore, Abdymomunov & Mihov (2017) complement this research by investigating the association between Operational Risk and the quality of risk management quality practices. Their investigation indicates that companies with weak risk management practices can incur on larger Operational Risk losses. Chernobai et al. (2011) did a thorough research on the determinants of Operational Risk considering U.S. Financial Institutions firms. Their results show a strong link between losses and firm-specific covariates, whereas macroeconomic variables seem to have a less important effect. According to their findings, younger and more complex firms are more likely to suffer Operational Risk events, there is a positive correlation between the frequency of events and equity volatility and cash-to-assets as well as negative correlation with market-to-book and Tier 1 capital ratio. In accordance with Chernobai et al. (2008), factors such as capital structure, profitability and volatility have an impact in operational loss. However, Abdymomunov et al. (2020) find that profitability is not significantly related to the macroeconomic sensitivity of Operational Risk.

Another determinant of Operational Risk which has been increasing in the literature is the macroeconomic environment. To begin with, Allen & Bali (2004) find proof on the association between cyclical components of operational loss event and macroeconomic variations, while Allen & Bali (2007) present evidence on the presence of cyclical components of Operational Risk. Hess (2011) and Hambuckers et al. (2018) researches support these findings. Moosa (2011) analyses the relationship between unemployment rate and operational loss events, which shows a significantly positive association between unemployment rate and operational loss severity, however the frequency of losses shows an insignificant relation. Prokop & Pakhchanyan (2013) find a negative and strong relationship between unemployment rate and Operational Risk. Their study also indicates that GDP growth rate is positively correlated with Operational Risk. Similar results are found in Abdymomunov (2014), Moosa & Li (2015) and Cope et al. (2012). To corroborate these findings, Hambuckers et al., (2018) show there is a strong association between Operational Risk and unemployment rate, GDP growth rate, leverage ratio and housing prices. However, Cope et al. (2012) and Alifano et al. (2019) find unemployment rate to be insignificantly related with Operational Risk. Hambuckers et al. (2018) uncover a positive association between leverage ratio and operational loss. Arfiffy et al. (2018) study the influence of firm specific factors in terms of average collection period and daily stock prices on Operational Risk. However, this research does not find any correlation between Operational Risk and macroeconomic factors. Recently, Abdymomunov et al. (2020) examine the association between operational losses in the US banking sector and macroeconomic conditions. They find that Operational Risk tends to occur in adverse macroeconomic periods and that larger and more leveraged organizations tend to incur more operational losses. Hence, Alifano et al. (2019) found a positively relationship between operational risk and inflation rate, however the estimator was not relevant.

Moreover, Cope et al. (2012) study the association between operational loss events and various regulatory indicators. They found significant correlation between losses and different governance and regulatory indicators, including rule of law, control of corruption, accounting standards, labour regulation, and shareholder protection. Moosa & Li (2015) have analysed operational losses on a country level in terms of the size of the economy, the standard of living, the legal system, the regional factor, and governance indicators. Governance indicators, particularly regulatory quality, are found to be negatively significant of the loss severity. Thus, Alifano et al. (2019)'s research also studied the relationship between operational losses and several regulatory indicators, however only regulatory quality was found to be significant and positively related with operational losses.

3. METHODOLOGY

3.1. DATA

Financial institutions use different data sources for modelling Operational Risk, including consortium, public or insurance data. The determinants of Operational Risk are analysed by using data collected from three different sources: SAS OpRisk Global Data[1], OECD, and World Bank. SAS OpRisk Global Data provides data on operational losses, while OECD and the World Bank have data available on different macroeconomic factors.

SAS OpRisk Global Data is the world's largest, most comprehensive, and accurate repository of information managed by SAS, which is widely used by financial institutions. The repository has more than 32 000 events across all industries worldwide and provides data in accordance with Basel II Event classification standards. Losses in financial services firms are assigned to generic business and sub-business lines, also in compliance with Basel II Standards. This database gathers worldwide publicly operational losses above US$100,000 from news reports, court filings and SEC filings. This implies that not all losses are reported, as most large losses are more often disclosed than small losses, which means this database have a significant reporting bias. SAS OpRisk Global Data provides the description of each event, including dates of occurrence and settlement, loss amount, geographical location, Business Line Level 1 and Level 2, Event Type and Sub Event Type. It is also available firm-specific variables that could be indicative of the size of the firm – revenues, assets, net income, number of employees and shareholder equity. All reported loss values are denoted in USD and CPI-adjusted, which allows for the comparison of prices in different years.

Our sample includes only losses occurred in European countries, in financial institutions, between 2000 and 2020. Upon applying some filters to the dataset, the final sample used in this study contains records of 2306 operational loss events from 744 institutions and 37 countries: United Kingdom, Germany, Italy, France, Netherlands, Switzerland, Turkey, Spain, Ukraine, Ireland, Estonia, Belgium, Austria, Czech Republic, Denmark, Lithuania, Sweden, Greece, Norway, Iceland, Romania, Latvia, Portugal, Hungary, Poland, Cyprus, Finland, Liechtenstein, Slovakia, Croatia, Luxembourg, Belarus, Serbia, Macedonia, Malta, Bosnia and Herzegovina and Bulgaria. As shown in Figure 1, the top 10 countries with the highest severity are UK, Germany, Italy, France, Netherlands, Switzerland, Turkey, Spain, Ukraine, and Ireland. UK, France, Italy, Ireland, Germany, Spain, Switzerland, Sweden, Netherlands, and Greece are the Top 10 countries with the highest frequency. To note that only United Kingdom represents 36% of all losses reported.

The maximum loss amount reported belongs to Unicredito Italiano which had incurred in a loss of 23.24 billion dollars, whereas the minimum loss amount belongs to Abbey National PLC with 100 thousand dollars, which corresponds to the threshold of losses to be included in SAS

[1] SAS® OpRisk Global Data. Copyright, SAS Institute Inc. Cary, NC, USA. All Rights Reserved

OpRisk Global Data. The mean, median and standard deviation are, respectively, 90.44 million, 2.18 million and 751.46 million. As these results suggest, the severity distribution of operational loss events is skewed to the right. Similar studies presented different statistics which might be explained by the different time period selected. Gillet et al. (2010) reported mean loss amount of 277 million USD for the 49 largest losses in 47 European companies, while Sturm (2013) reported average operational loss of 140 million euro for 136 loss events in European financial institutions. In addition, (Prokop & Pakhchanyan, 2013) documents mean operational losses of 21 million euro and median 368 thousand euro in German-speaking countries.

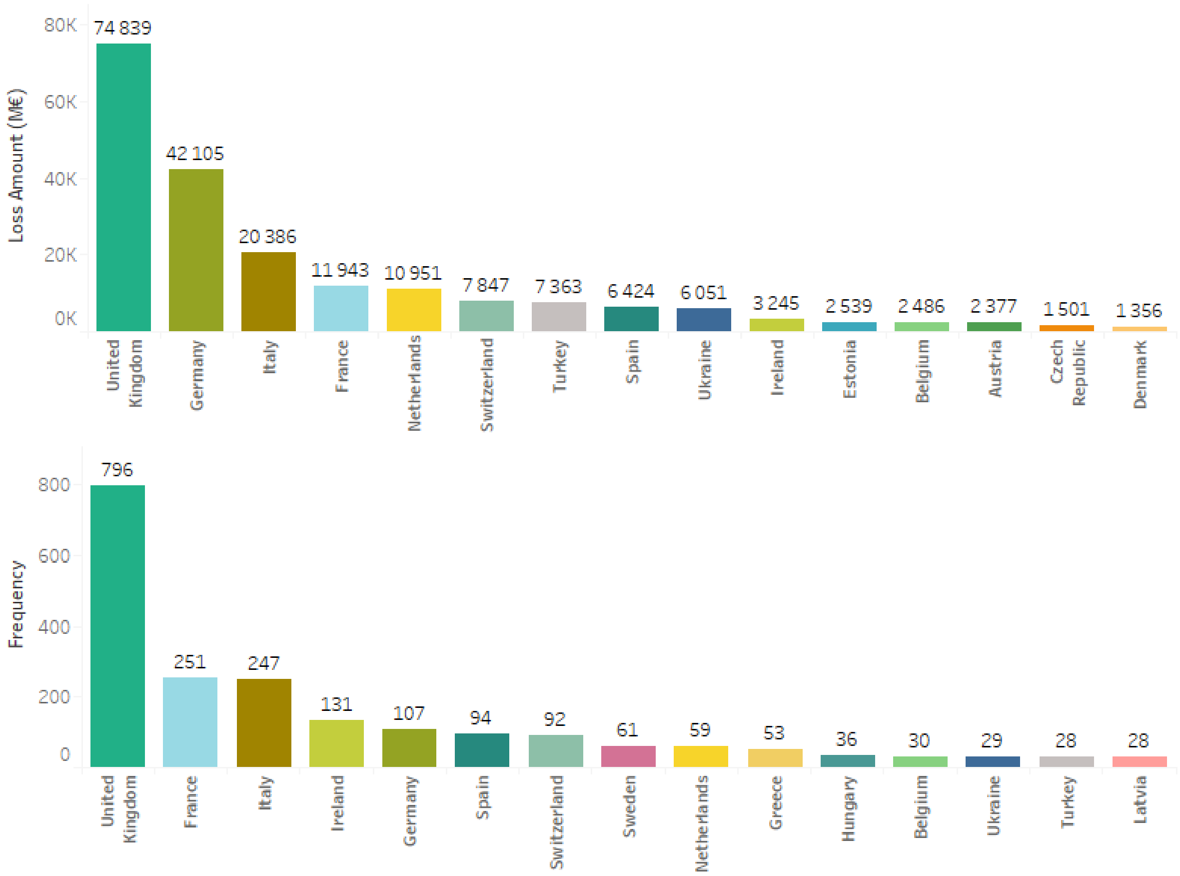

Figure 1 – Loss amount (M€) and number of operational loss events (frequency) by Country *(Source: Author's calculation)*

Figure 2 illustrates the distribution of Operational Risk losses. The higher bar shows a high frequency, low severity but also extremely large losses (outliers). This indicates the severity distribution of operational losses is skewed to the right, which is consistent with the existing literature (Cummins et al. (2006), Chernobai et al. (2011), Sturm (2012)).

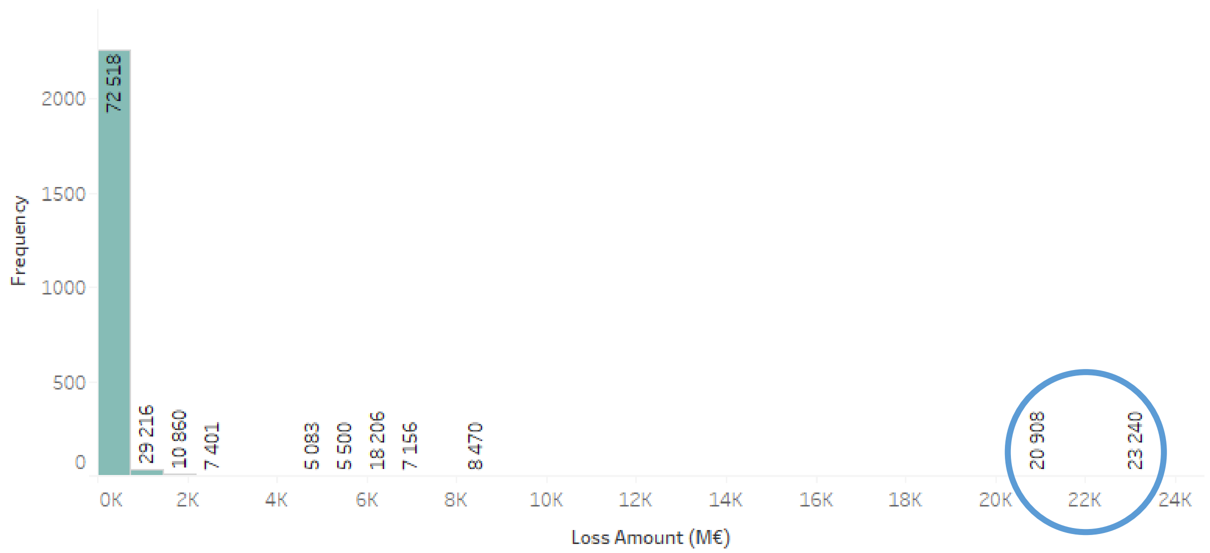

Figure 2 – Loss Distribution *(Source: Author's calculation)*

Annual operational loss severity distribution and event frequency distribution are presented below in Figure 3. The years with most losses are between 2005 and 2008, which corresponds to the periods before and during the financial crisis, with 2015 being the year with the maximum amount of losses, recording 38.3 billion dollars. To note that 50% of all losses reported occurred before 2007. On the other hand, year 2015 showed a minimum loss amount of 555 million euros. Total losses are relatively small at the end of the reporting period, which can be explained by the fact that it is quite typical for operational losses to take time before an occurred incident is detected and the actual loss is materialized. However, a few possible explanations can be the increased awareness of Operational Risk, the strengthened of Basel II Accord after the Financial Crisis of 2008 and the efforts Banks made to mitigate their risks.

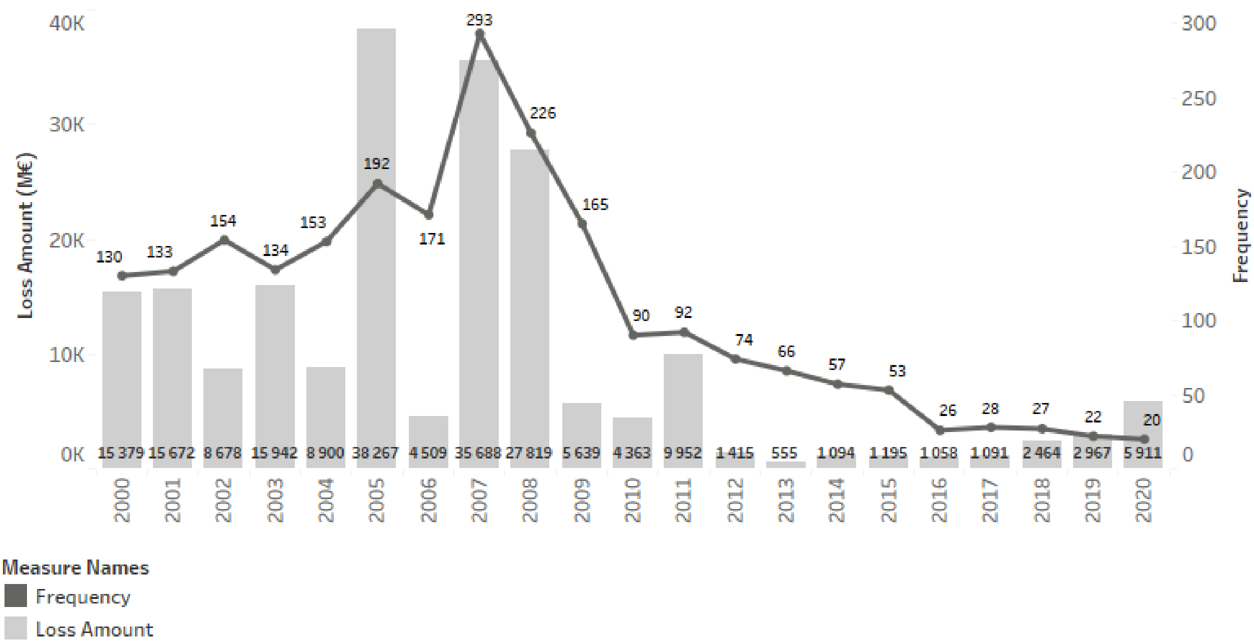

Figure 3 – Annual operational loss amount (M€) and frequency distribution *(Source: Author's calculation)*

Table 3 indicates that, in 2020, although it is shown low frequency, the average loss severity is the highest among all the years. Furthermore, the connection between frequency and severity indicates, in most years, average severity per loss to be small, which means that low severity, but high frequency is dominating the statistics. However, the year 2019 and 2020 are exceptions with higher average severity, which indicates that most of the extreme events occurred during this period.

Table 3 – Annual operational losses *(Source: Author's calculation)*

Year	% of Total Loss	Loss	Avg. Loss	Std. dev. of Loss	Loss Frequency
2000	7,37%	15 379	118	574	130
2001	7,51%	15 672	118	297	133
2002	4,16%	8 678	56	155	154
2003	7,64%	15 942	119	740	134
2004	4,27%	8 900	58	419	153
2005	18,35%	38 267	199	1 754	192
2006	2,16%	4 509	26	111	171
2007	17,11%	35 688	122	1 244	293
2008	13,34%	27 819	123	575	226
2009	2,70%	5 639	34	108	165
2010	2,09%	4 363	48	175	90
2011	4,77%	9 952	108	663	92
2012	0,68%	1 415	19	48	74
2013	0,27%	555	8	19	66
2014	0,52%	1 094	19	59	57
2015	0,57%	1 195	23	63	53
2016	0,51%	1 058	41	183	26
2017	0,52%	1 091	39	152	28
2018	1,18%	2 464	91	287	27
2019	1,42%	2 967	135	464	22
2020	2,83%	5 911	296	369	20

In order to define the regions, the 36 European countries were distributed into five regions according to their location. The regions are as follows:

Table 4 – Representative countries by regional categories *(Source: Author's calculation)*

Region	Countries
British Isles	Ireland, United Kingdom
Eastern Europe	Belarus, Bosnia and Herzegovina, Bulgaria, Croatia, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Macedonia, Poland, Romania, Serbia, Slovakia, Turkey, Ukraine
Northern Europe	Denmark, Finland, Iceland, Norway, Sweden
Southern Europe	Cyprus, Greece, Italy, Malta, Portugal, Spain

Western Europe	Austria, Belgium, France, Germany, Liechtenstein, Luxembourg, Netherlands, Switzerland

Figure 4 summarizes the distribution of loss amount and loss frequency for each region. The results show that most operational loss events occurred in the British Isles, representing 37,44% of all losses, followed by Western Europe with 37,34% of all reported losses. Nevertheless, in Table 5 it is indicated that the average severity is the highest in countries from western Europe.

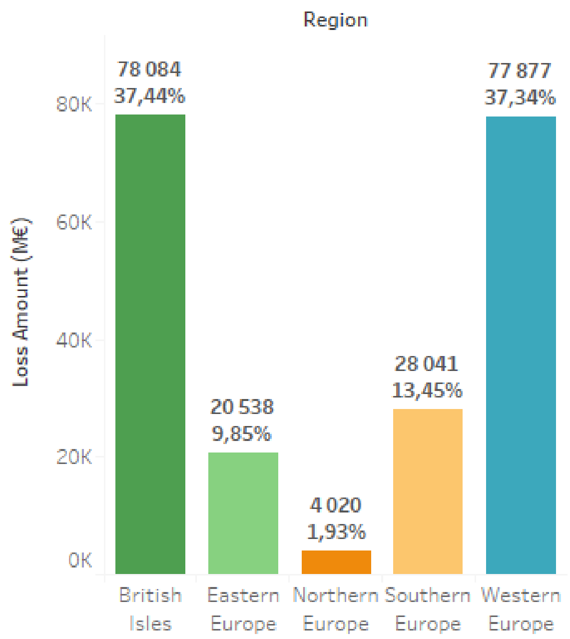

Figure 4 – Distribution of Operational Risk losses per Region (Source: Author's calculation)

Table 5 - *Operational loss event severity (M€) and frequency per region (Source: Author's calculation)*

Region	% of Total Loss	Loss Amount	Loss Frequency	Severity
British Isles	37,44%	78 084	927	84
Western Europe	37,34%	77 877	564	138
Southern Europe	13,45%	28 041	439	64
Eastern Europe	9,85%	20 538	252	81
Northern Europe	1,93%	4 020	124	32

The reported losses are classified by event types and by business lines according to BCBS's classification. As shown in Table 6, the largest event type category is Clients, Products & Business Practices, representing 64% of all losses (133,6 billion dollars), followed by Internal Fraud with 19% of all losses (40 billion dollars). In terms of number of events, events related to Clients, Products & Business Practices are the most frequent, followed by External Fraud. As for the most serious events, measured by the total losses divided by the number of events (frequency), are Damage to Physical Assets and Internal Fraud followed by Clients, Products & Business Practices. It is also evident that event types Business Disruption and System Failures and Damage to Physical Assets are the ones with less events reported, representing 3,12% and 0,36% of all losses. Therefore, we will not include the losses associated with Damage to Physical Assets due to its representativeness and random nature.

Table 6 – Operational loss amount (M€), frequency and severity per Event Type *(Source: Author's calculation)*

Event	% of Total Loss	Loss Amount	Loss Frequency	Severity
Clients, Products & Business Practices	64,06%	133 602	1 054	127
Internal Fraud	19,30%	40 256	456	88
External Fraud	7,49%	15 611	493	32
Execution, Delivery & Process Management	4,33%	9 032	207	44
Damage to Physical Assets	3,12%	6 504	22	296
Employment Practices and Workplace Safety	1,35%	2 811	52	54
Business Disruption and System Failures	0,36%	743	22	34

These results are consistent with the ones presented by Chernobai & Yu (2008), with 47.4% of total losses being related with Clients, Products and Business Practices and 15.1% with Internal Fraud events, and by Abdymomunov (2014), with Clients, Products and Business Practices event type category comprising 7% of the total industry losses in the sample, followed by Execution, Delivery and Process Management with 18% of the total losses. Gillet et al. (2010), Sturm (2012) and Cummins et al. (2006) also present very similar results, with the greatest amount of total losses being related with Clients, Products and Business Practices, followed by Internal and External Fraud. Most of the losses in this category are related to improper transaction processing. Furthermore, according to Sturm (2012), Clients, Products and Business Practices is the most frequent event type in operational loss data based on publicly available information when compared with databases gathering internal information (see Basel (2009)).

Regarding business lines, we can see below in Figure 5 that most operational loss events occured in Retail Banking, representing 47,5% of all losses in terms of frequency. As fas as the amount of losses are concerned, Retail Banking represents 37% of all losses, with a total of 77 billion dollars reported.

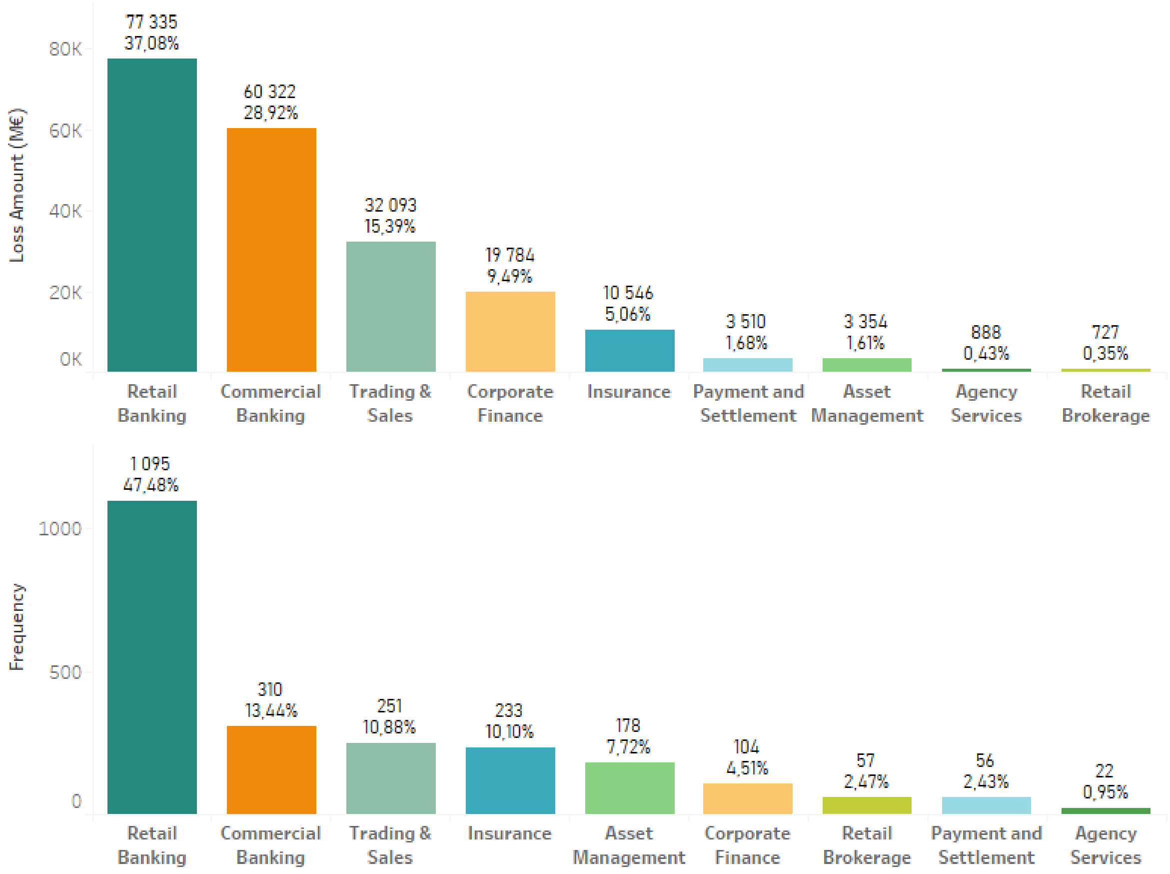

Figure 5 – Operational loss amount (M€) and number of operational loss events (frequency) per Business Line *(Source: Author's calculation)*

Table 7 and Table 8 show a two-way classification of the same loss events by event type and business line. Regarding event type Clients, Products and Business Practices, most losses are distributed amongst Commercial Banking and Retail Banking.

Table 7 – Two-way classification of operational loss amount (M€) *(Source: Author's calculation)*

BI1	Internal Fraud	External Fraud	Business Disruption and System Failures	Clients, Products & Business Practices	Damage to Physical Assets	Employment Practices and Workplace Safety	Execution, Delivery & Process Management
Agency Services	168	33		501			186
Asset Management	302	82	3	2 781		38	148
Commercial Banking	8 149	6 100		41 052	4 867	10	144
Corporate Finance	125	593		18 246	585	97	138
Insurance	332	52		9 062	2	12	1 087
Payment and Settlement	2 167	123	67	915			239
Retail Banking	16 525	7 759	673	46 635	1 050	2 566	2 126
Retail Brokerage	26	55		612		17	17
Trading & Sales	12 462	813		13 799		72	4 947

Table 8 – Two-way classification of number of operational loss events (frequency) *(Source: Author's calculation)*

BI1	Internal Fraud	External Fraud	Business Disruption and System Failures	Clients, Products & Business Practices	Damage to Physical Assets	Employment Practices and Workplace Safety	Execution, Delivery & Process Management
Agency Services	6	4		10			2
Asset Management	23	8	2	123		2	20
Commercial Banking	59	103		116	9	3	20
Corporate Finance	13	4		73	1	8	5
Insurance	42	19		141	1	4	26
Payment and Settlement	3	14	2	28			9
Retail Banking	261	337	18	387	11	16	65
Retail Brokerage	5	1		39		2	10
Trading & Sales	44	3		137		17	50

Explanatory variables

The explanatory variables for the model are chosen based on data availability and on the previous research, which includes:

Table 9 – Explanatory variables (Source: Author's calculation)

Variable Name	Definition	Source
GDP	Gross Domestic Product	OECD
GDPgr	Gross Domestic Product Growth Rate	OECD
UnemRate	Unemployment Rate	OECD
HPI	House Price Index	OECD
Inflation	Inflation Rate	OECD
IntRate	Interest Rate	OECD
Assets	Total Assets	SAS OpRisk Global Data
LevRatio	Leverage Ratio (Equity Multiplier)	SAS OpRisk Global Data
ROE	Return on Equity	SAS OpRisk Global Data
ROA	Return on Assets	SAS OpRisk Global Data
VA	Voice and Accountability	World Bank
PolStab	Political stability and absence of violence	World Bank
GovEff	Government Effectiveness	World Bank

RegQual	Regulatory Quality	World Bank
RuleLaw	Rule of Law	World Bank
CCorrupt	Control of Corruption	World Bank

Total assets are a proxy for the size of the firm and is available in the SAS OpRisk Data, as well as the net income and equity which are essential to calculate return on equity, return on assets and leverage ratio. The Worldwide Governance Indicators were collected from the World Bank Database. As for the remaining explanatory variables, they were collated from the public OECD website.

Total Assets

In the table above, we include all variables used in this analysis. Among the included covariates, we use the total assets as a proxy for the size of the firm. The relation between operational losses and the size of the firm is quite intuitive as we would expect bigger firms to incur in larger losses. Besides that, the Basel Committee of Banking Supervision had issued the Basic Indicator Approach which calculates the capital charge for Operational Risk based on the gross income, which is a proxy for the firm size.

GDP

Regarding macroeconomic indicators, GDP is a measure of the size of a country's economy over a period of time. We consider that richer countries incur in larger losses.

Unemployment

Such as GDP, unemployment rate provides insights of the general state of the economy. High unemployment rate negatively impacts purchasing power, increases poverty and debt and influences banks' performance. Higher unemployment rate implies an increase of non-performing loans, lowering bank liquidity, which may facilitate an explosion of fraud events and other criminal activities.

Inflation

Inflation refers to an overall increase in the Consumer Price Index (CPI), which is a weighted average of prices for different goods. In a market economy, the prices of goods and services are subject to change. Some prices might go up, whereas other may go down. As a result, the overall value of the CPI will be determined by the weight of each of the goods with respect to the whole basket. The connection between the inflation and operational losses is quite intuitive given that inflation causes a reduction in the purchasing power of currency due to a rise in prices across the economy. Based on these arguments, we believe that as the inflation rate of a country rises, the magnitude of operational losses is likely to rise as well.

Interest Rate

Real interest rate is the lending interest rate adjusted for inflation to reflect the real cost of funds to the borrower. The purpose of this calculation is to assess the purchasing power of money. Interest rates have an inverse correlation with economy growth, impacting the cost of loans. When interest rates are low, more people are able to borrow money which means consumers have more money to spend, causing the economy to grow. As the banking sector's profitability increases when interest rate also increases, we may expect a positively correlation between interest rates and operational losses.

Equity Multiplier

Firm-specific variables may also impact operational losses. The equity multiplier assesses the company's financial leverage, which is the ratio of a company's total assets to its stockholders' equity. The ratio evaluates how much of a company's assets are funded by debt. If the ratio is high, it indicates that the company is too dependent on debt. On the contrary, if the ratio is low, it means that a company is generally financed by stockholders, avoiding the use of debt. This may sound positive, however the downside is that the company will have low growth prospects and, as a result, low financial leverage. Therefore, it is expected a positive correlation between the equity multiplier and Operational Risk severity.

Return on Equity

The return on equity is a measure of financial performance calculated by dividing net income by shareholder's equity. ROE is considered a measure of profitability and measures the permanent capital made available to the company by its shareholders. An increasing ROE suggest that a company is more successful in generating profit using its investors' funds. In contrast, a declining ROE may indicate that management is less efficient using equity capital to generate profit. However, this indicator should be used with caution since a company that depends excessively on debt can increase its ROE, which does not necessarily mean that the company is increasing its profitability. Consequently, it is expected for financial institutions with lower ROE to incur in more losses.

Return on Assets

Return on assets is an indicator of how profitable a company is relative to its total assets. This ratio indicates how well a company is performing by comparing the profit (net income) it is generating to the capital it has invested in assets. As the higher the ROA, the better the management, we would expect a negatively relationship between ROA and operational losses.

House Price Index

The HPI is a tool that captures price changes of all residential properties across a designated market. The rise of house prices can lead to a higher economic growth. When prices fall, the opposite tends to happen, triggering an economic recession. Therefore, it is expected to incur in more losses when the house prices are decreasing.

The definitions of the governance indicators proposed by (Kaufmann et al., 2010) are the following:

Voice and Accountability

Voice and Accountability captures perceptions of the extent to which a country's citizens are able to participate in selecting their government, as well as freedom of expression, freedom of association, and a free media.

Political Stability and Absence of Violence/Terrorism

Political Stability and Absence of Violence/Terrorism captures perceptions of the likelihood that the government will be destabilized or overthrown by unconstitutional or violent means, including politically motivated violence and terrorism.

Government Effectiveness

Government Effectiveness captures perceptions of the quality of public services, the quality of the civil service and the degree of its independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies.

Regulatory Quality

Regulatory Quality captures perceptions of the ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development.

Rule of Law

Rule of Law captures perceptions of the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence.

Control of Corruption

Control of Corruption capturing perceptions of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as "capture" of the state by elites and private interests.

Table 10 reports the summary statistics for the sample of 2306 loss events.

Table 10 – General statistics (Source: Author's calculation)

	Standard Deviation	Mean	Median	Maximum	Minimum
Operational risk losses	761,463	90,442	2,180	23 240,000	0,100
Firm specific					
Assets	831 573,440	690 408,540	297 187,100	4 309 712,800	0,020
Nb Employees	78 938,740	62 729,460	28 982,500	482 152,000	-
Macroeconomic					
Unemployment Rate	3,567	7,392	6,777	31,110	0,500
GDP	1 086 228,660	1 611 611,020	1 784 473,920	3 963 767,530	2491,820
GDP Growth Rate	2,883	1,822	2,324	25,163	-14,759
House Price Index	23,483	88,308	86,090	162,690	40,180
Inflation	5,039	2,853	2,121	86,826	-9,728
Interest Rate	2,857	2,061	2,088	19,298	-31,827
Governance Indicators					
Voice and Accountability	0,310	1,238	1,321	1,740	-0,519
Political Stability	0,479	0,591	0,555	1,760	-2,021
Governance Effectiveness	0,591	1,374	1,602	2,354	-0,844
Regulatory Quality	0,855	0,501	0,603	2,098	-0,629
Rule of Law	0,575	1,360	1,627	2,096	-0,819
Control of Corruption	0,729	1,374	1,633	2,470	-1,053
Return on Assets	0,540	- 0,009	0,004	5,843	-16,597
Return on Equity	5,344	0,216	0,081	247,755	-16,732
Leverage Ratio (Equity Multiplier)	137,717	21,914	17,173	6 486,320	-288,029

After analysing the relevance of the variables, it is necessary to understand their correlation to avoid problems of redundancy and reduce the dimensionality of the data. Thus, through the correlation matrix in Table 11, it is possible to analyse and interpret the correlation of the variables. Due to the high correlation between assets and number of employees, we have decided to include only one of the variables in the model. Between governance indicators, it is clear the relationship between rule of law, control of corruption, governance effectiveness and voice & accountability. Therefore, and with regards to previous studies including these covariates (Cope & Labbi, 2008), we will include rule of law due to its better performance. Consequently, control of corruption, governance effectiveness and voice & accountability are excluded from the set of variables included in the model. As a complementary analysis, it was examined the variance inflation factor (VIF) as well as the tolerance values for each variable. As a rule of thumb to get rid of multicollinearity, VIF should not be greater than 10 and tolerance should not be less than 0,1. Thus, the variables with either very large VIF or small tolerance were deleted one by one from the model, starting from the most significant values, until the VIF and tolerance for all remaining variables fitted to the appropriate interval.

Table 11 – Correlation matrix *(Source: Author's calculation)*

	Assets	Control of Corruption	GDP	GDP_GR	Governance Effectiveness	HPI	Inflation	Nb Employees	Unemployment Rate	Political Stability	Regulatory Quality	Rule of Law	Voice & Accountability	ROA	ROE	Equity Multiplier
Assets	1,000															
Control of Corruption	0,150	1,000														
GDP	0,240	0,275	1,000													
GDP GR	-0,062	0,049	-0,205	1,000												
Governance Effectiveness	0,152	0,952	0,242	0,050	1,000											
HPI	-0,033	-0,339	-0,139	-0,092	-0,466	1,000										
Inflation	-0,104	-0,362	-0,231	0,085	-0,385	-0,038	1,000									
Nb Employees	0,748	0,054	0,180	-0,058	0,069	-0,026	-0,064	1,000								
Unemployment Rate	-0,066	-0,497	-0,137	-0,183	-0,445	0,203	-0,071	-0,012	1,000							
Political Stability	-0,019	0,430	-0,291	0,166	0,447	-0,059	-0,286	-0,072	-0,298	1,000						
Regulatory Quality	-0,098	-0,401	-0,392	-0,047	-0,334	0,207	-0,004	-0,065	0,319	0,212	1,000					
Rule of Law	0,164	0,959	0,293	-0,001	0,948	-0,227	-0,425	0,067	-0,434	0,470	-0,363	1,000				
Voice & Accountability	0,152	0,858	0,266	-0,027	0,860	-0,167	-0,475	0,065	-0,430	0,530	-0,276	0,881	1,000			
ROA	0,019	0,022	0,053	0,026	0,018	-0,014	-0,030	0,003	-0,019	-0,028	-0,050	0,024	0,020	1,000		
ROE	-0,024	-0,057	-0,021	0,011	-0,068	-0,028	0,100	-0,014	-0,012	-0,026	-0,014	-0,069	-0,074	-0,008	1,000	
Equity Multiplier	0,021	0,034	-0,011	0,004	0,034	-0,064	-0,023	-0,004	-0,020	0,045	0,022	0,029	0,041	0,006	0,025	1,000

It is important to highlight that the variables chosen for this analysis do not cover the full set of determinants of operational loss. It is possible that there are other factors impacting Operational Risk levels which were not yet investigated and studied previously. Thus, some of the variables included might not even have significant impact on operational losses.

3.2. MODEL

Proper model specification is critical for the successful application of constrained optimization to the panel regression. Following other similar operational risk studies (e.g. Abdymomunov & Mihov (2017), Alifano et al. (2019), Cope et al. (2012) and Dahen & Dionne (2010)), in this section we present our unbalanced truncated panel data regression model with time and firm fixed effects and introduce the maximum likelihood estimators.

Given the structure of the database, we formalize the regression as follows. We denote firms in the cross-section dimension by i = 1,…,N and t = 1,…,T denotes years in the time-series dimension. Each firm i is observed for Ti periods.

We consider the following scheme:

$$y_{it}^{*} = X_{it}^{\prime}\beta + \alpha_i + \lambda_t + u_{it}$$

Where y_{it} corresponds to the dependent variable, X_{it} is the vector of the explanatory variables and β is a vector of coefficients. The error u_{it} is the idiosyncratic error term or time-varying error for the reason that it represents unobserved factors that change over time and affect y_{it} (Wooldridge, 2013). In this context, y_{it} represents the operational loss amount for the *i-th* firm in the *t-th* time period. We assume each firm as the aggregation of a specific bank in a specific country. X_{it} contains a set of variables such as interest rate, unemployment rate, inflation, GDP, house price index, leverage ratio, return on assets, return on equity, assets, regulatory quality, rule of law and political stability. GDP and assets are measured in logarithmic terms.

Panel data sets very often have missing data for at least some cross-sectional units in the sample. For this reason, or perhaps just because of the way the data were recorded, panels in which the group sizes differ across groups are called unbalanced panels. Therefore, the panel data studied is unbalanced in both the time and the country dimensions, because of entry and exit of banks from given countries. As so, according to Wooldridge (2010), fixed effects can often be applied in unbalanced panel data to produce consistent estimators. Wooldridge (2013) notes that the estimation of fixed effects with an unbalanced panel is not much more difficult than with a balanced panel. We treat the duration of each bank in each different country as a random variable. Hence, $\alpha_i + \lambda_t$ are unit and time fixed effects, respectively, also called unobserved effects. In this model α_i captures any unobservable individual-specific effects and λ_t captures any unobservable time-specific effects. The individual-specific effects do not vary with time, while the time-specific effects do not vary across individuals. The inclusion of unit and time fixed effects accounts for both unit-specific and time-specific unobserved confounders in a flexible manner (Imai & Kim, 2021). The two ways fixed effects estimator is consistent if the idiosyncratic error u_{it} is uncorrelated with each explanatory variable across all time periods, allowing for arbitrary correlation between α_i, λ_t and the explanatory variables in any time period (Wooldridge, 2013). Many social scientists use the two-way fixed effects regression with unit and time fixed effects as the default methodology for estimating causal effects from panel data (Imai & Kim, 2021).

Since we only observe losses above a given threshold, the “natural” approach to deal with this type of data is a truncated panel model. Truncation is a common phenomenon in applied economics and, in this case, occurs because SAS OpRisk database only report losses is above 10,000€. Because of the properties of the dataset on losses described above, we have the following scheme:

$$y_{it} = \begin{cases} n.a.\ if\ y_{it}^* < 10k \\ y_{it}^*\ if\ y_{it}^* \geq 10k \end{cases}$$

where it is observed only if y_{it}^* cross a threshold.

The essential problem of the panel regression for a truncated dependent variable is because the sample we can observe is chosen at least somewhat based on the value of y_{it}^* . Therefore, selection based on y_{it}^* causes problems for standard Ordinary Least Squared analysis on the selected sample, resulting in biased estimates (Cope et al. 2011). According to (Antweiler, 2001, p. 299), “it will become apparent that unbalanced panels cannot be easily moulded into a feasible generalized least squares (FGLS) transformation for OLS estimation” and that “in applications, it is usually found that, compared with consistent maximum likelihood estimates, the OLS estimates are biased toward zero” (Greene, 2002, p. 761). Wooldridge (2013) also mentioned that maximum likelihood method is essential for the estimation of limited dependent variables given that when maximum likelihood estimation is based on the distribution of y given X, the heteroskedasticity in Var($y|X$) is automatically accounted for. Consequently, estimation based on Maximum Likelihood is used.

After performing some preliminary investigation and testing for the data, we decided to analyse operational losses for each Event Type. This analysis enables to identify possible differences and similarities between event types. As the sample size is small for some categories, we only kept variables that are significant in the regression analysis.

4. RESULTS

4.1. ANALYSIS

The previous chapters provided a thorough understanding of Operational Risk and presented the data used and the methodology employed. This section presents the findings of an unbalanced panel data by displaying the effects of macroeconomic, governance and firm specific variables on operational losses. The following independent variables are used: interest rate, unemployment rate, inflation, GDP, house price index, leverage ratio, return on assets, return on equity, assets, regulatory quality, rule of law and political stability.

Table 12 summarizes the results, identifying the statistically significant variables among those deemed relevant to the study. We assess significance based on the p-value of the T-test, therefore whenever the p-value is less than 0.10, the Table indicates the direction (increasing, decreasing, or nonmonotonic) of the relationship. The asterisks represent p-values below 0.05, 0.01, and 0.001.

Table 12 – Parameter estimates of the panel regression *(Source: Author's calculation)*

Variables	**Estimate**	**Std. Error**	**z-statistic**
Intercept	-3,997	2,292	-1,744*
IntRate	0,116	0,065	1,782*
Inflation	0,224	0,082	2,744**
UnemRate	0,118	0,067	1,764*
Log(GDP)	0,151	0,151	0,998
HPI	-0,003	0,006	-0,612
Log(Assets)	0,170	0,025	6,799***
LevRatio	0,000	0,000	-0,568
ROE	-0,001	0,053	-0,022
ROA	0,894	0,661	1,351
PolStab	0,555	0,376	1,475
RegQual	-0,392	0,215	-1,820*
RuleLaw	0,793	0,479	1,653*

* Log-likelihood: -1045.062 (14 free parameters)

Firstly, we need to test the global significance of the Model by applying a Likelihood Ratio test as follows:

$$LR = -2ln\left(\frac{L(H_0)}{L(H_1)}\right) = 2(loglik(H_1) - loglik(H_0))$$

, where H_0 corresponds to the null model and H_1 corresponds to the full model.

Therefore, the results can be found in Table 13. The likelihood ratio test statistic is 3044,2 (distributed chi-squared) with 12 degrees of freedom and the associated p-value is p < 0,001, indicating that the model with the 12 predictors fits significantly better than the null model.

Table 13 – Likelihood ratio test (Source: Author)

	LogLik	Df	Chisq
Null model	-2567,2	-12	3044,2***
Full model	-1045,1		

In terms of estimates' statistical significance, 6 out of the 12 hypothesised determinants present a significant relationship with operational losses. Firstly, we focus on the interpretation of the macroeconomic covariates in Table 9. We have hypothesized that periods of economic recessions, represented by higher inflation and unemployment rate, are positively related with Operational Risk losses. Our empirical results support this hypothesis, where unemployment rate and inflation estimates are significant and positively related with operational losses. Moreover, house price index shows a weak and negative relationship with operational losses which is expected since falling house prices can contribute to economic stress. With respect to GDP, we have hypothesized that richer countries should incur in larger losses. The results support this theory, however the estimate on the logarithm of GDP is not significant. We obtain similar results for interest rate, where we find that the estimate is significant and positive.

Concerning governance indicators, one estimate (regulatory quality) revealed an inverse relationship with operational loss severity, which was intuitive and logical since countries with more regulations and stricter policies should incur in less operational losses. Nevertheless, political stability and rule of law are found to be positively related to Operational Risk.

Regarding firm specific estimates, we find that leverage ratio is not significant and negatively related to operational losses, contrarily of what was hypothesized previously. The estimate on the logarithm of assets is positive and significant. This hypothesis goes hand in hand with the conjectured hypothesis that larger firms show higher Operational Risk exposure than smaller firms. With respect to the profitability measure (proxied by ROE), we find that it is negatively related with operational losses. This hypothesis is not supported since these results are not statistically significant (p-value > 0.10). Regarding the estimate on ROA, there seems to be no significant relationship.

<u>Analysis by Event Type</u>

The tables presented below contain the results disaggregated by Basel Event Types.

The analysis does not include the Event Type “Damage to Physical Assets” due to its random nature, as explained before. Thus, the Event Type “Business Disruption and System Failure” was also excluded from the analysis due to the small data sample available.

Internal Fraud (IF)

Table 14 - Parameter estimates of the panel regression – Internal Fraud *(Source: Author’s calculation)*

Variables	Estimate	Std. Error	z-statistic
Intercept	0,503	3,642	0,138
Inflation	0,249	0,135	1,851*
UnemRate	0,139	0,089	1,568
Log(GDP)	-0,055	0,233	-0,236
HPI	0,001	0,008	0,112
Log(Assets)	0,006	0,073	0,089
LevRatio	-0,016	0,013	-1,218
ROE	-1,238	0,934	-1,326
ROA	11,142	6,082	1,832*
PolStab	0,383	0,681	0,563
RegQual	-0,200	0,257	-0,780
RuleLaw	0,729	0,995	0,732

Concerning macroeconomic variables, only inflation is significant and positively associated with internal fraud losses. In terms of firm specific estimates, we find return of assets (as a proxy for profitability) to be significant and positively related with internal fraud incidents. We obtain weaker results with respect to governance covariates as the estimates are not significant.

External Fraud (EF)

Table 15 – Parameter estimates of the panel regression – External Fraud *(Source: Author’s calculation)*

Variables	Estimate	Std. Error	z-statistic
Intercept	10,021	6,881	1,456
IntRate	0,178	0,168	1,056
Inflation	0,091	0,272	0,336
UnemRate	0,084	0,137	0,618
Log(GDP)	-0,487	0,417	-1,168
HPI	-0,013	0,013	-0,994
Log(Assets)	-0,193	0,094	-2,065*
LevRatio	0,019	0,012	1,632
ROE	0,806	0,351	2,296*
ROA	-16,965	12,554	-1,351
PolStab	0,339	0,725	0,468
RegQual	-1,176	0,475	-2,475*
RuleLaw	0,524	1,116	0,469

External Fraud losses are negatively related with regulatory quality, which is expected and consistent with the regression including all types of losses. We find that return on equity is significant and positively related with external fraud events. The estimate on the logarithm of assets is also significant, yet it shows a negatively effect with external frauds. Additionally, there seems to be no significant relationship between external fraud events and the macroeconomic environment since none of the estimates are relevant.

Client, Products and Business Practices (CPBP)

Table 16 - Parameter estimates of the panel regression – Client, Products and Business Practices *(Source: Author's calculation)*

Variables	Estimate	Std. Error	z-statistic
Intercept	-8,739	2,836	-3,082**
IntRate	0,164	0,082	2,010*
Inflation	0,167	0,104	1,604
UnemRate	0,147	0,085	1,730*
Log(GDP)	0,340	0,176	1,938*
HPI	0,002	0,007	0,296
Log(Assets)	0,215	0,032	6,813***
LevRatio	0,000	0,000	-0,579
ROE	-0,021	0,056	-0,367
ROA	1,047	0,690	1,517
PolStab	0,686	0,505	1,360
RegQual	-0,276	0,281	-0,982
RuleLaw	1,547	0,600	2,579**

Client, Products and Business Practices events are positively related with all macroeconomic covariates, however the estimates are only significant for interest rate, unemployment rate and GDP. Among the governance indicators, we find rule of law to be positively related with compliance events. We obtain generally weaker results with respect to firm specific variables, nevertheless the size of the firm (represented by the logarithm of assets) is highly related with CPBP events.

Execution, Delivery and Process Management (EDPM)

Table 17 - Parameter estimates of the panel regression – Execution, Delivery and Process Management *(Source: Author's calculation)*

Variables	Estimate	Std. Error	z-statistic
Intercept	-4,187	12,287	-0,341
IntRate	0,183	0,253	0,724
Inflation	-0,256	0,265	-0,966
UnemRate	0,012	0,270	0,046
Log(GDP)	0,367	0,983	0,373
HPI	-0,024	0,016	-1,486
Log(Assets)	0,165	0,080	2,078*
LevRatio	0,018	0,023	0,757
ROE	0,010	0,154	0,064
ROA	0,144	2,011	0,072
PolStab	0,125	1,208	0,104
RegQual	-0,596	0,961	-0,619
RuleLaw	0,614	1,885	0,326

The results for the event type Execution, Delivery and Process Management losses are weak, with the only relevant and significant estimate being the logarithm of assets. This result is consistent with the majority of regressions.

Employment Practices and Workplace Safety (EPWS)

Table 18 - Parameter estimates of the panel regression – Employment Practices and Workplace Safety *(Source: Author's calculation)*

Variables	Estimate	Std, Error	z-statistic
Intercept	88,861	24,679	3,601***
IntRate	0,128	0,400	0,320
Inflation	3,263	1,129	2,890**
UnemRate	-0,133	0,378	-0,353
Log(GDP)	-5,215	1,961	-2,660**
HPI	-0,055	0,026	-2,162*
Log(Assets)	0,207	0,133	1,557
LevRatio	0,008	0,011	0,673
ROE	-1,138	3,244	-0,351
ROA	40,245	33,315	1,208
PolStab	-3,485	1,987	-1,754*
RegQual	-2,845	1,352	-2,105*
RuleLaw	-8,660	4,810	-1,801*

Employment Practices and Workplace Safety losses show a significant and positive relationship with inflation and house price index. However, contrarily of what was hypothesized, unemployment rate and GDP show a negatively association with Operational

Risk losses. Concerning governance variables, regulatory quality, rule of law and political stability are significant and negatively associated with losses.

4.2. Discussion

Concerning macroeconomic indicators, at an aggregate level, we find evidence of a positive connection of losses with unemployment rate. The results are aligned among all models, except for the event type Employment Practices and Workplace Safety. The results are consistent with Hambuckers et al. (2018), Alifano et al. (2019) and Moosa (2011), however Chernobai & Yu (2008) and Prokop & Pakhchanyan (2013)'s findings show a negatively impact of unemployment rate on Operational Risk losses and Cope et al. (2012) examined an insignificant relationship. As for the interest rate, it was hypothesized, and in accordance with the study done by Prokop & Pakhchanyan (2013), that it should be positively associated with Operational Risk losses. The results in the study are supported by the literature and are consistent among all models. Regarding inflation rate, it was found evidence of a positive relationship with Operational Risk losses for all models, except for Execution, Delivery and Process Management. The results are supported by Alifano et al. (2019), however Cipriano et al. (2018) show a negative impact of inflation rate on losses, result which can only be found for the event type Execution, Delivery and Process Management.

Firm specific variables are largely insignificant. When significant, which is the case of total assets, they are positive, suggesting a connection between size of the firm and losses. Apart from the event type External Fraud, which shows a negative relationship with Operational Risk losses, all other event types are coherent with the aggregated results. These results are supported by Abdymomunov (2014), Abdymomunov & Mihov (2017), Abdymomunov et al. (2020), Cope & Labbi (2008), Dahen & Dionne (2010), Na et al. (2006), Prokop & Pakhchanyan (2013), Shih et al. (2000) and Wei (2006).

Amongst the three governance indicators studied, only political stability was found to be insignificant in all models. Moosa & Li (2015) and Alifano et al. (2019)'s findings show a negative relationship between regulatory quality and Operational Risk losses, while it was found a positive association between rule of law and operational losses (Alifano et al., 2019). These findings are consistent with the results presented in this study. In contrast, Cope et al. (2012) show a negative impact of rule of law in Operational Risk losses, which is only consistent with the results for the event type Employment Practices and Workplace Safety.

The remaining covariates are ignored in this analysis since they are not significant.

5. CONCLUSIONS

The aim of this study was to examine macroeconomic, firm and governance specific factors as determinants of operational risk losses in European countries and to simultaneously test and possibly validate some of the key findings of the previous research. The analysis includes a total of 2306 operational loss events over two years in 37 countries. We developed an unbalanced panel data regression where banks operate in different countries over time in which the operational losses are a function of macroeconomic, firm and governance indicators. In more detail, the determinants of Operational Risk under investigation in this study were interest rate, unemployment rate, inflation, GDP, house price index, leverage ratio, return on assets, return on equity, assets, regulatory quality, rule of law and political stability.

Consistent with prior studies, the aggregated results show that operational risk losses are strong and positively related with several macroeconomic indicators, including unemployment rate, inflation, and interest rate. The results also show that operational losses are related to different governance indicators, particularly regulatory quality and rule of law. Our results show that regulation has a negative impact on operational losses, in the sense that high quality regulations reduce operational risk losses. Regarding rule of law, the results show a positive impact on operational losses, which was expected given that rule of law assesses how well which countries adhere to the rule of law in practice. Ultimately, bank specific variables were found to be insignificant, with the exception of assets which was found to be positive and significantly connected with losses. The irrelevant effect of firm specific variables might be due to the lack of detailed firm specific data and, therefore, further research would be needed. House price index and political stability were found to be globally insignificant.

In a second stage we investigated whether there is a different relationship between operational risk losses and the explanatory variables across the various Event Types. Most of the time, the only statistically significant determinants are macroeconomic variables. Unemployment rate and interest rate were found to be insignificant in all event types, with the exception of Clients, Products and Business Practices. Globally, the covariate GDP is not statistically relevant to explain the operational losses, however it was found to be significant for Clients, Products and Business Practices and for Employment Practices and Workplace Safety. Additionally, inflation rate was found to be significant only for Internal Fraud and Employment Practices and Workplace Safety. Curiously, when we disaggregate losses by event type, we notice that rule of law is not significant in the case of External Fraud, contrarily to what was expected. Yet, rule of law was found to be insignificant in all event types, with the exception of Clients, Products and Business Practices and Employment Practices and Workplace Safety, both related with compliance and legal incidents. Regulatory quality was found to be significant and negatively related with operational losses for External Fraud and Employment, Practices and Workplace Safety. When it comes to firm specific variables, return on assets was found to be significant and positively related with Internal Fraud. Return on Equity was found to be significant and positively related with External Fraud. Moreover, we find that among all event types, with the exception of Internal Fraud and Employment Practices and Workplace Safety, losses are the highest in biggest firms (represented by the logarithm of assets).

We conclude that the results in this study reveal that operational losses are mostly linked with macroeconomic and governance indicators. In addition to contributing to the limited literature on the topic, this research has important and meaningful contribution since it supports quantitative approaches on the link between financial institutions' losses and macroeconomic, governance and firm variables through statistical methods. Although financial institutions have implemented internal controls to mitigate or avoid operational risk, they haven't been able to deal with it effectively. Therefore, this study is directly relevant to risk managers at financial institutions, regulators and supervisions.

6. LIMITATIONS AND RECOMMENDATIONS FOR FUTURE WORK

Throughout this dissertation we underline the importance of understanding the key determinants of operational risk, as large operational losses can lead to the collapse of financial institutions. However, there may be some limitations in this study.

Due to confidentiality reasons, the main limitation of this research is the sensitivity of the internal information which, consequently, could not be used in this study. Supplementing internal data with external data could have significantly enhance the study results given that external data are limited since only high-severity losses are publicly released. Sensitive information like fraud and corruption are not disclosed very often, as it may impact both the financial condition and the reputation of banks. Therefore, it would be interesting to extend this study by examining operational risk losses using both internal and external data.

Because of the insignificant impact of firm specific indicators in this study, it would be extremely interesting if future studies could address the relationship between operational losses and some detailed firm specific data such as employees and internal control data. As mentioned by Moosa & Li (2015), the major source of operational losses is the risk of incurring losses because of the failure of people. Certainly, obtaining internal information would be difficult as the data required for this analysis would have a confidential and sensitive feature. Thus, this is the type of analysis that financial firms could consider internally.

In economics, we often see a delay between an economic action and a consequence. Therefore, it would also be interesting to extend this study and understand the timeframe in which macroeconomic variables start to impact on Operational Risk levels.

In summary, future research may conduct similar analysis exploring other determinants of operational risk.

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