LUT School of Business and Management

Laskentatoimen maisteriohjelma

Master's Thesis

Determinants of operational loss severity in the financial industry in Europe

Author: Heini Kiili

1st Supervisor: Pasi Syrjä

2nd Supervisor: Timo Leivo

ABSTRACT

Author:	Heini Kiili
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The Purpose of this thesis is to examine both firm and country specific factors as determinants of operational loss severity in Europe and to simultaneously test and possibly validate some of the key findings of the previous research. In more detail, the determinants of operational risk under investigation in this study are the size of the firm, the geographic region, the size of the economy (GDP), business line, event type and three governance indicators which are the rule of law, regulatory quality and political stability.

The empirical study was conducted by using Ordinary Least Squares regression analysis and the full data of 87485 operational loss events was divided into three groups based on the loss severity in EUR when performing the analysis. The results of this study suggest that operational loss events of different sizes cannot necessarily be explained by the same determinants. In other words, it can be that extreme loss events are caused by different things than high frequency and low severity loss events. Furthermore, consistent with the previous studies, the results indicate no systematic association between operational loss severity and firm size. Finally, the results indicate that operational losses tend to be more severe in larger geographic regions.

TIIVISTELMÄ

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Tämän tutkielman tarkoituksena on selvittää, mitkä tekijät vaikuttavat operatiivisten riski-insidenttien vakavuuteen finanssialalla Euroopassa. Tutkielmassa tarkastelun kohteena olevat tekijät ovat yrityksen koko, sen maantieteellinen sijainti, maantieteellisen alueen koko (BKT), yrityksen sisäinen toimilinja, insidentin tyyppi, sekä kolme erilaista hallinnon tasoa kuvaavaa mittaria.

Tutkielman empiirinen osuus toteutettiin regressioanalyysiä hyödyntäen. Lopullinen aineisto koostui 87485 operatiivisestä riski-insidentistä, ja analyysivaiheessa se jaettiin kolmeen osaan insidettien euromääräisen vakavuuden mukaan. Tutkielman tulosten mukaan eri kokoisia riski-insidenttejä ei luultavasti voida hyvin selittää samoilla tekijöillä. Lisäksi, tulosten mukaan operatiivisten riski-insidenttien vakavuudella ja yrityksen koolla ei näyttäisi olevan systemaattista yhteyttä. Tämä löydös on myös linjassa aiempien tutkimustulosten kanssa. Tulokset antavat myös viitteitä siihen suuntaan, että riski-insidentit olisivat vakavampia BKT:llä mitatusti suuremmilla maantieteellisillä alueilla.

Acknowledgements and disclaimer

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All views in this thesis are the author's own and do not represent those of the ORX.

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1 INTRODUCTION

The backbone of this Master's thesis is the concept of operational risk which is according to the Basel Committee on Banking Supervision (2006), defined as "the risk of loss resulting from inadequate or failed internal processes, people and systems or from external events". The purpose of the first chapter of this thesis is to introduce the topic and why it makes sense to study it from this angle, as well as to set the scene for the empirical part of this thesis.

1.1 Background and motivation

Although the existence of operational risks is not a new phenomenon as such, it has only during the recent decades become a more common conversation piece. Due to the rapidly changing operational environment, increasing uncertainty, developments of e-commerce, automated technology, and the like, operational risk and its management has received increasing amount of attention from researchers, practitioners and regulators during the recent years (Tursunalieva, & Silvapulle, 2016), not to mention the impact from the increasing size and complexity of financial institutions (de Fontnouvelle et al., 2006). Furthermore, the introduction of Basel II accord has played a significant role in pushing operational risk upwards on the agenda. The Basel II accord, issued by the Basel Committee on Banking Supervision in 2006, obliges internationally active financial firms to pay more attention and be more transparent regarding both qualitative and quantitative aspects of their risk exposure, including now also operational risk (Basel Committee on Banking Supervision, 2006). From the quantitative point of view this means that the firms are required to develop models for quantifying the capital requirement also for operational risk, and not only to credit and market risk (Basel Committee on Banking Supervision, 2006).

What makes operational risk especially interesting and explains the increased amount of attention it has attracted, is the exceptional and fatal nature of it. The

reason for this are particularly the most extreme operational risk events which constitute threats rather than risks, as they are hard to measure and even more difficult, if not impossible, to predict, purely because they have often never occurred before (Jobst, 2007). During the recent years, there have occurred many severe incidents which have underlined the dangerousness of operational risk. One of the most famous of them is the collapse of the Barings Bank, orchestrated by one man in 1995 which, according to Moosa & Silvapulle (2012), contributed significantly to the emergence of nowadays widely used term “operational risk”. Just to mention a couple additional examples, in September 2017, eight Indian banks suffered a total loss of INR 49.3 billion in a commercial loan fraud, and in January 2017 it was announced that Western Union will pay USD 591 million in relation to anti-money laundering and wire fraud failures (Operational Riskdata eXchange Association (ORX), 2017a). Furthermore, a good example of possible major operational risk for financial firms is the possibility of not being compliant with many of the new regulations, such as the General Data Protection Regulation (GDPR) and Markets in Financial Instruments Directive (MIFID II). The threats connected to operational risks have also been identified in large corporations around the globe, as according to KPMG’s 2017 Global CEO Outlook, Operational risk was seen as the highest concern for CEOs globally, leaving behind other widely recognized sources of risk, such as emerging technologies and cyber security (KPMG, 2017). Moreover, the global financial crisis has also played a significant role in proving the dangerousness of operational risk, as the crisis exposed multiple deficiencies in the risk management and internal control in the banking industry (Hess, 2011; McNulty & Akhigbe, 2017).

Many deficiencies have been identified in connection to the previous research on operational risks in financial firms which indicates a need for further research. To begin with, operational risks are described as unique and distinct and generally not as well understood as for example credit and market risk (Chernobai, Jorion, & Yu, 2011). In addition, due to the huge financial impacts caused by the materialised operational risk incidents as well as the regulatory push caused by Basel II, it has become clear that more comprehensive research is needed regarding different aspects of operational risk (Dahen & Dionne, 2010).

1.2 Preliminary literature review

Operational risk in the banking industry is not one of the most common topics of academic research, but the amount of research on it has been increasing during the recent decades. However, only a couple of broader literature reviews have been done on operational risk in the financial industry (Moosa, 2007; Pakhchanyan, 2016). As argued by Pakhchanyan (2016), especially little empirical research has been done on the determinants of operational risk which as an important topic would deserve more attention. Moreover, for the few studies made on the topic, the main trigger to study that area has been the introduction of the Basel II accord (Li & Moosa, 2015). However, some smaller pieces of this large puzzle have been studied more thoroughly, as there is, for example, some research that examines operational risk events caused by fraud (e.g. Carminati et. al. (2015); van der Meulen, 2013; Baker, Cohanierb & Leo, 2017), as well as the reputational impact caused by operational risk incidents (e.g. Sturm, 2012; Fiordelisi, Soana & Schwizer, 2012; and Gillet, Hübner & Plunus, 2010).

In the quite narrow existing literature on the determinants of operational risk the explanatory variables has quite often been derived from the firm specific factors. For example, Chernobai, Jorion, & Yu (2011) did a comprehensive study in the US markets regarding the impact of firm-specific and macroeconomic variables on the incidence of operational loss events. They found that some firm-specific factors have a significant connection to operational risk, as according to their findings young and more complex firms (measured by number of segments) are more likely to face operational risk events. Dahen & Dionne (2010) had a different approach as they aimed to correct the scaling bias and to make better use of external losses by creating a scaling model for the severity and frequency of external losses. Their research show that external loss severity can be explained with firm size (measured by total assets), business line and risk type variables and that loss frequency can be explained by at least firm size (Dahen & Dionne, 2010).

Moosa & Silvapulle (2012) have also studied the impact of some internal factors on operational loss severity as part of their empirical analysis of operational losses in the financial industry in Australia. Their primary focus is on the effect operational loss events have on a firm's market value, but they also study the relationship between operational loss severity and some firm specific factors. Consistent with Dahen & Dionne (2010), their findings indicate that the losses tend to be more severe in certain business lines, but then again, inconsistent with Dahen & Dionne (2010) their results indicate that there is no connection between firm size and loss severity (Moosa & Silvapulle, 2012). However, Moosa & Li (2013) found similar results regarding the connection between operational risk severity and both business line and firm size as Moosa & Silvapulle (2012) in their research on operational risks in the Great Britain.

Moreover, another determinant of operational risk which has been considered in the existing literature is corporate governance. To begin with, Wang & Hsu (2013) have studied the relationship between board composition and operational risk events of financial institutions. According to their findings both board size and age heterogeneity contribute positively to sound operational risk management (Wang & Hsu, 2013). Li & Moosa (2015) have also studied the connection between operational risk and governance, but instead of using firm-specific corporate governance indicators, they have used country specific governance factors, such as rule of law, control of corruption, voice and accountability and political stability & absence of violence/ terrorism. In addition to the governance indicators, they have also modelled the connection between operational risk and the size of the economy, the standard of living, the legal system and the regional factor (Li & Moosa, 2015). Their findings indicate that the average severity of operational loss events is positively related to the size of the economy, and the standard of living, and that frequency is positively related to GDP and governance and negatively to the standard of living. Moosa (2015) found similar results in his study which showed that the severity of operational losses is positively related to the GDP of the economy. The results also indicate that higher scores in governance indicators lead to lower severity of operational losses (Moosa, 2015).

Cope, Piche, & Walter (2012) have quite similarly studied operational risk in terms of the country level legal, regulatory, and economic environment in which banks operate globally, but they have studied only the severity. They studied the different operational risk event types separately and found indications of significant correlations between Internal Fraud and constraints on executive power and the prevalence of insider trading. Clients, Products and Business Practices events are connected to securities and shareholder protection laws, supervisory power, restrictions on banking activity, and the prevalence of insider trading. Other event types are related to a governance index and GDP per capita. (Cope, Piche, & Walter 2012)

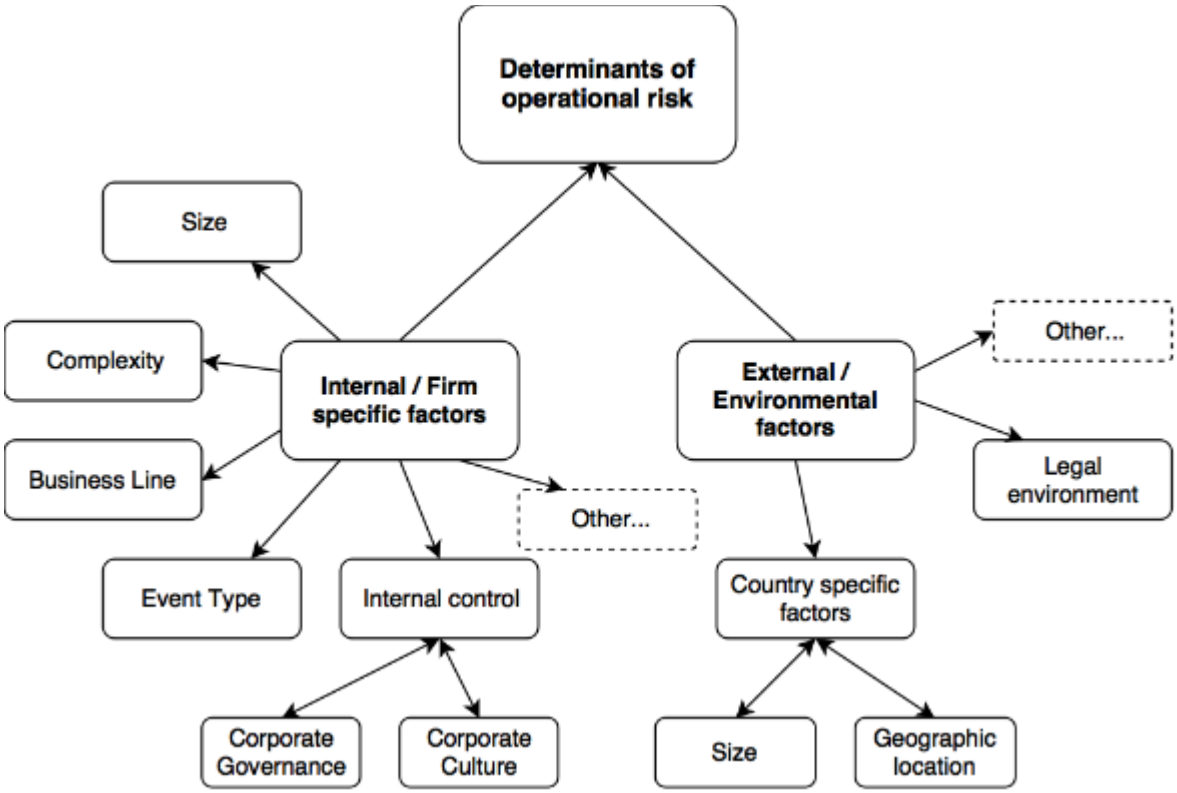
Moreover, Hess (2011) analysed operational risk in the context of the 2007–2009 financial crisis by using the value- at-risk (VaR) method, and found that the financial crisis had a significant impact on Business lines Trading and Sales as well as Retail Brokerage while other business lines were not affected. The results were caused by losses caused by the market failure of auction rate securities in investment banks (Hess, 2011).

All in all, the existing academic research on the determinants of operational risk is still rather exploratory and early research and thus, not yet comprehensive. More extensive research on this topic would also be very valuable for the practitioners as it would provide useful information regarding the risk drivers for banks' risk managers for estimating a bank's operational risk exposure (Pakhchanyan, 2016). This highlights the need for further research.

1.3 Research objectives and scope

The objectives of this thesis are defined based on the above illustrated shortages in the existing research on the determinants of operational risk. The overall aim of this study is to examine both firm and country specific factors as determinants of operational loss severity in Europe and to simultaneously test and possibly validate some of the key findings of the previous research.

Figure 1: Theoretical framework of determinants of operational risk



The connection between the determinants of operational risk, as well as the connections between the research questions of this thesis are illustrated in Figure 1 which demonstrates the theoretical framework of this thesis. In more detail, the determinants of operational risk under investigation in this study are the size of the firm, the geographic region, the size of the economy (GDP), business line, event type and three governance indicators which are the rule of law, regulatory quality and political stability. These variables were chosen as this study aims to possibly validate some of the existing academic findings and as these variables have been considered in the previous academic research on this topic. It would have been interesting to include more firm specific variables in the study, but that was not possible due to the confidentiality of the ORX loss data which does not allow to identify which loss is reported from which financial organisation.

Rather than focusing on integrated or comprehensive risk management, the focus of this thesis is limited to operational risk. The nature of operational risks is quite

unique in the financial firm's risk landscape due to which it makes sense to study operational risks separately (Chernobai, Jorion, & Yu, 2011). The geographical scope of the study is Europe unlike in any of the previous studies. Limiting the study to Europe ensures some homogeneity in the sample data as Europe as a market is after all quite consistent in comparison to for example Asia. The geographical scope has varied in the previous research, as some studies are examining only one country (Moosa & Li, 2013; Moosa & Silvapulle, 2012), while some analyse the loss events globally (Cope, Piche, & Walter, 2012). Furthermore, from the industry point of view, this study limits to the financial institutions. The risk environment for a financial firm is very different than for a non-financial firm, and thus it is sensible to study the highly risk oriented banking industry independently (Bessis, 2002; Linsley & Shrives, 2006; Jobst, 2007).

The specific target of the research has also varied in the existing research quite much as some studies concentrate on modelling the frequency of the operational loss events (Chernobai, Jorion, & Yu, 2011), some on the severity of the losses (Cope, Piche, & Walter, 2012) and some both frequency and severity (Li & Moosa, 2015). The aim of this thesis is to concentrate on the severity of the loss events.

Based on the above defined research opportunities created by the gaps in the existing literature and considering the restrictions and scope of this study, the aim of this thesis is to answer the following main question.

Q: What are the determinants of operational loss severity in the financial industry in Europe?

In order to dig a little bit deeper and to find to potentially find more specific results, the following supporting questions were formulised which aim to focus more specifically on the different variables under consideration in this study.

q1: Does the size of the firm have an impact on the severity of operational loss events?

q2: Does the level of governance have an impact on the severity of operational loss events?

q3: Does the geographic region have an impact on the severity of operational loss events?

q4: Does the operational loss events tend to be more severe in geographic regions with higher Gross Domestic Product (GDP)?

q5: Does the operational loss events tend to be more severe in specific event types?

q6: Does the operational loss events tend to be more severe in specific business lines?

1.4 Data and Methodology

The empirical part of the study is conducted by using quantitative research methodology. The analysis is performed by using the SAS EG software and Ordinary Least Squares (OLS) regression analysis with multiple explanatory variables is used as the study method. The data for the dependent variable, operational loss severity, is obtained from the ORX operational risk database. ORX is a global, not for profit association which aims to enable anonymous exchange of high quality operational loss data exchange around the globe (Operational Riskdata eXchange Association (ORX), 2017b). Upon applying several filters to the loss data, the final sample consists of 87485 operational risk events among multiple European financial institutions from 2006 to 2015. The data for the explanatory variables is collected from the public World Bank database.

After performing some preliminary investigation and testing for the data, it was decided to separate the empirical analysis into three sections based on the severity

of the operational losses. The reason for this is the wide variety of different possible event types and sources for operational risk (Basel Committee on Banking Supervision, 2006; Brown, 2012). Thus, based on preliminary examination of the operational loss data used in this study, it was assumed that it can be reasonable to predict that the high frequency and low severity events are not necessarily affected by same determinants as the extremely rare low frequency but high severity events. Therefore, the analysis was decided to be performed individually for small events, medium events and large events.

1.5 Limitations

There are naturally some factors that set boundaries for this study. Firstly, due to the relatively scarce existing literature on determinants of operational risk in the banking industry, some of the material used in this thesis consider either operational risk overall and not only in the financial sector, or risk management as a whole instead of focusing only on operational risk.

Furthermore, the quality of the data provides a limitation for the study, mainly due to the confidentiality of the ORX loss data which reveals neither the company in which a specific loss has occurred nor the exact country. In other words, this limits the empirical part of this thesis so, that some variables were not possible to include in the model and some variables needed adjustments to fit to the study. Furthermore, the extremely heterogeneous nature of operational risks complicates the modelling of the loss data as the risks defined as operational can vary from external natural disasters to internal fraud (Moosa, 2007; Li & Moosa, 2015).

1.6 Structure

The previous sections of this chapter have provided rationale and objectives for this thesis as well as an overview of the data and methodology of the actual empirical study. Before going into detail, the structure of the study is presented by giving the

reader simultaneously an understanding on how the different chapters and their inner sections are bound to each other.

The actual study begins with the theoretical part, chapters 2 and 3, that starts with the definition of operational risk followed by an overview of the regulatory aspects that have a significant effect on operational risk in the financial industry. Furthermore, that section gives an overview on the determinants of operational risk that will be discussed all along the thesis. The purpose of the theoretical part of the thesis is to give the reader a sufficiently comprehensive overview of operational risk, its determinants as well as other relevant aspects in the context of financial industry.

The data and methodology chapter, namely Chapter 4, begins by providing both visual and written description of the data used in the research highlighting also some possible deficiencies in the data which might affect the results of the study. Before going into detail on the actual results, the empirical research method and its prerequisites are also explained in detail.

The core part of the study is the empirical section that represents the results from the quantitative model. In this section, the results of the study are also presented in comparison with previous academic literature. Finally, the last chapter of this thesis provides the concluding remarks for the work by summarising the whole study followed by some suggestions for further research.

2 OPERATIONAL RISK

This chapter formulates the theoretical part of this thesis. The aim of this chapter is to provide an insight into operational risk. The topics covered in this section are: definition and characteristics of operational risk, Basel II as well as other relevant regulations, i.e. the regulatory push for operational, and finally the key factors of management and measurement of operational risk.

2.1 Definition and characteristics of operational risk

On general level, risk can be defined as the possibility for deviating from the expected outcome. This deviation is also usually harmful. (Rosenberg & Schuermann, 2006). Then again, according to the Basel Committee on Banking Supervision (2006), operational risk is more specifically defined as “the risk of loss resulting from inadequate or failed internal processes, people and systems or from external events.” According to the definition, legal risk is included in the operational risk, but strategic and reputational risk is not as the definition refers only to losses that are direct and measurable (de Fontnouvelle et al., 2006).

The definition alone is quite broad and thus, indicates that defining and describing operational risk can be difficult in practice (Moosa, 2007). It has even been defined as a “fuzzy concept” because it can be very difficult to identify which events actually are operational risks and which are just regular instabilities the companies are facing in their everyday operations (Crouchy, 2001). Hence, operational risk has quite often in the past been considered as a residual of enterprise risk after credit risk and financial risk (Brown, 2012), or simply as everything else than market risk and credit risk (Moosa, 2007). However, it has been argued, that this kind of negative definition cannot be used in measuring or managing the risk itself which is why more specific descriptions, such as the Basel Committee’s definition, has been formulated (Moosa, 2007). Moreover, the difficulties to define the concept of operational risk have even triggered a conversation whether it is even important to have a precise

definition. On one hand, some say that things cannot be measured unless it is defined (Moosa, 2007), whereas on the other hand, it has been said that it would be more value adding to focus on the actual operational risk management rather than spending a lot of time on formulating a perfect definition (Lam, 2008).

The Basel Committee's definition for operational risk is broadly used and acknowledged in the existing literature. However, some arguments have also been expressed regarding possible deficiencies in it. For example, Hemrit & Mounira (2012) have argued that the BCBS definition is not optimal in practical context as according to the definition operational risk denotes only a potential loss. Furthermore, the exclusion of reputational risk from the definition has been challenged as it has been experienced that operational risk incidents can and in many cases, have a significant impact on a firm's reputation if those incidents are interpreted to indicate for example as control weaknesses or unethical behaviour (de Fontnouvelle et al., 2006). Furthermore, by examining the market reactions, Sturm (2012) demonstrated that operational risk events have a strong negative impact on firm's reputation, and that this causality seems to be largely unaffected by the size of the firm as well as the value-growth characteristic of firms. Fiordelisi, Soana & Schwizer (2012), then again, have done an exploratory study on the determinants of reputational risk after an operational risk incident, and identified 6 possible factors which are: bank riskiness, profitability, level of intangible assets, capitalization, size, the entity of the operational loss and the business units that suffered the operational loss. All in all, it seems that in theory the concepts of operational and reputational risk are often treated as separate issues which have a connection while in practise the connection can be so significant that it is very difficult to separate the two concepts.

The definition of operational risk can be further categorized to external and internal risks, as the BCBS (2006) definition for operational risk also indicates, by dividing the causes for operational risk to processes, people, system and external events. In other words, external operational risk is caused by factors that are external to the firm under examination and usually out of the firm's control, such as terrorism, natural disasters and vandalism, whereas internal operational risk is the

consequence of errors and other events in the firm's internal environment during the regular, daily operations (Jobst, 2007). The internal operational risks can be further defined in the following way: 1) process risk is the risk of failure in the established processes, not following the process or insufficient process mapping in the organization; 2) people risk is the risk of failure in the organizational structure or management or other people related failure such as human error cause by insufficient training, failing controls, non-competent staff or other factors; 3) system risk is the risk of breakdown or disruption in system that affects the firm's operations (Zamorski, 2003).

Based on the above, it is obviously characteristic for operational risk to be inherently multidimensional as people, processes and systems can fail in many ways (Brown, 2012). The Basel Committee has clustered the operational risk events based on the type of the event (Basel Committee on Banking Supervision, 2006). Based on this classification, there are 7 + 1 event types for the operational risk events which are explained in table 1 including also the subcategories and official explanatory examples. By listing very many factors related to a firm's operations to the event type categorization, the Basel Committee on Banking Supervision indicates that operational risk incidents tend to happen more often due to factors that are internal to the firm rather than external. However, this kind of classification based on causes has argued to be quite vulnerable and thus, a possible source for errors in reporting and handling operational loss events as the causes and effects of operational loss events are often confused (Moosa, 2007).

Table 1: Loss event type classification (Basel on Banking Supervision, 2006)

Event type Category (level 1)	BCBS Definition	Sub-categories (level 2)	Official BCBS examples (level 3)
Internal Fraud (IF)	Losses due to acts of a type intended to defraud, misappropriate property or circumvent regulations, the law	Unauthorized Activity	Transactions not reported (intentional) Transaction type unauthorized (w/monetary loss) Mismarking of position (intentional)

	or company policy, excluding diversity/ discrimination events, which involves at least one internal party	Theft and Fraud	Fraud / credit fraud / worthless deposits Theft / extortion / embezzlement / robbery Misappropriation of assets Malicious destruction of assets Forgery Check kiting Smuggling Account take-over / impersonation / etc. Tax non-compliance / evasion (willful) Bribes / kickbacks Insider trading (not on firm's account)
External Fraud (EF)	Losses due to acts of a type intended to defraud, misappropriate property or circumvent the law, by a third party	Theft and Fraud	Theft/Robbery Forgery Check kiting
		Systems Security	Hacking damage Theft of information (w/monetary loss)
Employment Practices and Workplace Safety (EPWS)	Losses arising from acts inconsistent with employment, health or safety laws or agreements, from payment of personal injury claims, or from diversity / discrimination events	Employee Relations	Compensation, benefit, termination issues Organized labor activity
		Safe Environment	General liability (slip and fall, etc.) Employee health & safety rules events Workers' compensation
		Diversity & Discrimination	All discrimination types
Clients, Products and Business Practices (CPBP)	Losses arising from an unintentional or negligent failure to meet a professional obligation to specific clients (including fiduciary and suitability requirements), or from the nature or design of a product.	Suitability, Disclosure & Fiduciary	Fiduciary breaches / guideline violations Suitability / disclosure issues (KYC, etc.) 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 practices Market manipulation Insider trading (on firm's account) Unlicensed activity Money laundering
		Product Flaws	Product defects (unauthorized, etc.) Model errors
		Selection, Sponsorship & Exposure	Failure to investigate client per guidelines Exceeding client exposure limits
		Advisory Activities	Disputes over performance of advisory activities
Damage to Physical Assets (DPA)	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 (terrorism, vandalism)
Business Disruption and System Failures (BDSF)	Losses arising from disruption of business or system failures	Systems	Hardware Software Telecommunications Utility outage / disruptions
Execution, Delivery and Process Management (EDPM)	Losses from failed transaction processing or process management, from relations with trade counterparties and vendors	Transaction Capture, Execution & Maintenance	Miscommunication Data entry, maintenance or loading error Missed deadline or responsibility Model / system misoperation Accounting error / entity attribution error Other task misperformance Delivery failure Collateral management failure Reference Data Maintenance
		Monitoring and Reporting	Failed mandatory reporting obligation Inaccurate external report (loss incurred)
		Customer Intake and Documentation	Client permissions / disclaimers missing Legal documents missing / incomplete
		Customer / Client Account Management	Unapproved access given to accounts Incorrect client records (loss incurred) Negligent loss or damage of client assets
		Trade Counterparties	Non-client counterparty misperformance Misc. non-client counterparty disputes

		Vendors and Suppliers	Outsourcing Vendor disputes

This wide range of different types of operational risks indicates also the dangerousness linked to operational risks as it is extremely difficult for a firm to manage and prevent the huge range of risks threatening it. It has even been stated that operational risk has the potential to cause greater damage than the other risk sources (Jobst, 2007). Hence, it has also been suggested that the amount of capital reserved for operational risk will often be at least as much or even more than capital reserved for market risk (de Fontnouvelle et al., 2006; Jarrow, 2008). In the worst case the impact of an operational risk incident can be catastrophic for the company in which it materialises. A good example is the collapse of the Barings Bank in 1995 which was caused by intentional and unauthorized trading activities of one man which was also overlooked by the relevant manager due to insufficient risk management; internal control and reporting (Drennan, 2004). Of course, a good example of a disaster caused by operational risk, although outside the financial sector, is also the famous Enron Scandal.

Furthermore, due to the variety of risk types, there is also differences in the ways how operational risks materialize and how they are detected. For example, according to Chernobai, Jorion, & Yu (2011) as well as Embrechts & Hofert (2011), it might take months or even years for some risks to materialise. Operational risk incidents are typically structured so that one event leads to one loss, but scholars have found indications that operational losses can also occur as a series of losses caused by a single event (Mizgier & Wimmer, 2018). Moreover, these kinds of series of losses are indicated to be more common for the financial industry than for example in the manufacturing industry (Mizgier & Wimmer, 2018).

In today's global financial industry, the impact of operational loss event can also go beyond the direct financial impact for the company in which the risk occurred. For example, the customers may be impacted if the operational risk incident affects the customer serving operations. Examples of such incidents could be treacherous sales activities and business critical IT tool disturbances (de Fontnouvelle et al., 2006). Furthermore, the financial system and its stability may be affected in case

the operational loss event occurs in fundamentally important institution (Hemrit & Mounira, 2012). Finally, and as explained earlier, operational risk events are also often negatively affecting the firm's reputation (de Fontnouvelle et al., 2006; Sturm, 2012; Jiang, 2018).

Although operational risk is only one piece of financial institutions' comprehensive risk picture, there are many reasons why it makes sense to examine it as an individual topic. For example, the financial industry can simply be labelled as more risk oriented than many other industries (Bessis, 2002; Linsley & Shrives, 2006). Furthermore, due to its exceptional and diverse characteristics and as it is merely internal than external, operational risk is fundamentally quite different from the other risk types (Helbok & Wagner, 2006). Furthermore, operational risk has been argued to be more connected to the culture of the company than for example market and credit risk (Moosa, 2007). Moreover, according to Moosa & Silvapulle (2012), the term operational risk did not even formally exist prior to early 1990s. This indicates that operational risk is rather understudied in comparison to the other risk types. However, it should also be noted that operational risk is to some extend linked to the other common risks for financial firms. Chernobai, Jorion, & Yu (2011) have for example identified a positive correlation between credit risk and operational risk. In some cases, it can thus also be difficult to separate which part of an occurred incident is linked to credit and which to operational risk (Brown, 2012).

Table 2: Mapping of Business Line (Basel on Banking Supervision, 2006)

Business Line (level 1)	Business Line (level 2)	Activity Groups
Corporate Finance (CF)	Corporate Finance	Mergers and acquisitions, underwriting, privatisations, securitisation, research, debt (government, high yield), equity, syndications, IPO, secondary private placements
	Municipal/Government Finance	
	Merchant Banking	
	Advisory Services	
Trading & Sales (TS)	Sales	Fixed income, equity, foreign exchanges, commodities, credit, funding, own position securities, lending and repos, brokerage, debt, prime brokerage
	Market Making	
	Proprietary Positions	
	Treasury	
Retail Banking (RB)	Retail Banking	Retail lending and deposits, banking services, trust and estates
	Private Banking	Private lending and deposits, banking services, trust and estates, investment advice

	Card Services	Merchant/commercial/corporate cards, private labels and retail
Commercial Banking (CB)	Commercial Banking	Project finance, real estate, export finance, trade finance, factoring, leasing, lending, guarantees, bills of exchange
Payment and Settlement (PS)	External Clients	Payments and collections, funds transfer, clearing and settlement
Agency Services (AS)	Custody	Escrow, depository receipts, securities lending (customers) corporate actions
	Corporate Agency	Issuer and paying agents
	Corporate Trust	
Asset Management (AM)	Discretionary Fund Management	Pooled, segregated, retail, institutional, closed, open, private equity
	Non-Discretionary Fund Management	Pooled, segregated, retail, institutional, closed, open
Retail Brokerage (RB)	Retail Brokerage	Execution and full service

Moreover, reporting operational risks in financial firms is also segmented by the different business lines which the Basel Committee on Banking Supervision is also applying (Basel Committee on Banking Supervision, 2006). There are 8 business lines which are illustrated with also level 2 definitions and activity group examples in table 2. Mapping the operational risk events towards these widely used and common business lines is an important feature in the operational risk management and measurement environment as it makes understanding and analyzing the huge variety of operational risks even slightly easier. Furthermore, it enables identifying trends within the business lines which are also quite different in comparison to each other and thus, tend not to have similar operational risk incidents.

All in all, based on the above mentioned, it is not clear whether operational risk can overall be said to be more systematic or idiosyncratic (Moosa, 2007; Pakhchanyan, 2016). Due to the many different sources and different event types, it can even be argued that sometimes operational risk events can purely be random events which could not be explained by anything concrete (Pakhchanyan, 2016). These are also very important matter for this study and will considered in the empirical part of this thesis.

2.2 Regulatory push and capital requirements for operational risk (Basel II)

As mentioned earlier, operational risk has not been a hot topic in the risk management context for a long time. Year 2006 can be considered as the revolutionary year after which operational risk has received more and more attention among both researchers and practitioners. This is because the new guidelines for international Convergence of Capital Measurement and Capital Standards, also known as the Basel II accord, was published in June 2006 with the requirement to be implemented in more than 100 countries by early 2007 (Basel Committee on Banking Supervision, 2006). This regulators' increasing interest in operational risk can, in a nutshell, be explained by the rather large change in the companies' risk profiles above all caused by e-commerce and huge dependency on technology (Moosa, 2007). Furthermore, the Basel II also aimed to increase the risk sensitivity in the capital requirement calculations (Pakhchanyan, 2016).

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). Furthermore, given the nowadays truly existing possibility for a rare but severe operational incident, it is evident that protection against such incidents is needed (Cope, et al., 2009). New regulations do not however materialize out of thin air, and thus it is worth mentioning that there have of course also been various other factors that have brought more attention to operational risk, such as the nowadays rapidly developing operational environment and growing size and complexity of financial institutions (Tursunalieva, & Silvapulle, 2016).

Furthermore, a rather heavy focus in the existing operational risk literature is on the Basel II requirement for financial firms to determine their capital exposure for operational risks. Hence, it is value adding to shed light also on the three calculation methods approved by the Committee which are from simple to sophisticated: i) the basic indicator approach (BIA), ii) the standardized approach (SA), and iii) the

advanced measurement approach (AMA) (Basel Committee on Banking Supervision, 2006).

Banks have the freedom to choose which method to use, but they should also aim to develop their operational risk measurement systems, and hence move towards the AMA (Chernobai, Jorion, & Yu, 2011; Brown, 2012). Furthermore, it is not allowed to move down along the spectrum once a more sophisticated method has been applied without supervisor's approval (Basel Committee on Banking Supervision, 2006). BIA and SA methods are in general assessing threats caused by operational risk from top down perspective, whereas the AMA approach is clearly the most detailed and bottom-up method (Chernobai, Jorion, & Yu, 2011).

The basic indicator approach (BIA) is the most straightforward method, and thus also easiest to implement. In the BIA method, operational risk is being examined at the enterprise level based on historical data (Brown, 2012). In the BIA approach bank's capital requirement for operational risk equals to the average of a fixed percentage (denoted alpha) of positive annual gross income over the previous three years. Negative annual gross income figures should be excluded from the calculations. (Basel Committee on Banking Supervision, 2006) According to Schwartz-Gârliste (2013), the alpha is usually approximately 15% of the annual gross revenue.

In the standardized approach (SA), the capital requirement is then again calculated by utilizing the eight Basel Committee's business lines (see section 2.1). The capital charge is first calculated for each business line by multiplying gross income by a factor (denoted beta) defined for that specific that business line. The beta represents the industry-wide link between operational risk loss experience for a specific business line and the total gross income per that business line. The total capital requirement is calculated as the three-year average of the sum of the capital charges across each of the business lines in each year, taking only positive gross incomes into account. (Basel Committee on Banking Supervision, 2006)

The most complicated and multifaceted is then again, the advanced measurement approach (AMA) which requires analyzing the bank's entire internal operational risk measurement and management system including both quantitative and qualitative factors (Basel Committee on Banking Supervision, 2006). The AMA approach requires banks to calculate the risk exposure at the 99.9th percentile of the loss distribution which in practice means that banks need to estimate the severity of an annual loss event that would occur on average every thousand years (Cope et al., 2009). The aim of this kind of bottom–up approach is to quantitatively measure the magnitude of the most extreme events across the different business areas of the bank (Brown, 2012).

Using AMA requires also approval from the relevant supervisor, and it obliges financial firms also to use both internal and external data when determining their operational risk exposures (Basel Committee on Banking Supervision, 2006). While data on internal operational loss events reflect the firm's current operational risk environment comprehensively, external data provide a valuable supplement, especially regarding large, and possibly fatal, losses (Chernobai, Jorion, & Yu, 2011). On the other hand, external data can also rationalise the situation for example in case a firm has exceptionally severe observations in its internal data and vice versa (de Fontnouvelle et al., 2006).

The usage of external data is relevant also because in risk management, it is important to consider risks that have not been materialized yet, and especially with operational risks the range of possible event types is very wide, as explained in section 2.1. However, in some cases it is possible that the use of external data can also bias the calculations which should be considered in the model specification (Dahen & Dionne, 2010). According to Wilson (2007), there are three kinds of bias that are characteristic for external data usage which are: 1) Reporting bias – caused by the different reporting thresholds used by the firms reporting to the external database 2) Control bias – caused by the differences in firms' internal control systems; and 3) Scale bias – caused by the different size and complexity of the reporting firms. On the other hand, nowadays the availability of structured external data is much better although there are still databases with different features (such

as data from “members” vs. from public sources, open for public vs. confidential) (Pakchanyan, 2016).

In addition to the quantitative data requirements, AMA requires banks also to consider the qualitative aspects of its operational risk management when calculating the capital requirement (Basel Committee on Banking Supervision, 2006) and it requires them to do it so that they can allocate the operational risk capital realistically to the major business lines (Embrechts & Hofert, 2011). Furthermore, banks need to have an independent management function for operational risk, and the banks must ensure that the internal operational risk measurement system is well implemented into the everyday risk management processes (Embrechts & Hofert, 2011).

Furthermore, in the AMA approach, banks must use scenario analysis of senior operational risk expert opinion regarding the external data to evaluate its exposure to high-severity events (Basel Committee on Banking Supervision, 2006). Scenario analysis should also be used to estimate the potential impact of deviations from the correlation assumptions included in the bank’s operational risk measurement processes, especially, to evaluate potential losses arising from operational loss incidents that could happen at the same time (Embrechts & Hofert, 2011). Moreover, when using the AMA method, banks are also obliged to consider the impact of their business environment and internal control factors on their risk profiles (Basel Committee on Banking Supervision, 2006).

All in all, the AMA method is clearly the most detailed and complicated of the BCBS methods, but given the lack of clear best practices and standard methods, it also enables banks in practice to modify and adjust the actual method quite much (Cope at al., 2009). Despite the calculation method being used, many studies show that the amount of capital to be allocated to operational risk is significant in comparison to market and credit risk and can for the largest banks be several billion dollars (de Fontnouvelle et al., 2006). However, as the AMA method gives the banks quite much freedom to develop their calculation methods, and as there are multiple different models that can be used for calculating the capital requirement, an

important observation is that the result, that it, the required amount of capital, can vary quite much depending on what kind of calculation method is applied (Dutta & Perry, 2007). Furthermore, as a side product of the many attempts to apply the AMA method and to model operational loss data has according to Cope et al. (2009) promoted the spread of sufficient risk culture within different parts of financial firms.

In addition to the capital requirement, the Basel II requires also more transparency in banks' operational risk reporting. Generally, this so-called disclosure requirement, or pillar three, means that among other risk types, banks must describe their operational risk management objectives and policies, including strategies and processes, the structure and organization of the operational risk management function, the scope and nature of risk reporting and measurement systems, as well as the policies, strategies and monitoring processes for hedging and mitigating risk (Basel Committee on Banking Supervision, 2006).

Although this kind of disclosure requirements are generally a positive thing and potentially encourage market discipline, it has been stated that the BCBS requirements are too qualitative and general (Barakat, & Hussainey, 2013; Willesson, 2014). Of course, it should also be noted that before the Basel II accord was established, there were not a single regulatory disclosure requirements regarding operational risk (Helbok & Wagner, 2006). Due to this, both content and quality of the operational risk reporting in for example financial institutions annual reports are not very consistent (Barakat, & Hussainey, 2013). Furthermore, as the external risk reporting is mostly vague and not sufficiently transparent, it is also difficult to analyze and can thus create a problem of asymmetric information (Willesson, 2014).

In addition to the Basel II, there are multiple other regulations affecting operational risk management and measurement in the financial industry. In the European context, significant players in this field are naturally the European Union (EU) and the European Banking Authority (EBA). An important document regarding this is the 2013 published EU directive 2013/36/EU on the license to operate of credit institutions and the prudential supervision of credit institutions and investment firms.

This directive has triggered the creation of multiple guidelines and supervisory activities in the EBA as well as in the national financial supervisors, such as Finanssivalvonta in Finland. A significant document created based on that directive is the EBA Guidelines on Internal Governance, also known as GL44 which sets significant boundaries for financial institutions' internal control covering for example organizational structure, risk culture and framework used for internal control (EBA, 2017).

2.3 Operational Risk Management

Based on the above-mentioned characteristics of operational risk it is clear that it should also be measured and managed, and the existence of the above-mentioned Basel II as well as GL 44 among other regulations and guidelines indicates that the regulators are encouraging banks to do so. The purpose of this sub-chapter is to only provide a glimpse to what managing operational risks means. Due to the diverse characteristics of operational risk, providing a comprehensive and detailed description of operational risk management would be a topic wide enough to be the title of another master's thesis.

In history, operational risk has been often considered as abnormal failures of controls and not something that could be measured and managed (de Fontnouvelle et al., 2006). In the most extreme cases operational risk has even been labeled as an inevitable consequence of doing business that should just be accepted (Schwartz-Gârliste, 2013). However, because of the many severe actual incidents and other factors it has become clear that operational risk most certainly can and should be measured and managed, and consequently, many banks in fact have had to either significantly improve their existing or develop entirely new measures and processes to sufficiently manage their operational risks to cope with the requirements today (Brown, 2012).

Furthermore, managing operational risk in financial industry is quite different from the other risk types, as it requires a risk management approach that concentrates

mainly on the so-called tail events, and especially on the low frequency but high impact end of the loss distribution (Jobst, 2007). In other words, managing operational risks requires managing the unexpected, rare and severe as well as the expected high frequency and low impact events rather than the most usual and average cases. Furthermore, as operational losses tend quite often materialize months or even years after the risk event occurred (Chernobai, Jorion, & Yu, 2011), simply the detection of an operational risk event is not a straightforward task, not to mention measuring and managing it. This also highlights the importance of having a functioning internal control environment in firms.

There are also many direct and potential benefits from operational risk management that have been identified among the existing literature. Generally, implementation of effective operational risk management practices has been connected to better performance, soundness and resilience (Liu & Cortes, 2014). However, according to de Fontnouvelle et al. (2006), the most important benefit of managing operational risk is evidently securing a firm's business continuity by preventing the most severe operational risks from materializing. Drennan (2004) has even pointed out that some major corporate failures could be prevented with functioning mixture of regulation, legislation, risk management and effective sanctions. Moreover, a study by Hemrit & Mounira (2012) indicates that a functioning operational risk management system can even be treated as valuable intangible asset for a firm.

However, the huge variety of different event types is also causing challenges for the management of operational risk, especially in terms of prioritization (Bickford et al., 2016). In many financial institutions, the operational risk management expenses have been increased by more than 50 % during the recent years. However, according to the Boston Consulting Group, in many cases the executive management has started to question the value add from these investments: "We seem to default to rote, tick-the-box exercises that satisfy our regulators but aren't risk based or aligned with business value. There has to be a better way to do this" (Bickford et al., 2016).

The Basel Committee on Banking Supervision has also naturally acknowledged the need for proper management of operational risk, and not only via the Basel II accord, but also by publishing in 2011 the "*Principles for the Sound Management of Operational Risk and the Role of Supervision*". The purpose of this publication is to compile the adequate practices of operational risk management which have been defined "*through ongoing exchange of ideas between supervisors and industry since 2003*". As a result, eleven key principles of sound operational risk management ended up on the document with the fundamental aim to promote and improve operational risk management efficiency throughout the banking system. (Basel Committee on Banking Supervision, 2011). The first two principles are labelled as the fundamental principles and those are:

1. *"The board of directors should take the lead in establishing a strong risk management culture. This should exist throughout the organization."*
2. *"Banks should develop, implement and maintain a Framework that is fully integrated into the bank's overall risk management processes. "*

The remaining nine principles are covering governance (in terms of both board of directors and senior management), risk management environment (identification and assessment), monitoring and reporting, control and mitigation, business resiliency and continuity and role of disclosure (Basel Committee on Banking Supervision, 2011).

Consistent with the BCBS principles, scholars have found evidence that financial institutions' CEOs and other senior management can have a significant impact on the firm's behaviour, outcomes and by impacting the risk management policies, and corporate culture (Bushman et al., 2017). However, in addition to the top-down attention, operational risk requires simultaneously also sufficient bottom-up governance if a bank is to have an effective operational risk management framework (Basel Committee on Banking Supervision, 2011).

Considering all above mentioned and the shortage of common practices, it is clear that operational risk management is not a simple task and with also the growing pressure from the regulators, some firms are struggling as they are trying to measure and manage all kinds of operational risks coming from all directions (Bickford et al., 2016). However, from the practical viewpoint, operational risk management should be linked to the common business objectives and bank's overall goals, and it should include clear roles and responsibilities and focus strongly on preventing emerging risks rather than fighting only against risks that have already been materialized (Bickford et al., 2016).

3 DETERMINANTS OF OPERATIONAL RISK

Considering the wide range of possible types operational risk events explained in chapter 2, it is clear that there are also many different determinants of operational risk. According to Li & Moosa (2015), operational risk can be on a high level determined by firm-specific factors but also by macroeconomic factors and multiple aspects of the environment in which the firm operates. To create theoretical premises for the empirical study, this chapter introduces factors that have been studied as determinants of operational risk in order to give the reader a good overview and basic knowledge of the topic.

Furthermore, an important purpose of this chapter is also to provide detailed background and justification for the research questions of this thesis. However, it shall be noted that all the factors mentioned in this chapter are not considered in the empirical analysis of this study mostly due to confidentiality reasons that restrict the usage of the operational loss data utilized in this thesis. For the sake of clarity, this chapter has been divided into two parts in which different categories of potential determinants of operational risk are presented and analyzed. These categories are firm specific and environmental factors.

3.1 Firm-specific factors

As majority of operational risk incidents are happening inside organizations (Basel Committee on Banking Supervision, 2006; Li & Moosa, 2015), it is inevitable that firm-specific factors might have a connection between certain operational losses. In this thesis, the firm-specific factors under investigation are the size and complexity of the firm, the business line and event type as well as corporate governance.

3.1.1 Size of the firm

One firm-specific factor which has received researchers' attention is the size of the firm. Generally, common sense would probably in most cases imply that bigger firms would have larger operational losses as they simply are larger and thus for example able to process both larger individual transactions and bigger volumes of transactions. Similarly, the Basel Committee (2006) has acknowledged the possible positive correlation between firm size and operational loss by designing the BIA method to calculate the capital charge directly from the positive annual gross income over three years.

There are naturally also many ways to measure the size of a firm, such as total assets, total revenues, total deposits, number of employees, and total equity, but as these variables are usually correlated (Dahen & Dionne, 2010), it should not make huge difference which one is selected to a study. Dahen & Dionne (2010), for example, used total assets as the measurement of the firm size in their study. Their findings support the BIA method approach as they indicate that both operational loss severity and frequency can be explained by the firm size (Dahen & Dionne, 2010). However, Moosa & Silvapulle (2012) as well as Moosa & Li (2013) made contradictory findings and found no connection between firm size and loss severity although they also used total assets as measurement of size. These opposite findings could be explained at least to some extend by the fact that larger firms tend to have better internal controls than small firms (Chernobai, Jorion, & Yu, 2011).

The First hypothesis of this thesis has been derived based on the above evaluation of the existing literature. Although the Basel Committee's BIA method suggests bigger banks to confront bigger operational losses, hypothesis 1 has been formulated in line with the empirical findings which suggest that no significant relationship between operational risk and the size of the firm should be expected. The measurement used for firm size in this study is restricted by the confidentiality of the ORX loss data. Thus, it is measured in verbal terms with scale small, small/medium, medium, medium/large and large.

H1: Operational loss severity is not significantly affected by the size of the firm.

3.1.2 Business line

The nature of operational risk incident has also proven to vary across the different business lines within the financial companies, meaning that in some business lines operational losses tend to be larger or they are occurring more frequently than in the other business lines. For instance, according to both Dahen & Dionne (2010) and Cope, Piche, & Walter (2012), the clear majority of losses are reported from Retail Banking and Commercial Banking. However, in the study by Dahen & Dionne (2010), the average loss amount was significantly higher in Payment and Settlement than in the other Business lines, whereas Cope, Piche, & Walter (2012) found out Retail Banking and Corporate Finance losses to be the most severe. Moreover, retail banking was the largest business line also in the study by Moosa & Silvapulle (2012). Furthermore, it shall be noted that the scope of these studies was not completely the same as Dahen & Dionne (2010) examined a broader spectrum of industries whereas Cope, Piche & Walters (2012) concentrated on financial firms.

H2: Operational loss events tend to be more severe in some Business lines.

3.1.3 Event type

The distribution of operational losses varies also significantly within the different types of operational loss events. In the data used by Dahen & Dionne (2010), the event type categories with biggest numbers of reported losses were Client, products, and business practices (46%), External fraud (25%) and Internal fraud (17%) whereas Damage to physical assets and Business disruption and system failures covered together less than 1% of the losses. However, the few losses in Damage to physical assets category were clearly severe as the average loss for that event type category was clearly the highest ($45 million) (Dahen & Dionne, 2012). Cope, Piche, & Walter (2012) found similar indication as in their data losses

related to Clients, Products and Business Practices and External fraud had very high frequency. However, their study indicated fraud related losses to usually have low severity. In Moosa's & Silvapulle's (2012) study, Client, products, and business practices, External fraud and Internal fraud were both the most frequent and severe event types. Their results also suggest that the losses from a certain event type tend to be bigger in a particular business line.

H3: Operational loss events tend to be more severe in some Event Types.

3.1.4 Internal control and corporate governance

A factor that is often linked to operational risk is corporate governance and internal control. The level of corporate governance has proven to have an impact on multiple factors of financial firms, such as financial performance, and as terms like "governance" and "control" traditionally link to risk management, it would make sense to assume that internal control and corporate governance impact operational risk (Peni & Vähämaa, 2012). Corporate governance and internal control are very much related, but to clarify the definitions and causalities between these things, McNulty & Akhigbe (2017) suggest that the failures in internal control occur due to weaknesses in the corporate culture and corporate governance which, then again leads to operational risk. However, according to Pakhchanyan (2016), many studies indicate a lack of clear definitions of the business environment as well as the internal control factors which of course makes studying these as determinants for operational risk more difficult.

A good real life example of this is the collapse of the Bearings Bank which was explained in section 2.1. Another illustrative example of the connection between internal control and operational risk is the global financial crisis. According to Robertson (2011), a significant cause of the crisis was the international domino effect of due diligence failures and lack of functioning internal control systems in the financial industry. Furthermore, according to a review on risk management and corporate governance by OECD (2014), corporate governance is needed to ensure

that risks are understood, managed, and, when necessary, communicated. Although risk taking is often a prerequisite for successful business, the cost of risk management failures is often underestimated both inside and outside the companies, including the cost in terms of management time needed to contain and correct the situation (OECD, 2014).

Moreover, according to Chernobai, Jorion, & Yu (2011), majority of operational loss events occur due to deficiencies or failures of internal control systems which is consistent with Schwartz-Gârliste's (2013) argument that those instances of operational risk that include violations of internal controls and corporate governance principles are the most important types of operational risk. In concrete terms, these failures of internal controls are for example: weaknesses in information systems security, insufficient segregation of duties, poor or lacking training of employees and top management not paying the appropriate attention toward internal controls (Chernobai, Jorion, & Yu, 2011).

As also required in the Basel II Accord, it is nowadays essential that senior management and the board of directors actively participate in operational risk management. Specifically, it mandates that the operational risk exposure and loss experience are regularly reported to senior management and the board of directors, and that the risk management systems and processes are in the scope of by internal or external auditors reviews (Chernobai, Jorion, & Yu, 2011). Furthermore, the CEO and other senior management can have a significant impact on the culture of the financial firm which can then indirectly affects the banks internal control environment (Bushman et al., 2017) and thus, possibly serve as a source of operational risk (McNulty & Akhigbe, 2017). However, it is important to consider that culture as a concept is quite abstract and extremely difficult to measure (Bushman et al., 2017). However, the importance of corporate culture and managerial involvement in trying to shape it in context of operational risk has also been acknowledged by the practitioners (Deloitte, 2013).

There is also further concrete empirical evidence regarding the connection between operational risk and corporate governance. Li & Moosa (2015) as well as Moosa

(2015) studied the country level governance indicators as determinants of operational risk and found a negative correlation between loss severity and different governance indicators suggesting that in countries that have better governance tend to experience smaller operational losses. Cope, Piche, & Walter (2012) found similarly a decreasing relationship between the governance indicators and operational risk severity. They found out also that the relationship varies with different combinations of different business lines and governance indicators, and the most significant connection they identified was between Rule of Law and External Fraud losses (Cope, Piche, & Walter, 2012). The second hypothesis has been formulated in line with the previous empirical findings. Operational losses are expected to be smaller in countries that have higher corporate governance scores. Furthermore, it should be noted that due to the confidentiality of the loss data, the focus in this study is more on corporate governance that internal control.

H4: Operational loss events are less severe in geographic regions with better level of governance.

3.1.5 Complexity of the firm and other factors

Furthermore, another firm specific factor that has been considered in the existing literature is the complexity of the firm. Chernobai, Jorion, & Yu (2011) found that some firm-specific factors have a significant connection to operational risk, as according to their findings young and more complex firms (measured by number of segments) are more likely to face operational risk events. Consistent with this, McNulty & Akhigbe (2017) indicate that larger banks with for example multiple layers or investment banking subsidiaries, should have more detailed and complex systems of internal control as they also simply are more complex as organizations. The complexity of the firm is not considered in the empirical part of this thesis due to the confidentiality of the ORX loss data in which the identity of the firms is protected and thus, not available.

Finally, here are naturally also many other firm-specific factors that might contribute to the severity of operational losses. For example, according to the study by Wang & Hsu (2013), both the size and age heterogeneity of a firm's board of directors play important roles in initiating sound and efficient operational risk management. These findings are consistent with the existing empirical findings on the importance of the board monitoring and advising for the overall risk management and misconduct prevention in the banking industry (Nguyen, Hagendorff & Eshraghi, 2016). Furthermore, in addition to many other determinants, Chernobai, Jorion, & Yu (2011) investigated also the connection between CEO remuneration and operational risk and found that firms which have higher stock option holdings and bonus systems for their chief executive officers are more likely to encounter more severe operational losses. These, or other additional variables are, however, not considered in this study as the financial firms under investigation here are anonymous due to confidentiality matters.

3.2 Environmental factors

In addition to the firm-specific factors, another group of factors acknowledged as possible determinants of operational risk are the firm's environmental or external factors. There is empirical evidence suggesting that a firm's external environment has an impact on its financial performance (Chiu & Chen, 2009) due to which it would make sense that it also effects its operational risks.

3.2.1 Geographic region

One interesting environmental factor which has been considered in some of the previous studies as a determinant of operational risk is the geographic region where the losses have occurred. In their study, Cope, Piche, & Walter (2012) found a significant connection between geographic region and operational loss severity. However, as they studied the different BCBS event types separately, they found

differences among the event types as for example Northern Europe and United States had the smallest losses in one event type but, then again, largest in another.

Due to confidentiality reasons, instead of studying all European countries separately, there are 5 geographic regions under investigation in the empirical part of this study. These regions as well as other features of the data used in the study are explained in detail in the following chapter (4.1). Due to the scarce prior research on this determinant, the third hypothesis is left open and is defined in the following way.

H5: Operational loss events are more severe in some geographic regions than others.

3.2.2 Size of economy

Moreover, another external factor studied as determinant of operational risk is the size of the economy or other geographic region which is naturally usually measured with the gross domestic product (GDP). Similarly, like with firm size, common sense would in most cases suggest that operational losses are larger in larger countries. Similar to the findings regarding the firm size, some existing empirical findings seem to agree with this assumption as some scholars have found significant correlation between the size of the economy and operational risk (Cope, Piche, & Walter, 2012; Moosa, 2015). Thus, hypothesis 4 has been formulated based on the unanimous empirical findings and it is expected that operational losses are more severe in larger geographic regions. Instead of examining the European countries individually, they have been divided into 5 groups due to confidentiality reasons on of the operational loss data.

H6: Operational loss events are more severe in larger geographic regions (measured with GDP).

3.2.3 Legal and Regulatory environment

The final category of determinants of operational risk that has been considered in the existing academic literature is the legal and regulatory environment in which the loss occurs. One utilized determinant is the legal system origin, although only some weak connections have been identified between operational risk and legal system origin (Cope, Piche, & Walter, 2012; Li & Moosa, 2015). As it has been suggested that cross-country differences in legal investor protection for example can be linked to the different ownership and financing structures of companies (La Porta et al, 1998), it is also reasonable to suggest that the legal system can cause differences to operational risk incidents. Although all countries have somewhat different laws and legal systems, scholars have agreed that some countries' legal systems have similarities due to at least the historical background and development of the legal system, theories and hierarchies of sources of law as well as the legal institutions of the system (La Porta et al, 1998).

Nowadays, the commercial laws are from two origins: the English common law and the civil law which is further categorized to the German, French and Scandinavian civil laws (La Porta et al, 1998). The legal system affects for example how disputes are solved in a country or what rights, obligations and responsibilities financial institutions have (Cope, Piche, & Walter, 2012). For instance, the English common law system is characterized by relatively weaker dependency on statutes, independent judges and juries as well as private litigations, whereas the French civil law system is characterized by state-employed judges, strong trust on legal rules and codes, and a preference for state regulation over private litigation (La Porta et al, 2006).

Furthermore, some other regulatory variables have also been considered as possible determinants of operational risk. Li & Moosa (2015) have for example suggested that the degree of law enforcement would be a more significant determinant than the legal origin. Moreover, in their study on a global scale, Cope, Piche, & Walter (2012) included multiple variables regarding the legal and regulatory

environment in their research on the determinants of operational loss severity. They found significant connections between Internal Fraud, and Clients, Products and Business Practices and countries with a higher number of insider trading cases (Cope, Piche, & Walter, 2012).

However, no separate hypothesis has been formulated for neither the legal nor regulatory environment, because, as the countries have been divided into the 5 groups, legal system as a determinant is already included in the geographic region hypothesis as a possibly influencing factor. Thus, the legal system is in this study more value adding to consider when analyzing the relationship of operational risk and geographic region.

Finally, it is important to highlight that due to the heterogeneity of operational risk as well as the quite narrow and exploratory existing research on the determinants of operational risk, the set of above explained factors cannot be considered as a “one and only”, comprehensive list determinants of operational risk. On one hand, and as also speculated in this chapter, some of these factors might not even have an impact on the loss severity although they are listed here as possible contributors. On the other hand, there might and probably does also exist other factors that have significant impact on the severity of operational losses. All in all, creating a comprehensive list of determinants, would as a matter of fact be an extremely extensive task and for that reason it is not the fundamental aim of this thesis.

4 DATA AND METHODOLOGY

Continuing from the premises of previous academic research this chapter provides a detailed introduction into the data utilized and the methods used in this study. The purpose of this chapter is to provide a description of the material and means used to test the hypotheses described in the previous chapter.

4.1 Data description

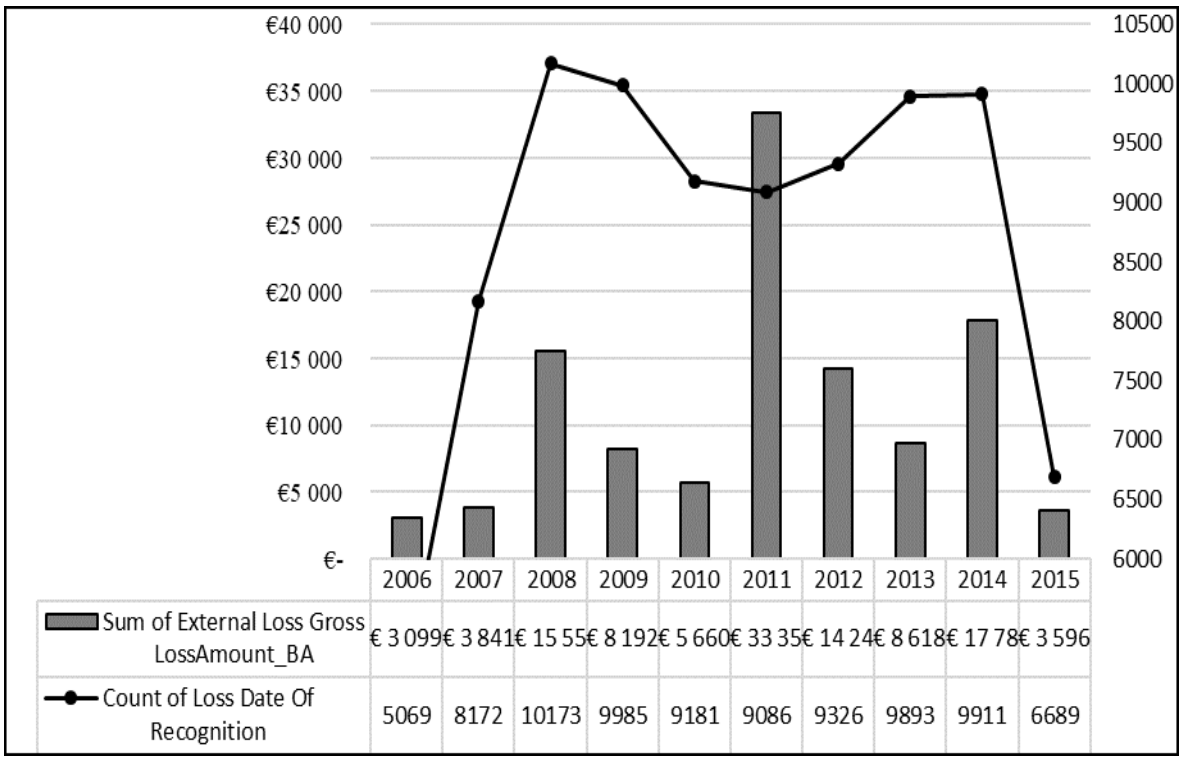
The determinants of operational risk severity are examined by using data on operational risk incidents and different country as well as firm specific factors. The data for the empirical part of this thesis has been collated from two different sources: data on operational loss events from the ORX Global Loss Database and data regarding the different macro-environmental factors from the World Bank Database.

The ORX Global Loss Database is managed by ORX (Operational Riskdata eXchange Association) which is a non-profit industry association that was formed in 2002 with the primary objective of enabling member banks to exchange high-quality operational loss data in a secure and confidential manner. At the final quarter of 2017, the consortium consisted of almost 100-member institutions from 20 countries, and the Global Loss Database contained records of over 500,000 operational loss events that have been reported by the members around the globe since 2002. The member firms report each operational loss events to the ORX consortium which have a gross loss value more than EUR 20,000. The consortium validates the quality of all reported loss events, and the records are treated as confidential information which encourages the member firms to provide complete and accurate information of their operational losses. (Operational Riskdata eXchange Association (ORX), 2017b & 2017c)

The ORX loss data provides a description of each event, including dates of loss occurrence and settlement, loss amount, geographical location of the event. In,

addition, the format of the data adheres to the BCBS event type and business line classifications. Upon applying some filters to the loss data, the final sample used in this study consists of 87485 operational risk events among multiple European financial institutions from 2006 to 2015.

Figure 2: Annual operational loss severity M€ distribution (left) and event frequency distribution (right)



The annual distribution of total loss amounts of operational loss events is presented in figure 2. On one hand, year 2011 stands out quite significantly from the figure with enormous total loss amount of 33,4 billion euros, whereas on the other hand, year 2015 with a low total loss of 3,6 billion euros. One possible explanation for the relatively small 2015 number can be 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 (Chernobai, Jorion, & Yu, 2011). This can also affect the quality of the loss data as in some cases the date of occurrence or detection that banks have assigned for the losses might be approximates (Embrechts & Hofert, 2011), so in other words, it is quite likely that the 2015 total loss amount will increase during the

upcoming years. Furthermore, total losses are relatively small at the beginning of the reporting period. One potential reason for that can be that the overall awareness of operational risk was significantly lower even less than a decade ago (de Fontnouvelle et al., 2006; Tursunalieva, & Silvapulle, 2016), and hence the institutions have not been reporting their operational loss events as actively as today.

Moreover, the basic characteristic of operational risk is quite clearly visible in figure 2. Although frequency and severity have their own scales on the figure, in most of the years the connection between frequency line and severity pillars is suggesting average severity per loss event to be relatively low which indicates that the amount of low severity, but high frequency events is dominating the statistics. However, year 2011 is an exception in this context as well. This indicates that relatively many of the rare but fatal tail events in the sample used for this study occurred in 2011. This assumption is also supported by the fact that the average event severity in 2011 was 3,6 million, whereas the next highest figures are only 1,8 million in 2014 and 1,5 million in 2008 and 2012.

Table 3: Operational loss event severity t€ per Event Type and Business Line

	BL01 - Corporate Finance	BL02 - Trading & Sales	BL03 - Retail Banking	BL04 - Commercial banking	BL05 - Payment and Settlement	BL06 - Agency Services	BL07 - Asset Management	BL08 - Retail Brokerage	Total
EL01 - Internal Fraud	€ 182	€ 570 534	€ 1 250 680	€ 539 324	€ 5 445	€ 23 620	€ 229 238	€ 178 840	€ 2 797 864
EL02 - External Fraud	€ 122 584	€ 2 301 538	€ 3 675 695	€ 4 355 938	€ 33 465	€ 25 625	€ 13 829	€ 7 186	€ 10 535 859
EL03 - Employment Practices and Workplace Safety	€ 22 834	€ 256 885	€ 361 138	€ 63 263	€ 1 076	€ 5 690	€ 23 968	€ 6 311	€ 741 166
EL04 - Clients, Products and Business Practices	€ 1 225 486	€ 12 522 643	€ 50 661 986	€ 12 078 503	€ 31 311	€ 276 784	€ 660 268	€ 430 380	€ 77 887 362
EL05 - Damage to Physical Assets	€ 271	€ 8 301	€ 171 439	€ 43 366	€ 1 082	€ 2 467	€ 24 329	€ 877	€ 252 132
EL06 - Business Disruption and System Failures	€ 4 704	€ 170 695	€ 563 591	€ 362 999	€ 52 278	€ 23 209	€ 14 415	€ 5 269	€ 1 197 160
EL07 - Execution, Delivery and Process Management	€ 443 240	€ 7 471 953	€ 5 355 988	€ 5 493 969	€ 260 890	€ 681 426	€ 757 837	€ 65 365	€ 20 530 668
Total	**€ 1 819 300**	**€ 23 302 548**	**€ 62 040 518**	**€ 22 937 363**	**€ 385 548**	**€ 1 038 822**	**€ 1 723 884**	**€ 694 228**	**€ 113 942 211**

Table 4: Operational loss event frequency by Event Type and Business Line

	BL01 - Corporate Finance	BL02 - Trading & Sales	BL03 - Retail Banking	BL04 - Commercial banking	BL05 - Payment and Settlement	BL06 - Agency Services	BL07 - Asset Management	BL08 - Retail Brokerage	Total
EL01 - Internal Fraud	2	61	2426	330	12	7	28	289	3155
EL02 - External Fraud	62	50	16662	5119	132	27	32	54	22138
EL03 - Employment Practices and Workplace Safety	74	346	1970	374	5	56	93	41	2959
EL04 - Clients, Products and Business Practices	141	972	9364	4552	31	116	293	2892	18361
EL05 - Damage to Physical Assets	5	30	668	109	10	10	9	4	845
EL06 - Business Disruption and System Failures	17	719	1006	324	126	81	80	37	2390
EL07 - Execution, Delivery and Process Management	312	9729	13515	8247	985	2794	1687	368	37637
Total	**613**	**11907**	**45611**	**19055**	**1301**	**3091**	**2222**	**3685**	**87485**

Furthermore, the frequency and severity of operational loss events by each business line and event type are presented in tables 3 and 4. Measured by both number of events as well as severity of events, the clear majority of operational losses have occurred in business line retail banking. Regarding severity, the second largest business line is trading & sale followed by commercial banking. Altogether, these three business lines form 95 % of the losses. Regarding frequency, the same business lines make it to the top three covering 88 % of the losses. However, the order is slightly different with commercial banking on the second place followed by trading & sales.

The largest event type category is, then again, client, products and business practices, when measured by the severity of losses, whereas for frequency it is execution, delivery and process management. This can be explained with the fact that the event type execution, delivery and process management can be assumed to refer to quite manual and ongoing business activities that are quite often handled by people. Regarding severity, the second largest event type is execution, delivery and process management and third external fraud, and for frequency, the second largest event type is external fraud followed by clients, products and business practices. These results regarding both event type and business line are different from for example the results from Dahen & Dionne's (2010) study. This, however, strengthens the fact that the financial industry is quite unique in comparison to the

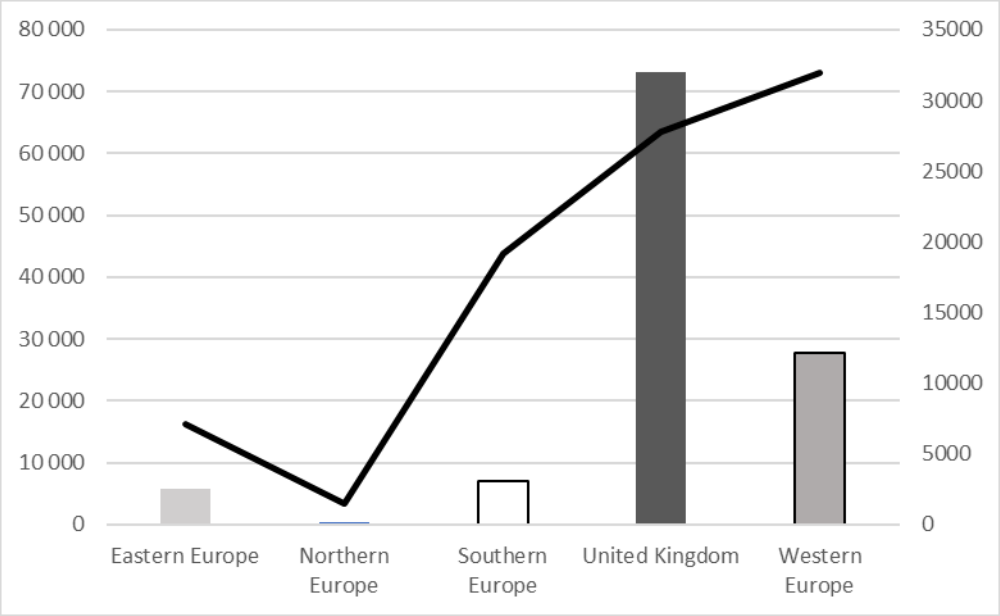
other basic industries as the scope in their study is all kinds of companies around the world. The results from Cope, Piche, & Walter's (2012) study are, however, somewhat like these although they only consider some of the event types.

Table 5: Representative countries by regional categories.

Region	Representative countries
Northern Europe	Åland islands, Denmark, Faroe Islands, Finland, Iceland, Norway, Svalbard and Jan Mayen, Sweden,
Eastern Europe	Albania, Belarus, Bosnia and Herzegovina, Bulgaria, Croatia, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Macedonia, Moldova, Montenegro, Poland, Romania, Russian Federation, Serbia, Slovakia, Slovenia, Turkey, Ukraine
United Kingdom	Guernsey, Ireland, Isle of Man, Jersey, United Kingdom
Southern Europe	Andorra, Gibraltar, Greece, Holy See (Vatican City State), Italy, Malta, Portugal, San Marino, Spain
Western Europe	Austria, Belgium, France, Germany, Liechtenstein, Luxembourg, Monaco, Netherlands, Switzerland

Due to the confidentiality of the data, specific country code for each loss is not available in the data, but the losses are mapped to geographic regions. The regions available in the ORX loss data are: Northern Europe, Eastern Europe, Southern Europe, Western Europe and United Kingdom. The representative countries by regional categories are listed in table 5.

Figure 3: Geographical operational loss severity (M€) distribution (pillar, left) and event frequency distribution (line, right)



Furthermore, the geographical total loss distribution is presented in figure 3. The United Kingdom is clearly the largest geographic region, measured by the total loss amount, whereas Northern Europe stands out as the clearly smallest geographic area. In terms of frequency, Northern Europe is again clearly the smallest, whereas Western Europe is the largest. According to figure 3, it seems that average loss severity is larger in United Kingdom than it is in other geographic regions. This might indicate that more very severe losses have been reported from United Kingdom as operational risk events are often either low severity and high impact or high frequency and low impact and very rarely high frequency and high severity events.

Overall, based on the existing research it can be generalized that operational loss data is usually “heavy-tailed” and hence not normally distributed. Typically, this means in practice that even in a moderate sized data set, the largest observations might be thousands or even tens of thousands of times greater than the median value (Cope et al., 2009). This creates also some challenges for the statistical modeling of the data (Dutta & Perry, 2006). This feature is also applicable for the dataset used in this study. Even after a quick examination it is clear that the vast

majority of the operational loss data consists of high frequency and low severity events, whereas the other end of the data is dominated by a relatively small amount of rare and extremely severe events. In other words, in this data where the minimum loss was set to EUR 35 000, the median loss is EUR 82 182 and standard deviation EUR 85 939 372. Using heavy-tailed data brings also some constrains to using it in a study. For example, it should be kept in mind that the data can cause instability of estimates as single events can have a very large effect on the variance or mean of the distribution (Cope et al., 2009). In addition, depending on how the data is divided and examined, the very dominant extreme losses can have a huge impact on a specific subset of the data if it is for example divided by the year of occurrence, event type or business line (Cope et al., 2009).

Furthermore, due to the sensitive nature of operational risk, it is generally likely that firms are not in general willing to disclose information regarding some of their operational risks. Thus, particularly when working with publicly available data, it is possible that the data is to some extend biased especially regarding the largest operational losses (Cope, Piche, & Walter, 2012). In other words, this is an additional feature that can bring possible restrictions to the usage of operational loss data in this study. However, as the ORX Loss data is treated as anonymous and not publicly available, the quality of the data also towards the largest events can be assumed to be better than in public sources.

Furthermore, as a side product, the performed preliminary data examination revealed also quite interestingly that in average the difference between the date of occurrence and reporting date is 2 years. However, it is also worth mentioning that the median difference is approximately 4 months which indicates that the distribution for time between occurrence and reporting is quite heavy tailed. Furthermore, measured in euros, 17 % of all losses had occurred before 2006. These findings are consistent with Chernobai, Jorion, & Yu's (2011) as well as Embrechts & Hofert's (2011) findings according to which it is characteristic for operational losses to materialize only after months or even years after the actual error has occurred. This feature of the operational loss data unavoidably invokes a question that, if there are

this many operational incidents that have occurred a long time before their consequences materialize, how many operational incidents are left unheeded?

The explanatory variables for the model have been derived from the previous research and they are the size of the firm, the geographic region (country), the size of the economy (GDP), business line, event type and three governance indicators which are the rule of law, regulatory quality and political stability. The firm-size is available in the ORX loss data in verbal terms due to confidentiality of the data with scale small, small/medium, medium, medium/large and large. Furthermore, as explained in the previous section, the geographic region, as well as event type and business line are also available in the ORX data. The European countries under examination in this study have been distributed into five regions in the data which are: Northern Europe, Eastern Europe, Southern Europe, Western Europe and United Kingdom.

Similarly, like Li & Moosa (2015) and Cope, Piche, & Walter (2012), the remaining explanatory variables, meaning the size of the economy and the governance indicators, have been collated from the public World Bank Database (Kaufmann, Aart & Massimo, 2010). The size of the economy, or gross domestic product (GDP) was collated as annual figures for each country under examination. Due to the confidentiality of the ORX loss data, the GDPs were then calculated to annual weighted averages for each 5 geographic regions as the country level figures could not be used as such in the study. The reason for using weighted averages of the GDPs is that the countries in the geographic regions are more or less different in terms of their size as well as other features.

Three of the available six governance indicators are considered in the study: Political stability and absence of violence/terrorism, Regulatory Quality and Rule of law. Only 3 of the 6 governance indicators were selected to this study, because as the previous studies has shown, due to the similar nature of these indicators, they are also heavily correlated with each other (Cope, Piche, & Walter, 2012; Moosa, 2015; Li & Moosa, 2015). Furthermore, these 3 governance indicators were chosen as they have performed better in the previous studies as determinants for

operational risk ((Cope, Piche, & Walter, 2012; Moosa, 2015; Li & Moosa, 2015). These indicators are country level figures, and consistent with the prior research, are in this study arguably considered as country level equivalents of firm level factors for internal control and corporate governance (Li & Moosa, 2015; Cope, Piche, & Walter, 2012). The definitions of the governance indicators selected to this study are the following (Kaufmann, Aart & Massimo, 2010).

- “Political Stability and Absence of Violence/Terrorism (PV) - capturing perceptions of the likelihood that the government will be destabilized or overthrown by unconstitutional or violent means, including politically-motivated violence and terrorism.”
- “Regulatory Quality (RQ) - capturing 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 (RL) - capturing 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.”

The World Bank governance indicators have been created resting on hundreds of variables from 31 different data sources, covering impressions from at least nongovernmental organizations, commercial business information providers, and public sector organizations worldwide (Kaufmann, Aart & Massimo, 2010). These indicators are widely used by practitioners as well as researchers, and the creation and background of them is explained with more details in the paper by Kaufmann, Aart & Massimo (2010). The raw scores of these three indicators are used in this study, and due to the geographical limitations of the loss data, regional, annual averages are calculated for the selected governance indicators. Furthermore, it is important to take into account that these variables consider the whole economy and are thus not only relevant to the financial industry.

Table 6: Details of the variables used in the study

Variable	Mean	Standard deviation	Variance	Minimum	Maximum	Median	N
Log loss	11.6626	1.1660	1.3597	10.4631	23.8284	11.3167	87485
GDP	2.1593773E12	580512649379	3.3699494E23	332112472347	2.8409981E12	2.4010432E12	87485
PV	0.5023	0.3499	0.1224	-0.5367	1.2667	0.5503	87485
RQ	1.3277	0.4701	0.2210	0.0969	1.8652	1.4599	87485
RL	1.3283	0.6062	0.3675	-0.2809	2.0395	1.6594	87485
F Size	4.1924	1.2875	1.6576	1.0000	5.0000	5.0000	87485
Region	3.8697	1.1681	1.3645	1.0000	5.0000	4.0000	87485
Business Line (BL)	3.5156	1.3975	1.9530	1.0000	8.0000	3.0000	87485
Event Type (ET)	4.7068	2.2050	4.8619	1.0000	7.0000	4.0000	87485

The general statistics of the variables are presented in table 6. The Operational loss severity is presented in natural logarithmic terms and variables for firm size, region, business line and event type can only be certain values as they all are categorical variables.

Table 7: correlations between the variables

Variable	Loss	GDP	PV	RQ+RL	F Size	Region	BL	ET
Loss	1							
GDP	0.05491	1						
PV	0.00808	0.70159	1					
RQ+RL	0.05156	0.81230	0.81230	1				
F Size	0.00421	0.24561	0.13239	0.23233	1			
Region	0.03435	0.86588	0.89233	0.84499	0.20003	1		
BL	-0.05520	-0.11064	-0.03414	-0.12804	-0.08623	-0.05357	1	
ET	-0.06440	0.27645	0.24169	0.32164	0.18525	0.24618	-0.10432	1

The correlations between all variables are presented in table 7. Overall, correlation greater that 0,8 is deemed as significant. Thus, variables RQ and RL were decided to be merged as the correlation between them was 0.969, which indicates that the impact of these variables is very similar. However, high correlation between those variables is very rational, as it can be assumed that in countries with sound policies and regulations, the authorities have influence and the likelihood of crime and violence is also lower. The combined variable is RQ+RL. However, there is also significant correlation between geographic region & GDP, geographic region & PV, geographic region & RQ+RL as well as RQ+RL & GDP. These significant correlations can cause bias to the results of the analysis.

4.2 Methodology

The hypotheses were tested by using the linear ordinary least squares regression analysis and the analysis was performed with SAS Enterprise Guide 7.1 – software. The empirical model to study the determinants of operational risk severity has been defined as follows.

$$L = \beta_0 + \beta_1 REG + \beta_2 REGS + \beta_3 FSIZE + \beta_4 RL\_RQ + \beta_5 PV + \beta_7 BL + \beta_8 ET + e$$

Where,

L = The operational loss event severity (€)

REG = Geographic region where the operational loss event occurred

REGS = Size of the geographic region

FSIZE = Size of the firm where the operational loss event occurred

RL + RQ = Combined variable for Rule of Law and Regulatory Quality

PV = Political Stability and Absence of Violence/Terrorism

BL = Business line in which the operational loss event occurred

ET = Event type of the operational loss event

e = regression residual

The fundamental basic assumptions for linear OLS regression model are i) linearity and additivity of the relationship between dependent and independent variables, ii) statistical independence of the errors, iii) homoscedasticity of the errors; and iv) normality of the error distribution. These assumptions were carefully tested during

the analysis and adjustments and corrections were performed when necessary. Also, 2 of the 3 governance indicators: regulatory quality and rule of law are presented here as 1 variable as they were merged to one variable due to their very high correlation.

After performing some preliminary investigation and testing for the data, it was decided to separate the empirical analysis into three sections based on the severity of the operational losses. The first group is losses less than EUR 100 000, the second losses between EUR 100 000 and EUR 500 000 and the third losses more than EUR 500 000. The reason for this is the wide variety of different possible event types and sources for operational risk (Basel Committee on Banking Supervision, 2006; Brown, 2012). Thus, based on preliminary examination of the operational loss data used in this study, it was assumed that it can be reasonable to predict that the high frequency and low severity events are not necessarily affected by same determinants as the extremely rare low frequency but high severity events. Therefore, the analysis was decided to be performed individually for small events, medium events and large events. This kind of grouping was also thought to enable to identify possible differences and similarities between the three loss groups.

Due to the nature of some of the variables, some modifications were required before conducting the analysis. Thus, all categorical variables, meaning the size of the firm and geographic region variables as well as the business line and event type variables were modified to dummy variables. Furthermore, with all these categorical variables, one level of the categories is not included into the model (Wissmann, Shalabh & Toutenburg, 2011). This, so called reference group is for geographic region Northern Europe, for firm size small-medium sized firms, for business line retail and brokerage, for event type damage to physical assets.

Furthermore, to make the model fit better, some modifications were made for the independent variable, meaning the loss severity. The distributions of the loss severity are naturally quite different for small, medium and large losses (see appendix 1). For small and medium sized events, the distributions are quite monotonous and constant, and therefore in these analyses the selected variable

modification for operational loss severity is square root. Natural logarithm was also tested for these models, but it affected the result of the regression negatively. For large events, then again, the data is due to the extreme events skew to right, so similarly like Cope, Piche & Walters (2012), the operational loss severity is presented in natural logarithmic terms. Moreover, the distributions of the other variables are also presented in appendix 1 and scatter plots of the dependent variables' residuals in appendix 2.

Moreover, as the model includes relatively many dummy variables of which many have also quite strong correlation between each other, some variables needed to be excluded from the model to tackle the problem of multicollinearity (Wissmann, Shalabh & Toutenburg, 2011). Of course, as many variables as possible wanted to be included in the model, but on the other hand the negative impact of multicollinearity on the conclusions of the study wanted to be restricted. This was done by first conducting the analysis with all variable, and then examining 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 (Marquardt, 1980) and tolerance should not be less than 0,1 (Lin, 2008). 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. The excluded variable from each analysis are presented in the following chapter.

5 EMPIRICAL RESULTS

The previous chapters have provided an outline on the existing literature on the determinants of operational risk, and in the latest chapter the data used, and the statistical model employed were explained. Thus, this section intends to present the findings from the actual statistical study and their influence on the precedent academic research. This chapter is divided into four subchapters based on the structure of the study. First, the overall results from the statistical analysis are presented followed by an analysis of the results in compared with the from prior academic literature. Furthermore, the earlier presented hypotheses will also be answered in this chapter.

Overall, the significance of each variable is assessed by looking at the p-value based on the F-statistics. Always when the p-value is less than 0,1 it is deemed as statistically significant. In the results, * indicates that the result is significant with 10%, ** with 5% and *** with 1% risk level. Furthermore, in all models, according to the White's test, the homoscedasticity assumption is not fulfilled, which indicates that the estimator of the covariance matrix of the parameter estimates can be biased and inconsistent (Hayes & Cai, 2007). For this reason, the White's heteroskedasticity-consistent standard error estimators are used in the models, although this problem does not bias the estimator of the regression parameters in OLS regression (White, 1980).

5.1 Small loss events

First the analysis was performed for small loss events for which the subset was created by filtering only the loss events which severity is less than EUR 100000. The subset consisted of 50035 events. The fundamental basic assumption of normality of the error distribution is not fulfilled according to the histogram (Appendix 3). This indicates that the results may be biased and should, thus be interpreted carefully.

Table 8: Coefficient of determination, significance and results from the White's test

R^2	F value	Pr > F	Pr > ChiSq
0,0048	12,79	<.0001	<.0001

The coefficient of determination, significance as well as the results from the White's test are presented in table 8. According to the F value, the model is statistically significant. However, it is only able to explain 0,48 % of the variabilities of the small loss event severities. To solve the problem of multicollinearity, the following variable were excluded from the model: dummy for region Southern Europe, sum RG+RL, dummy for event type Execution, Delivery and Process Management, dummy for region Western Europe and dummy for firm size large.

Table 9: Parameter estimates of the OLS regression for small loss events

Variable	Parameter estimate	Standard error	T value	Pr > |t|	Tolerance	Variance inflation
Intercept	239.98427***	1.27424	188.33	<.0001		0
PV	-2.24124***	0.83852	-2.67	0.0075	0.31415	3.18317
GDP	-1.0551E-10	4.56907E-10	-0.23	0.8174	0.37106	2.69501
Firm size ML	6.41831**	2.72609	2.35	0.0186	0.98262	1.01769
Firm size M	-1.18170***	0.41667	-2.84	0.0046	0.88484	1.13015
Firm size S	-0.31850	0.65596	-0.49	0.6273	0.93722	1.06699
Region UK	-1.79599***	0.46708	-3.85	0.0001	0.53375	1.87353
Region EE	-0.06259	0.95737	-0.07	0.9479	0.40859	2.44746
BL CF	1.31165	2.40588	0.55	0.5856	0.89210	1.12095
BL TS	1.61884*	0.96808	1.67	0.0945	0.27260	3.66843
BL RB	-1.51880*	0.81974	-1.85	0.0639	0.15631	6.39755
BL CB	1.47889*	0.88074	1.68	0.0931	0.21888	4.56863
BL PS	-0.73584	1.53700	-0.48	0.6321	0.70896	1.41051
BL AS	2.05987*	1.21566	1.69	0.0902	0.51439	1.94405
BL AM	1.38286	1.33448	1.04	0.3001	0.64232	1.55686
ET IF	4.71059***	1.09366	4.31	<.0001	0.91117	1.09749
ET EF	-2.02333***	0.43678	-4.63	<.0001	0.66286	1.50861
ET EPWS	1.71314*	0.88710	1.93	0.0535	0.93362	1.07111
ET CPBP	0.81351*	0.48016	1.69	0.0902	0.67064	1.49112
ET BDSF	0.91861	1.03401	0.89	0.3743	0.96008	1.04158

The parameter estimates of the OLS regression for small loss events are presented in table 9. The results of the regression for the small losses suggest that the smallest operational losses are not larger in larger countries measured by GDP. However, this result is not significant. Moreover, the results suggest a strong decreasing association between the governance indicator Political Stability and Absence of Violence/Terrorism. Furthermore, the results indicate that the severity of small

losses would have a positive association with the size on the firm, meaning that losses categorised as “small” would be larger in larger organisations. This is shown as a positive association between firm size Medium/Large and the small loss events and then again, as a negative association between firm size Medium as well as Small and the small loss events. Also, the results suggest that the losses would be smallest in geographic region United Kingdom.

Furthermore, the least severe losses occur in business line retail banking, whereas the most severe losses of the small loss events occur in Agency Services, followed by Trading and Sales as well as Commercial Banking. Regarding event type, clearly the most severe small losses occur in Internal Fraud, followed by Employment Practices and Workplace Safety and Clients, Products and Business Practices, whereas the least severe losses occur in External Fraud.

5.2 Medium loss events

Then the analysis was performed for medium loss events for which the subset was created by filtering only the loss events which severity is between EUR 100000 and EUR 500000. The subset consisted of 28317 events. The fundamental basic assumption of normality of the error distribution is not fulfilled according to the histogram (Appendix 3). This indicates that the results may be biased and should, thus be interpreted carefully.

Table 10: Coefficient of determination, significance and results from the White’s test

R^2	F value	Pr > F	Pr > ChiSq
0,015	22,64	<.0001	<.0001

The coefficient of determination, significance as well as the results from the White’s test are presented in table 10. According to the P value, the model is statistically significant. The R^2 is slightly better than for small events, but the model can still only explain 1,50 % of the variabilities of the medium loss event severities. To tackle the problem of multicollinearity, the following variable were excluded from the model:

dummy for region Southern Europe, sum RG+RL, dummy for event type Execution, Delivery and Process Management, dummy for region Western Europe and dummy for firm size large.

Table 11: Parameter estimates of the OLS regression for medium loss events

Variable	Parameter estimate	Standard error	T value	Pr > |t|	Tolerance	Variance inflation
Intercept	411,55427***	5.01013	82.14	<.0001		0
PV	3.04980	3.10684	0.98	0.3263	0.30459	3.28315
GDP	3.170786E-9*	1.699444E-9	1.87	0.0621	0.37531	2.66447
Firm size ML	-10.03839	8.96040	-1.12	0.2626	0.98558	1.01463
Firm size M	2.47985	1.64072	1.51	0.1307	0.89045	1.12302
Firm size S	3.43139	2.34136	1.47	0.1428	0.93343	1.07132
Region UK	-3.07073*	1.82304	-1.68	0.0921	0.53768	1.85984
Region EE	13.31009***	3.56836	3.73	0.0002	0.39033	2.56196
BL CF	43.00843***	8.79835	4.89	<.0001	0.82721	1.20889
BL TS	36.53108***	3.81579	9.57	<.0001	0.19342	5.17023
BL RB	14.15064***	3.35719	4.22	<.0001	0.12334	8.10738
BL CB	36.29496***	3.51164	10.34	<.0001	0.15779	6.33745
BL PS	21.85204***	6.18456	3.53	0.0004	0.69391	1.44111
BL AS	23.47443***	4.78064	4.91	<.0001	0.46430	2.15380
BL AM	27.06796***	4.93942	5.48	<.0001	0.54250	1.84331
ET IF	21.04687***	3.37703	6.23	<.0001	0.87464	1.14332
ET EF	-9.02009***	1.72038	-5.24	<.0001	0.69785	1.43296
ET EPWS	7.48316**	3.44868	2.17	0.0300	0.93083	1.07431
ET CPBP	1.04595	1.82835	0.57	0.5673	0.71097	1.40653
ET BDSF	-1.78261	3.80579	-0.47	0.6395	0.95775	1.04411

The parameter estimates of the OLS regression for medium loss events are presented in table 11. Overall, the parameter estimates from the analysis for medium events differ quite much from the results for small loss events. Unlike for small loss events, the results of the regression for medium losses suggest that the operational losses are larger in larger countries measured by GDP. Moreover, the results suggest an increasing association between operational loss severity and the governance indicator Political Stability and Absence of Violence/Terrorism, although this result is not significant. Furthermore, the results do not indicate any significant relationship between the severity of losses and the size on the firm. However, on the contrary to the results for small losses, medium losses seem to be least significant in firms that are categorised as Medium/Large. There is, however, some similarities between the two models as the results for medium losses also suggest that the losses are smallest in geographic region United Kingdom. The largest loss

events categorised as “medium” occur, then again, in geographic region Eastern Europe.

Quite interestingly all the Business Lines are significant in the model for medium events. As for the small losses, the least severe losses occur in business line retail banking, whereas the most severe losses of the medium loss events occur in Corporate Finance. Similarly like in the model for small losses, quite severe losses occur also in Commercial Banking and Trading and Sales. Regarding event type, the results are exactly similar as for small loss events. Clearly the most severe medium losses occur in Internal Fraud, followed by Employment Practices and Workplace Safety, whereas the least severe losses occur in External Fraud.

5.3 Large loss events

Finally, the analysis was performed for the large loss events for which the subset was created by filtering only the loss events which severity is more than and EUR 500000. The subset consisted of 9133 events. The fundamental basic assumption of normality of the error distribution is not fulfilled according to the histogram (Appendix 3). This indicates that the results may be biased and should, thus be interpreted carefully.

Table 12: Coefficient of determination, significance and results from the White’s test

R^2	F value	Pr > F	Pr > ChiSq
0,0454	24,09	<.0001	<.0001

The coefficient of determination, significance as well as the results from the White’s test are presented in table 12. According to the P value, the model is statistically significant. The R^2 is again low but slightly better than in for small and medium losses, as the model can explain 4,54 % of the variabilities of the large loss event severities. At first, the results indicated that the extremely severe losses would have large impact on the results, and thus, 15 most severe events were filtered from the sample. However, this change did not improve the model, and in fact lowered the

R^2, so the 15 extremely severe loss events were considered in the model. To solve the problem of multicollinearity, the following variable were excluded from the model: dummy for region Eastern Europe, dummy for region United Kingdom, dummy for event type Execution, Delivery and Process Management, dummy for firm size large, dummy for business line retail banking and sum RG+RL.

Table 13: Parameter estimates of the OLS regression for large loss events

Variable	Parameter estimate	Standard error	T value	Pr > |t|	Tolerance	Variance inflation
Intercept	13.93228***	0.06002	232.12	<.0001		0
PV	-0.12096**	0.05063	4.41	0.0169	0.28948	3.45442
GDP	1.18028E-10***	2.67818E-11	-2.39	<.0001	0.41869	2.38839
Firm size ML	-0.27540***	0.10669	-2.58	0.0099	0.98463	1.01561
Firm size M	-0.03794	0.03099	-1.22	0.2209	0.86486	1.15625
Firm size S	-0.04357	0.03917	-1.11	0.2660	0.88116	1.13487
Region WE	-0.02906	0.03818	-0.76	0.4466	0.41756	2.39488
Region SE	-0.32450***	0.03455	-9.39	<.0001	0.66245	1.50954
BL CF	0.40350***	0.09195	4.39	<.0001	0.95886	1.04290
BL TS	0.19842***	0.04022	4.93	<.0001	0.65171	1.53442
BL CB	0.09102***	0.02842	3.20	0.0014	0.74477	1.34269
BL PS	-0.07704	0.08897	-0.87	0.3866	0.95892	1.04284
BL AS	-0.09240	0.06292	-1.47	0.1420	0.91847	1.08877
BL AM	0.09827	0.07308	1.34	0.1787	0.92684	1.07893
ET IF	0.28030***	0.04771	5.88	<.0001	0.81752	1.22322
ET EF	0.20098***	0.03498	5.75	<.0001	0.69449	1.43990
ET EPWS	-0.20074***	0.05344	-3.76	0.0002	0.95634	1.04565
ET CPBP	0.49250***	0.03924	12.55	<.0001	0.79665	1.25525
ET BDSF	0.04213	0.06294	0.67	0.5033	0.95779	1.04408

The parameter estimates of the OLS regression for large loss events are presented in table 13. As for the medium losses, an on the contrary to the small losses, the results of the regression for the large losses indicate that operational losses would be larger in larger countries. Moreover, as for the small loss events, the results suggest a strong decreasing association between the governance indicator Political Stability and Absence of Violence/Terrorism. Quite interestingly, and on the contrary to the results from the results for small events, there is a strong negative association between firm size Medium/Large and the large loss events. Also, unlike the previous models, the results suggest a strong decreasing association between the geographic region Southern Europe and large loss events.

Furthermore, the most severe losses occur in business line commercial banking, followed by corporate finance and trading and sales, whereas the least severe losses occur in agency services although the result for it is not significant. Regarding event type, clearly the most severe losses occur in Clients, Products and Business Practices followed by Internal Fraud and External Fraud, whereas the least severe losses occur in Employment Practices and Workplace Safety.

Overall, all the results indicate that the selected variables are not able to explain the severity of operational losses. However, according to the results, it seems that it might be reasonable to assume that there are differences in the factors determining small, medium and especially large operational losses. This can for example be seen in the different parameter estimates in the models for small, medium and large loss events. Furthermore, the R^2 indicates that it is reasonable to separate the analysis based on the loss severity, as in this case the R^2 is higher in the analysis for large events. Based on this, it seems that the determinants selected in this study are most relevant for the large operational losses, whereas some other determinants would probably be more suitable to explain the small and medium operational losses.

Of course, the R^2 are very low in all the analyses conducted in this study, but that kind of results were expected from the beginning. That is, because creating a comprehensive list of determinants for operational risk would have been an extremely extensive task due to the huge variety of different kinds of operational loss events (Basel Committee on Banking Supervision, 2006; Brown, 2012). Moreover, due to the many different sources and different event types, it is also reasonable to assume that sometimes operational risk can purely be a random event which could not have been explained by anything concrete (Pakhchanyan, 2016).

5.4 Empirical results compared to the previous academic literature

The results regarding size of the firm as determinant for operational risk are not consistent in the three models. Hence, there is no systematic connection between firm size and operational loss severity, and H1 can be accepted. For small events the results indicates strong positive association, whereas for medium and large events the results are almost opposite, although the results are not significant for medium loss events. The results from the analysis for small loss events is consistent with the logic of Basel Committee's (2006) PIA methodology which indicate that larger firms should reserve more capital for operational risk than smaller firms. Overall, the mixed results regarding firm size as a determinant of operational loss severity could (Dahen & Dionne, 2010; Moosa & Silvapulle, 2012; Moosa & Li, 2013), to some extent, be explained by the assumption that losses of different sizes cannot be explained with the same determinants. Furthermore, one could argue that it is more likely for larger firms to have better internal control systems and risk culture as they also usually have more resources and often more regulations affecting them than smaller firms.

H2, then again, focused on the different business lines and regarding those the expected outcome was that some of the business lines would stand out. The hypothesis can be accepted and overall, for this variable, the results from the 3 models are quite similar. In all three models the second severe losses occur in trading and sales and third severe in commercial banking. Furthermore, similarly like in the study by Cope, Piche, & Walter (2012), for both medium and large events, the most severe losses occur in corporate finance. However, for small events the most severe losses occur in agency services. Overall and judged by common sense, it makes sense to have these business lines in top three, as these business lines include large financial services such as mergers & acquisitions, syndicated loans and project finance (Basel on Banking Supervision, 2006). It is also worth mentioning that these findings are not at all consistent with some previous studies (Dahen & Dionne, 2010; Moosa & Silvapulle, 2012). However, the both industrial as well as geographical scope of those studies is also different than in this study.

Regarding H3 which focuses on the event types, the results for small and medium events are rather similar, but the results for large events, then again, quite different which again supports the assumption that losses with different severity cannot necessarily be explained by the same factors. However, there are also some similarities as in all models, Internal Fraud is ranked either first or second in terms of having the most severe losses. Due to this, H3 can be accepted meaning that certain types of operational losses tend to be more severe than others. These results are also somewhat like the findings in Cope, Piche, & Walter's study (2012). For both small and medium losses, there is positive association also between the severity and Employment Practices and Workplace Safety, and the least severe losses occur in External Fraud. For large losses, the results for these business lines are, then again opposite.

For H4 it was expected that the operational loss events are larger when the level of governance is poor and vice versa. However, as only one of the three governance indicators made it to the models, this hypothesis was not managed to test thoroughly. As the only tested indicator, Political Stability and Absence of Violence/Terrorism, measures the likelihood that the government will be destabilized or overthrown, the results should show a strong increasing association to be able to accept H4. However, this is not the case as for small and large events there is a strong negative association and for medium events positive, but not significant connection. These results are opposite to the previous academical literature (Li & Moosa, 2015; Moosa, 2015; Cope, Piche, & Walter, 2012). Overall, if a similar study would be conducted again, it might be beneficial to include all six governance indicators to the models although they correlate quite strongly with each other. Then, after checking the possible multicollinearity issues, more governance related variables might be left in the study which could enable more specific results about the connection between operational loss severity and governance.

The results regarding H5, which focused on the geographical location, are again indicating that it cannot be assumed that operational losses with different severity could be explained by the same variables. The only similarity in the results is that for both small and medium events the least severe losses occur in United Kingdom.

For large events, the results are, however, very different as the least severe losses occurred in Southern Europe. Overall, these results are somewhat consistent with results by Cope, Piche & Walter (2012). They studied the different BCBS event types separately and found differences among the event types as for example Northern Europe and United States had the smallest losses in one event type but, then again, largest in another. However, due to the quite mixed results, H5 which expected operational losses to be more severe in some specific geographic regions cannot be accepted.

Finally, H6 which examined the connection between the size of the economy and operational loss severity, expected based on previous academic research, that operational losses would be larger in larger geographic regions (Cope, Piche, & Walter, 2012; Moosa, 2015). Quite interestingly, H6 can be accepted as the results indicate a trend that operational losses tend to be more severe in larger geographic locations as for large losses there is significant positive association and for medium as well although not as strong as for large losses. However, this is not the case for small loss events, so in this test, there is again some indications that it does not necessarily make sense to study all sized operational losses as equivalents.

6 CONCLUSIONS

Overall, the aim of this study was to examine both firm and country specific factors as determinants of operational loss severity in Europe and to simultaneously test and possibly validate some of the key findings of the previous research. In more detail, the determinants of operational risk under investigation in this study were the size of the firm, the geographic region, the size of the economy (GDP), business line, event type and three governance indicators which are the rule of law, regulatory quality and political stability. However, it is important to acknowledge that these findings do not warrant a causal association between the examined factors and operational loss event severity. The findings of this study intend to rather find common attributes or similar trends with the previous research.

Although there were quite many deficiencies in the model used, this study was, however, still effective in making important contributions to the existing literature. The most significant finding of this study was that operational loss events of different sizes cannot necessarily be explained by the same determinants. In other words, it can be that the extreme so called tail events are caused by different things than the high frequency and low severity loss events. However, further research would be needed to further examine this finding. It would also be interesting to study whether this is generally clearly more applicable for some variables than for others. All in all, combining this finding with the findings by Cope, Piche, & Walter (2012) that operational losses in different event types can be explained by different determinants, it can be assumed that it does not necessarily make sense to examine operational loss data as a large annual and country/area specific dumps.

Although there were significant differences between the three models, some similarities were still identified between this study and the previous research. Firstly, consistent with the previous studies, no systematic association was identified between operational loss severity and firm size (Dahen & Dionne, 2010; Moosa & Silvapulle, 2012; Moosa & Li, 2013). Furthermore, similarly like in the study by Cope, Piche, & Walter (2012), for both medium and large events, the most severe losses

occur in the business line corporate finance. Also, the results from this study regarding the connection of operational loss severity and level of governance are opposite to the previous academic literature (Li & Moosa, 2015; Moosa, 2015; Cope, Piche, & Walter, 2012). Moreover, and also consistent with some previous studies, the results indicate a trend that operational losses tend to be more severe in larger geographic regions (Cope, Piche, & Walter, 2012; Moosa, 2015). However, no clear results were gotten regarding the relationship between operational loss severity and geographic location.

There were also naturally some factors that set boundaries for this study. For example, due to the confidentiality of the ORX loss data some variables were not possible to include in the model and some variables needed adjustments to fit to the study. Furthermore, the extremely heterogeneous nature of operational risks complicates the modelling of the loss data as the risks defined as operational can vary from external natural disasters to internal fraud (Moosa, 2007; Li & Moosa, 2015). Also, according to the results and poor fulfilment of the fundamental basic assumptions for linear OLS regression model, the selected model, as well as the variables were not perfectly fit for purpose in this study.

Furthermore, it is still not clear whether operational risk can overall be said to be more systematic or idiosyncratic (Moosa, 2007; Pakhchanyan, 2016). This is also very important matter in the context of this study. That is because by examining the relationship and correlation between operational loss severity and different determinant, some systematic features between them are to some extent expected. However, based on the existing literature as well as the results of this study, it seems that this question remains unsolved with the conclusion that operational risk has both systematic and idiosyncratic features.

Moreover, creating a comprehensive list of determinants, would have been an extremely extensive task and for that reason was not the fundamental aim of this thesis. Of course, it would not even have been possible due to the confidentiality restrictions of the ORX loss data. The results can also be explained by the changes in the nature of operational loss events caused by the changing business

environment as well as existing megatrends such as digitalization (Bickford et al, 2016). The research period in this thesis is 10 years, and based on the existing academic literature it can be assumed that operational losses have evolved since 2006 (Bickford et al, 2016). Perhaps further results would have been made if the research period would have been divided to shorter periods and additional analysis would have been performed on those subsets.

Finally, as people are seen as one major source of operational risk losses (Basel Committee on Banking Supervision, 2006; Li & Moosa, 2015), an extremely interesting topic for further research would be to investigate the relationship between operational losses and some detailed firm specific employee data, such as the cost of employee training or employees' educational level or level of employee onboarding systems. Moreover, it would be extremely interesting to conduct a study on company level including detailed information about the internal control systems and HR management such as employee onboarding systems in the model as these have been suggested to be very much connected to operational loss events (Chernobai, Jorion, & Yu, 2011; Schwartz-Gârliste's, 2013; Pakhchanyan, 2016). However, getting this kind of data would be rather difficult in practice as the data needed for this would be sensitive and confidential firm specific information on their internal control systems and their weaknesses. Thus, this is something that financial firms could consider internally themselves in case they are not yet doing it.

REFERENCES

Baker, C., Cohanierb, B. & Leo, N. (2017) Breakdowns in internal controls in bank trading information systems. International journal of accounting information systems, vol. 26, pp. 20-31

Barakat, A. & Hussainey, K. (2013) Bank Governance, Regulation, Supervision, and Risk Reporting: Evidence from Operational Risk Disclosures in European Banks. International Review of Financial Analysis, vol. 30, pp. 254-273.

Basel Committee on Banking Supervision (2006) International Convergence of Capital Measurement and Capital Standards: A Revised Framework - Comprehensive Version. Bank for International Settlements, Basel, Switzerland.

Basel Committee on Banking Supervision (2011) Principles for the Sound Management of Operational Risk. Bank for International Settlements, Basel, Switzerland.

Bessis, J. (2002) Risk Management in Banking. Wiley, Chichester.

Bickford, J., Grüter, M., Le Boulay, G., Martin, D & O'Malley, B. (2016) The Five Practices That Set Operational Risk Leaders Apart. The Boston Consulting Group

Brown, S.J. (2012) Quantitative measures of operational risk: an application to funds management. Accounting & Finance, vol. 52, no. 4, pp. 1001-1011.

Bushman, R., Davidson, R., Dey, A. & Smith, A. (2017) Bank CEO materialism: Risk controls, culture and tail risk. Journal of Accounting and Economics, vol. 65, pp. 191–220.

Carminati, M., Caron, R., Maggi, F., Epifani, I. & Zanero, S. (2015) BANKSEALER: A decision support system for online banking fraud analysis and investigation. Computers & Security, vol. 53, pp. 175-186.

Chernobai, A., Jorion, P. & Yu, F. (2011) The determinants of operational risk in US financial institutions. Journal of financial and quantitative analysis, vol. 46, no. 6, pp. 1683-1725

Chiu, Y-H. & Chen, Y-C (2009) The analysis of Taiwanese bank efficiency: Incorporating both external environment risk and internal risk. Economic Modelling vol. 26, pp. 456–463.

Cope, E., Mignola, G., Antonini, G. & Ugoccioni, R. (2009) Challenges and pitfalls in measuring operational risk from loss data. The Journal of Operational Risk, vol. 4, no. 4, pp. 3-27.

Cope, E.W., Piche, M.T. & Walter, J.S. (2012) Macroenvironmental determinants of operational loss severity. Journal of banking & finance, vol. 36, no. 5, pp. 1362-1380

Crouchy, M. 2001. Risk Management. New York: McGraw Hill.

Dahen, H. & Dionne, G. (2010) Scaling models for the severity and frequency of external operational loss data. Journal of Banking and Finance, vol. 34, no. 7, pp. 1484-1496

de Fontnouvelle, P., Dejesus-Rueff, V., Jordan, J.S. & Rosengren, E.S. (2006) Capital and Risk: New Evidence on Implications of Large Operational Losses. Journal of Money, Credit and Banking, vol. 38, no. 7, pp. 1819-1846.

Deloitte (2013) Culture in Banking Under the Microscope. Deloitte Bank Survey 2013. [www document.] [Accessed 8 March 2018] Available

https://www2.deloitte.com/content/dam/Deloitte/uk/Documents/financial-services/deloitte-uk-culture-in-banking.pdf

Drennan, L. (2004) Ethics, Governance and Risk Management: Lessons from Mirror Group Newspapers and Barings Bank. Journal of Business Ethics, vol. 52, no. 3, pp. 257-266.

Dutta, K. & Perry, J. (2006) A tale of tails: An empirical analysis of loss distribution models for estimating operational risk capital. Working paper series // Federal Reserve Bank of Boston, vol. 6-13.

Embrechts, P. & Hofert, M. (2011) Practices and issues in operational risk modelling under Basel II. Lithuanian Mathematical Journal, vol. 51, no. 2, pp. 180-193.

European Banking Authority (2017) Guideline on internal governance under Directive 2013/36/EU. London, United Kingdom.

Fiordelisi, F., Soana, M. & Schwizer, P. (2013) The determinants of reputational risk in the banking sector. Journal of banking & finance, vol. 37, no. 5, pp. 1359-1371.

Gillet, R., Hübner, G. & Plunus, S. (2010) Operational risk and reputation in the financial industry. Journal of banking & finance, vol. 34, no. 1, pp. 224-235.

Hayes, A. & Cai, L. (2007) Using heteroskedasticity-consistent standard error estimators in OLS regression: An introduction and software implementation. Behavior Research Methods, vol. 39, no. 4, pp. 709-722.

Helbok, G. & Wagner, C. (2006) Determinants of Operational Risk Reporting in the Banking Industry. Journal of Risk, vol. 9, no. 1, pp. 49-74.

Hemrit, W. & Mounira, B. (2012) The major sources of operational risk and the potential benefits of its management. The Journal of Operational Risk, vol. 7, no. 4, pp. 71-92.

Hess, C. (2011) The impact of the financial crisis on operational risk in the financial services industry: empirical evidence. The Journal of Operational Risk, vol. 6, no. 1, Spring 2011 pp. 23–35

Jarrow, R.A. (2008) Operational risk. Journal of Banking & Finance, vol. 32, pp. 870–879.

Jiang, X. (2018) Operational risk and its impact on North American and British banks. Applied Economics, vol. 50, no. 8, pp. 920.

Jobst, A.A. (2007) The treatment of operational risk under the New Basel framework: Critical issues. Journal of Banking Regulation, vol. 8, no. 4, pp. 316–352

Kaufmann, D., Aart, K & Massimo, M. (2010) "The Worldwide Governance Indicators: Methodology and Analytical Issues". World Bank Policy Research Working Paper No. 5430

KPMG International Cooperative ("KPMG International") (2017) Disrupt and grow – 2017 Global CEO Outlook. [www document.] [Accessed 25 October 2017] Available https://assets.kpmg.com/content/dam/kpmg/xx/pdf/2017/06/2017-global-ceo-outlook.pdf

Lam, J. (2003) A unified management and capital framework for operational risk. (Operational Risk Management), The Risk Management Association, Philadelphia.

La Porta, R., Lopez-de-Silanes, F., Shleifer, A. & Vishny, R. (1998) Law and finance. Journal of Political Economy, vol. 106, no. 6, pp. 1113–1155.

La Porta, R., Lopez-de-Silanes, F. & Shleifer, A. (2006) What works in securities laws? Journal of Finance, vol. 61, no.1, pp. 1–32.

Li, L. & Moosa, I. (2015) Operational risk, the legal system and governance indicators: a country-level analysis. Applied Economics, vol. 47, no. 20, pp. 2053-2072

Lin, F. (2008) Solving Multicollinearity in the Process of Fitting Regression Model Using the Nested Estimate Procedure. Quality & Quantity, vol. 42, no. 3, pp. 417-426.

Linsley, P. & Shrives, P. (2006) Risk reporting: A study of risk disclosures in the annual reports of UK companies. The British Accounting Review. Vol. 38, no. 4, pp. 387-404.

Liu, H. & Cortes, M. (2015) An assessment of the efficiency of operational risk management in Taiwan's banking industry. The journal of operational risk, vol. 10, no. 1, pp. 127-156.

Marquardt, D. W. (1980) You should standardize the predictor variables in your regression models. Journal of the American Statistical Association vol. 75, p. 74–103.

McNulty, J.E. & Akhigbe, A. (2017) What Do a Bank's Legal Expenses Reveal about Its Internal Controls and Operational Risk? Journal of Financial Stability, vol. 30, pp. 181-191.

Mizgier, K. & Wimmer, M. (2018) Incorporating single and multiple losses in operational risk: a multi-period perspective. Journal of the Operational Research Society. Vol. 69, no. 3, p. 358-371.

Moosa, I.A. (2007) Operational Risk: A Survey. Financial Markets, Institutions & Instruments, vol. 16, no. 4, pp. 167-200.

Moosa, I. (2015) Governance indicators as determinants of operational risk. International Journal of Disclosure and Governance, vol. 12, no. 2, pp. 132-143.

Moosa, I. & Li, L. (2013) An operational risk profile: the experience of British firms. Applied Economics, vol. 45, no. 17, pp. 2491-2500.

Moosa, I. & Silvapulle, P. (2012) An empirical analysis of the operational losses of Australian banks. Accounting and finance, vol. 52, no. 1, pp. 165-185.

Nguyen, D., Hagendorff, J. & Eshraghi, A. (2016) Can Bank Boards Prevent Misconduct? Review of Finance, vol. 20, no. 1, pp. 1-36.

OECD (2014), Risk Management and Corporate Governance, Corporate Governance, OECD Publishing. [www document.] [Accessed 11 January 2018] Available http://dx.doi.org/10.1787/9789264208636-en

Operational Riskdata eXchange Association (ORX) (2017a) [www document.] [Accessed 26 October 2017] Available https://managingrisktogether.orx.org/orx-news/monthly-top-5-orx-news-losses-2017

Operational Riskdata eXchange Association (ORX) (2017b) [www document.] [Accessed 26 October 2017] Available https://managingrisktogether.orx.org/about

Operational Riskdata eXchange Association (ORX) (2017c) [www document.] [Accessed 29 November 2017] Available https://managingrisktogether.orx.org/activities/loss-data

Pakhchanyan, S. (2016) Operational Risk Management in Financial Institutions: A Literature Review. International Journal of Financial Studies, vol. 4, no. 4, pp. 1-21.

Peni, E. & Vähämaa, S. (2012) Did Good Corporate Governance Improve Bank Performance during the Financial Crisis? Journal of Financial Services Research, vol. 41, no. 1, pp. 19-35.

Robertson, D. (2011) So that's operational risk! Economics Working Paper 2011-1. Office of the Comptroller of the Currency, Washington, DC.

Rosenberg, J.V. & Schuermann, T. (2006) A general approach to integrated risk management with skewed, fat-tailed risks. Journal of Financial Economics, vol. 79, no. 3, pp. 569-614.

Schwartz-Gârliste, M. (2013) The Operational Risk Management in Banking - Evolution of Concepts and Principles, Basel II Challenges. Revista de Management Comparat International, vol. 14, no. 1, pp. 165-174.

Sturm, P. (2013) Operational and Reputational Risk in the European Banking Industry: The Market Reaction to Operational Risk Events. Journal of Economic Behavior and Organization, vol. 85, pp. 191-206.

Tursunalieva, A. & Silvapulle, P. (2016) Nonparametric Estimation of Operational Value-at-Risk (OpVaR). Insurance: Mathematics and Economics, vol. 69, pp. 194-201

van der Meulen, N. S. (2013) You've been warned: Consumer liability in Internet banking fraud. Computer Law & Security Review, vol. 29, no. 6, pp. 713-718.

Wang, T. & Hsu, C. (2013) Board composition and operational risk events of financial institutions. Journal of banking & finance, vol. 37, no. 6, pp. 2042-2051.

White, H. (1980) A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity. Econometrica, vol. 48, no. 4, pp. 817-38.

Willesson, M. (2014) New Experiences from Voluntary Risk Disclosures. Operational Risk in Nordic Banks. Journal of Financial Management, Markets and Institutions, vol. 2, n. 1, pp. 105-126.

Wilson, S. (2007). A Review of Correction Techniques for Inherent Biases in External Operational Risk Loss Data. Working Papers, Australian Prudential Regulation Authority.

Wissmann, M., Shalabh & Toutenburg, H. (2011) Role of categorical variables in multicollinearity in linear regression model. Journal of Applied Statistical Science, vol. 19, no. 1, pp. 99-133.

Zamorski, M. J. (2003) Joint supervisory guidance on operational risk advanced measurement approaches for regulatory capital – Board memorandum, FDIC, Division of Supervision and Consumer Protection, July. [www document.] [Accessed 24 January 2018] Available https://www.fdic.gov/regulations/laws/publiccomments/basel/boardmem-oprisk.pdf

Appendix

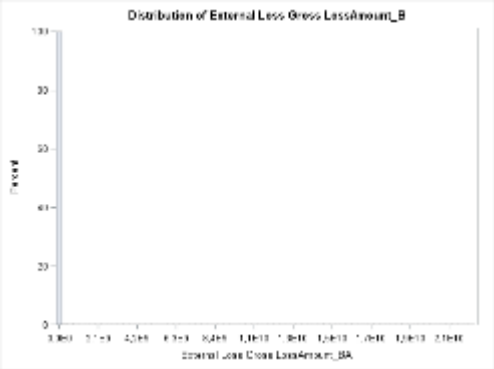
Appendix 1 Distributions of the variables

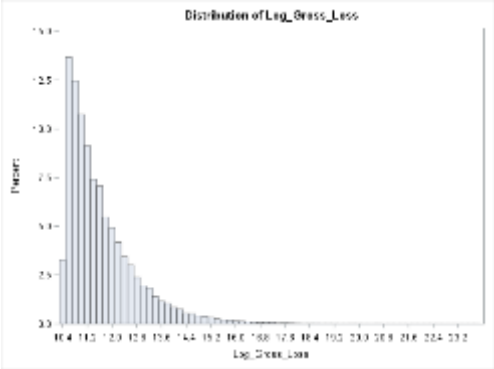
Appendix 2: Scatter plots of the dependent variables' residuals

Appendix 3: residuals examination of the models

Appendix 1: Distributions of the variables

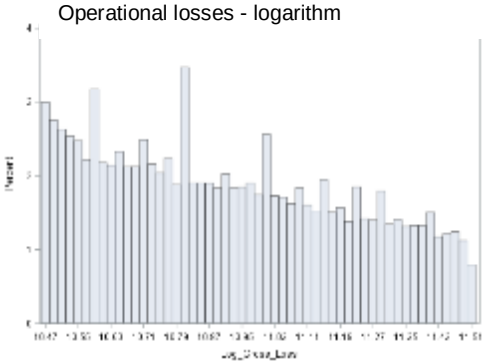
Distribution of gross loss and distribution of ln gross loss (full dataset)



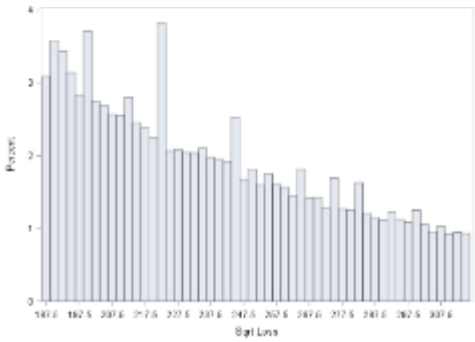


Distribution of variables from dataset for small events (EUR 35000-99999)

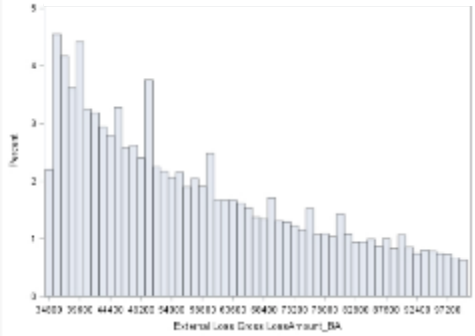
Operational losses - logarithm



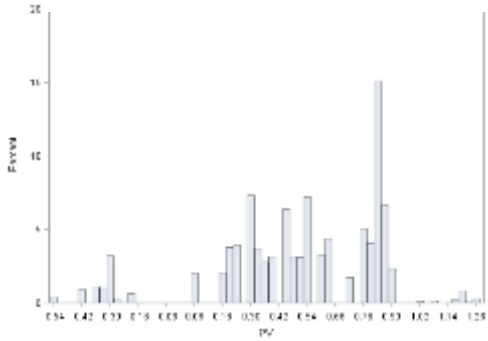
Operational losses – square root



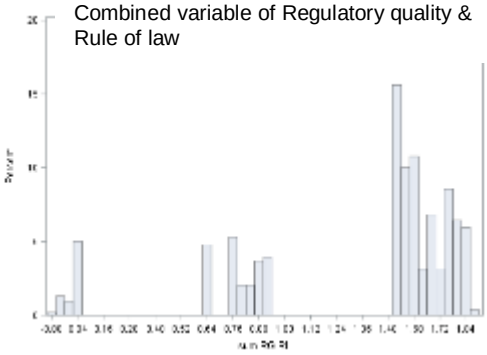
Operational losses



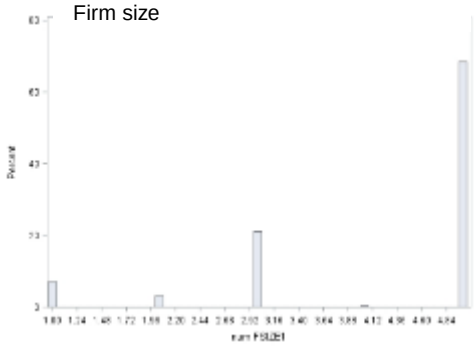
Political Stability and Absence of Violence/Terrorism



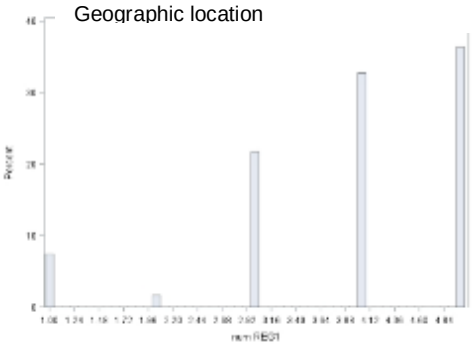
Combined variable of Regulatory quality & Rule of law



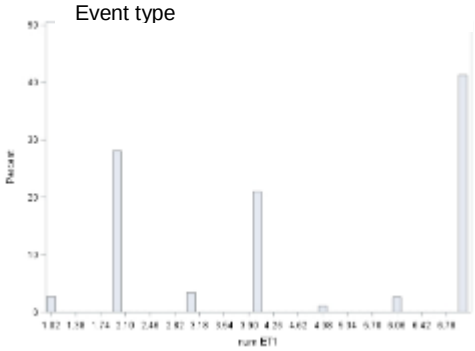
Firm size



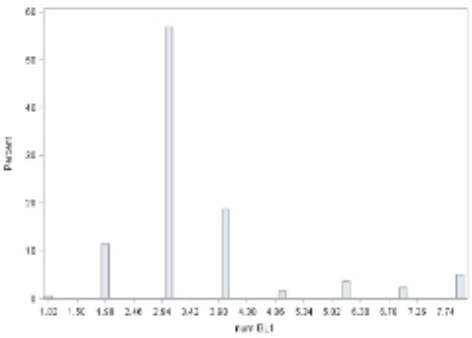
Geographic location



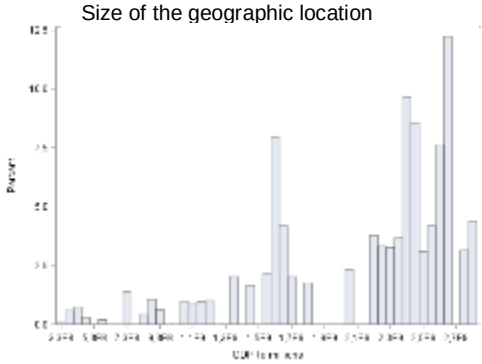
Event type



Business line

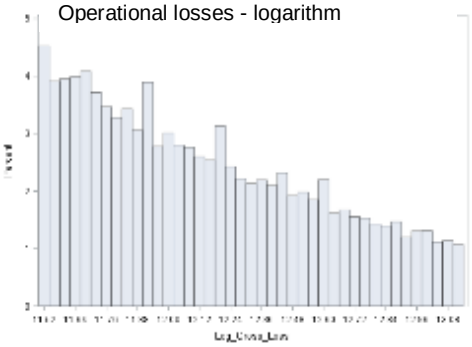


Size of the geographic location

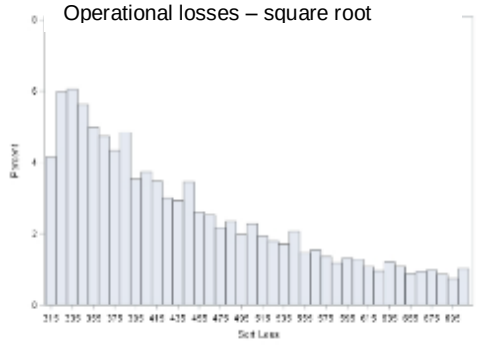


Distribution of variables from dataset for medium events (EUR 100000- 499999)

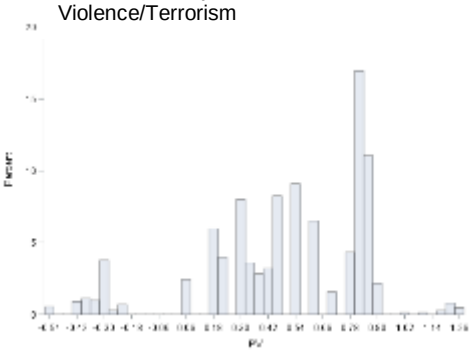
Operational losses - logarithm



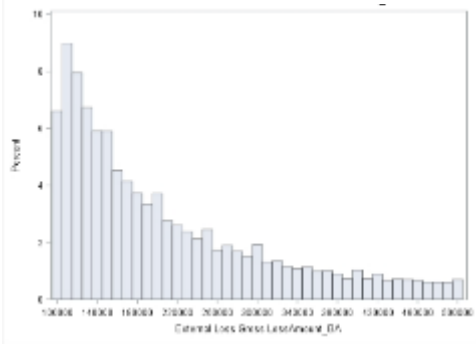
Operational losses – square root



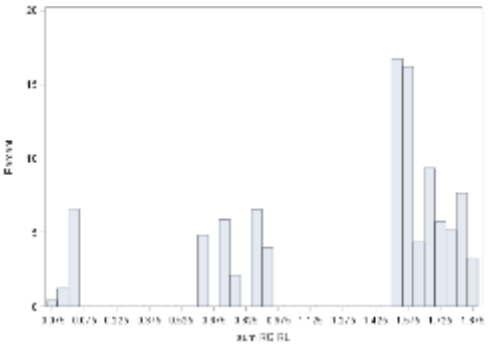
Political Stability and Absence of Violence/Terrorism



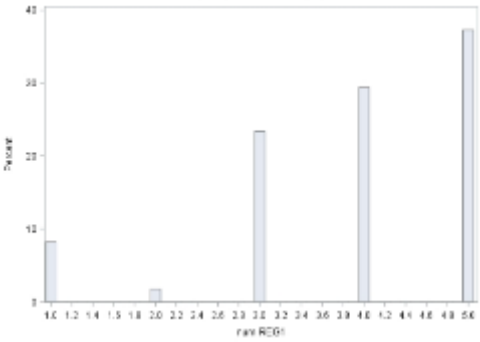
Operational losses



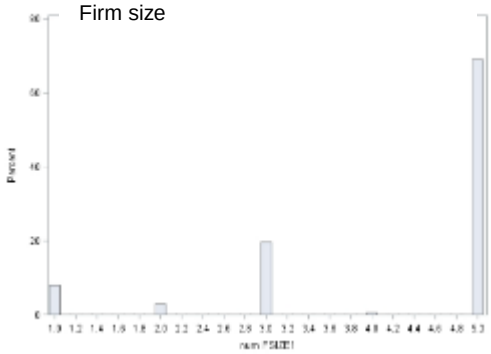
Combined variable of Regulatory quality & Rule of law



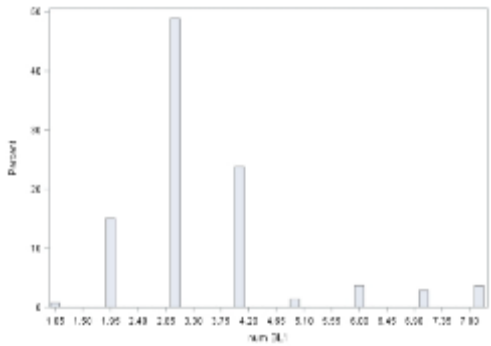
Geographic location



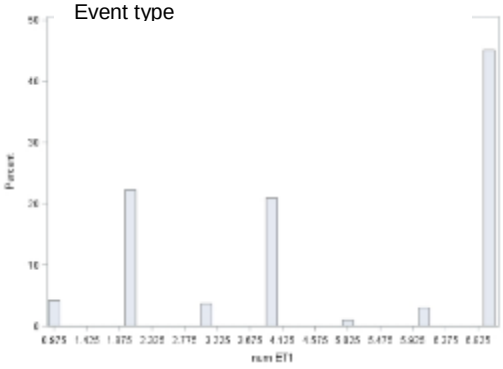
Firm size



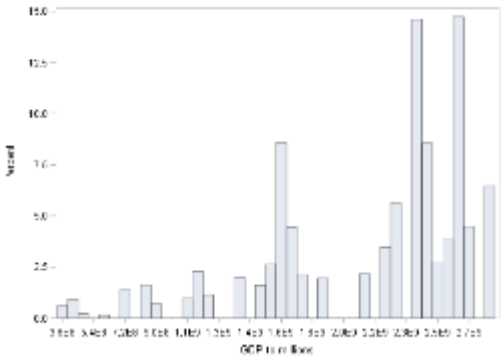
Business line



Event type

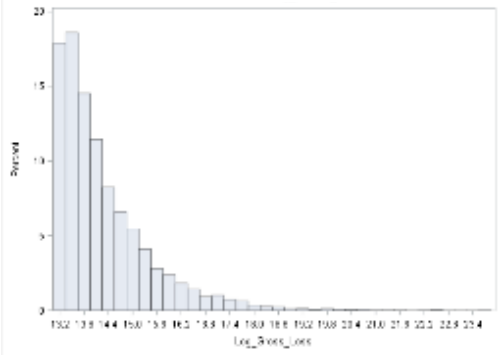


Size of the geographic location

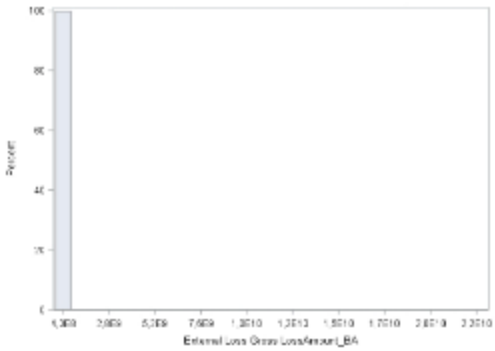


Distribution of variables from dataset of large events (EUR 500000 →)

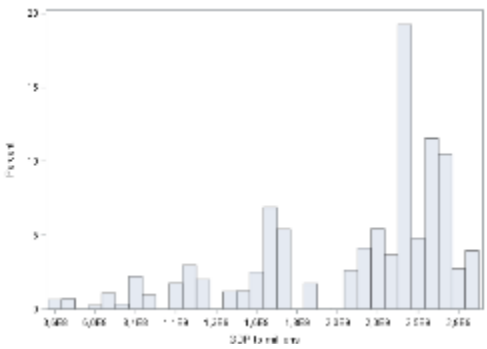
Operational losses - logarithm



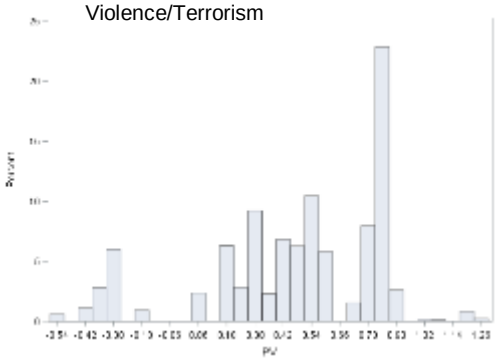
Operational losses



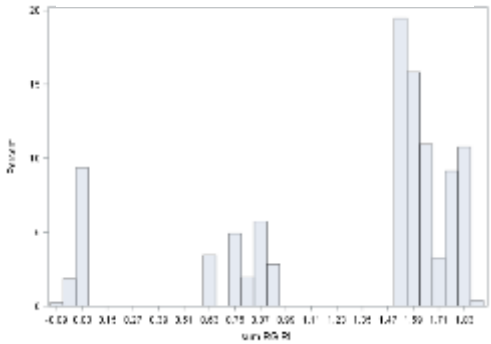
Size of the geographic location



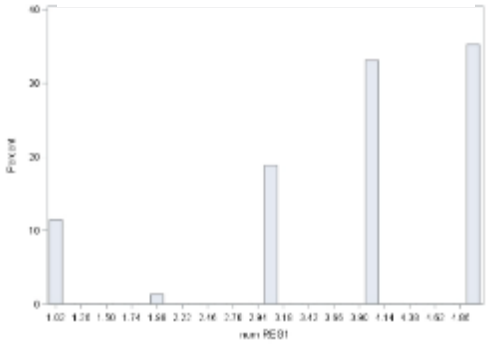
Political Stability and Absence of Violence/Terrorism



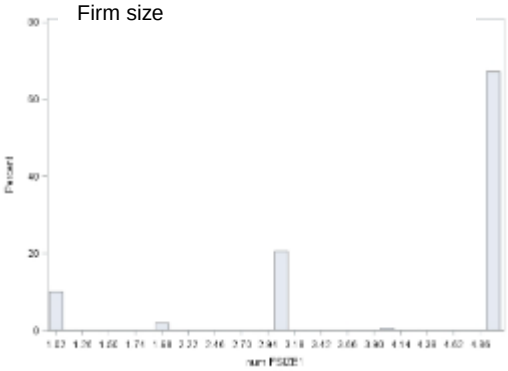
Combined variable of Regulatory quality & Rule of law



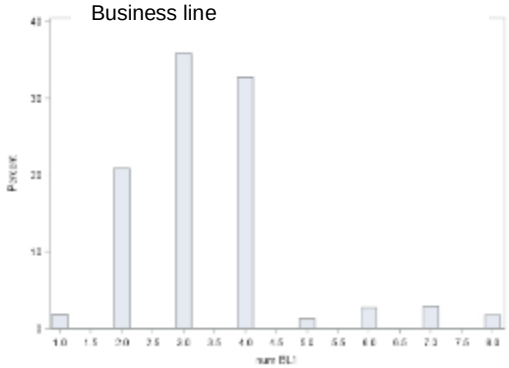
Geographic location



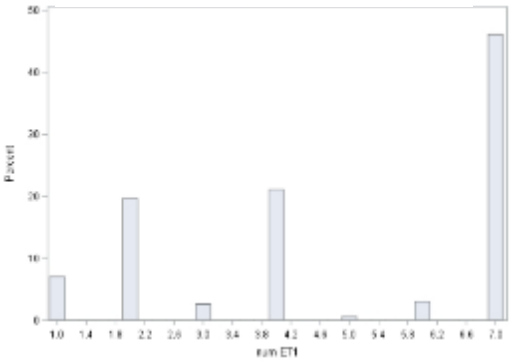
Firm size



Business line

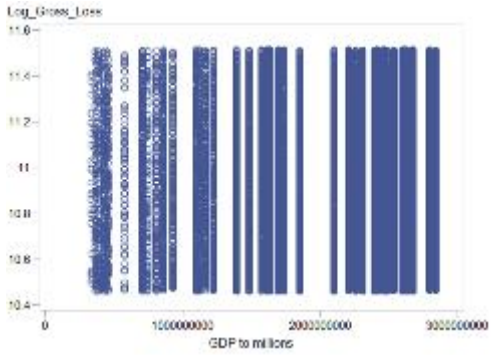


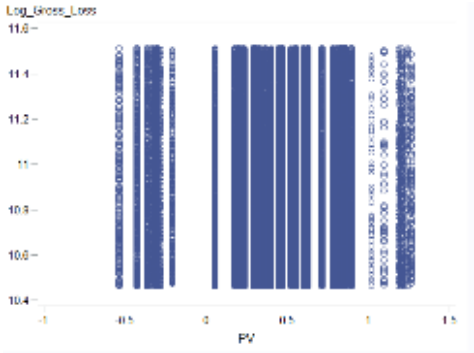
Event type

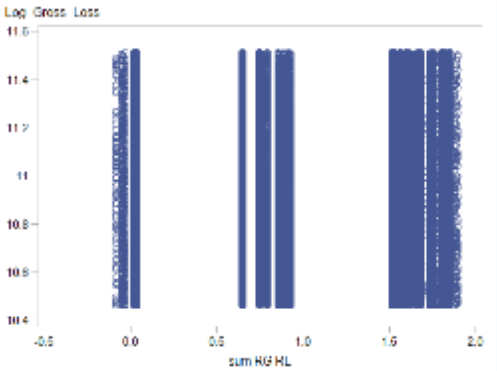


Appendix 2: Scatter plots

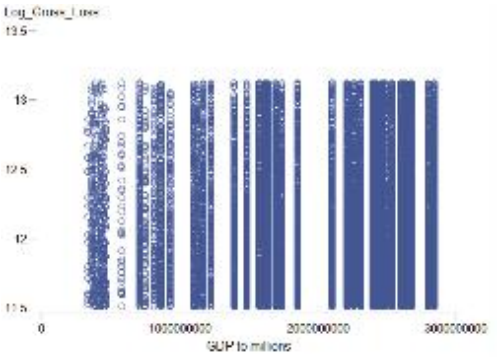
Small events (EUR 35000-99999)

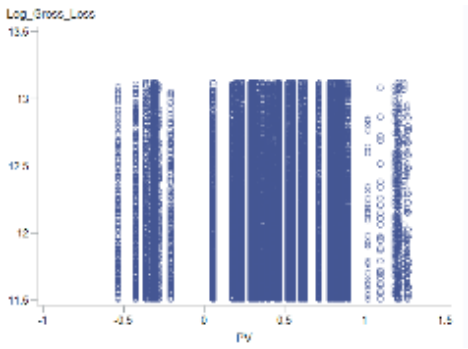


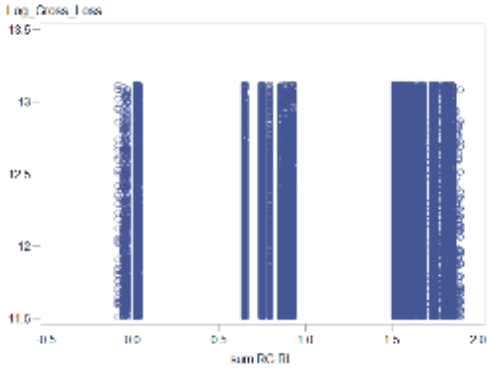




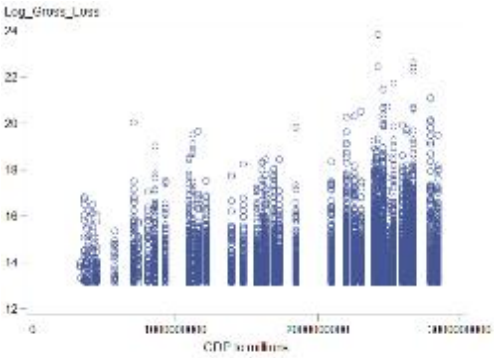
Medium events (EUR 100000- 499999)

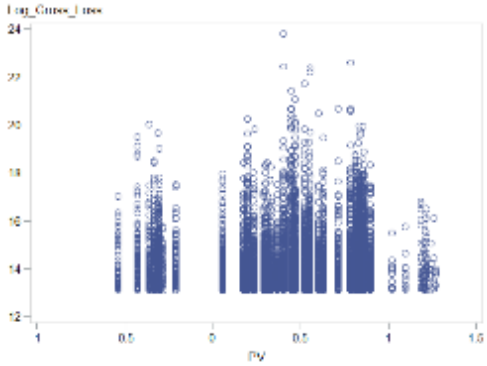


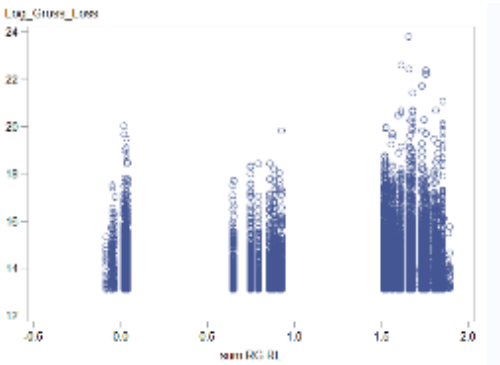




Large events (EUR 500000 →)

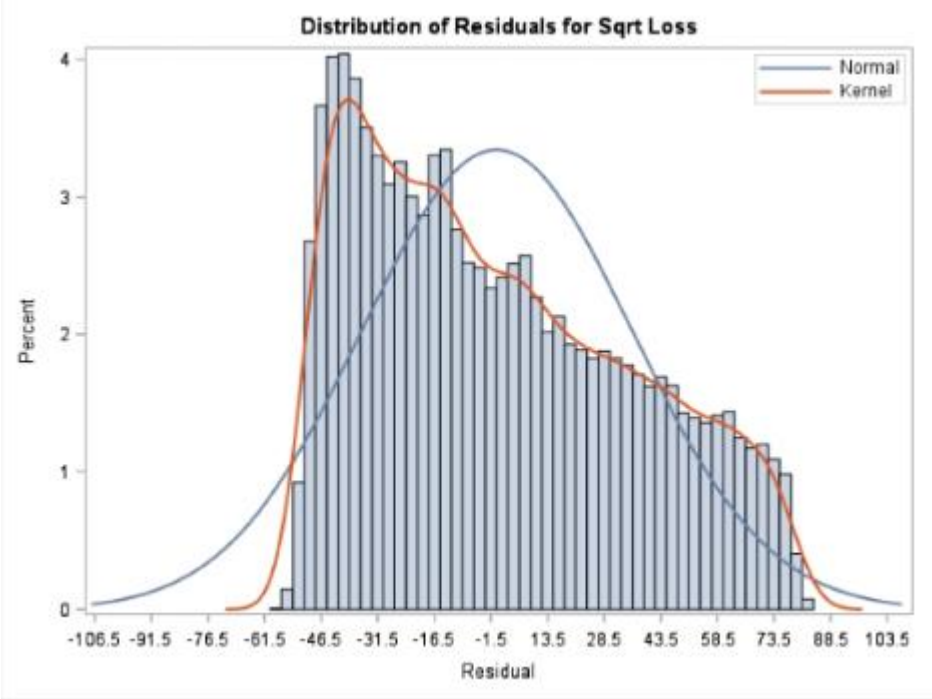


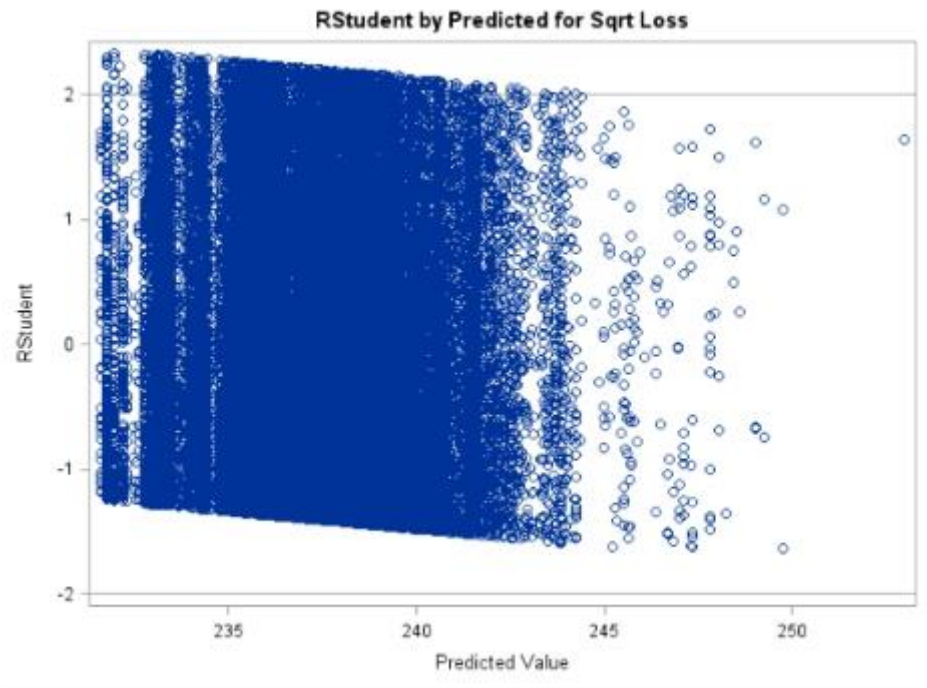


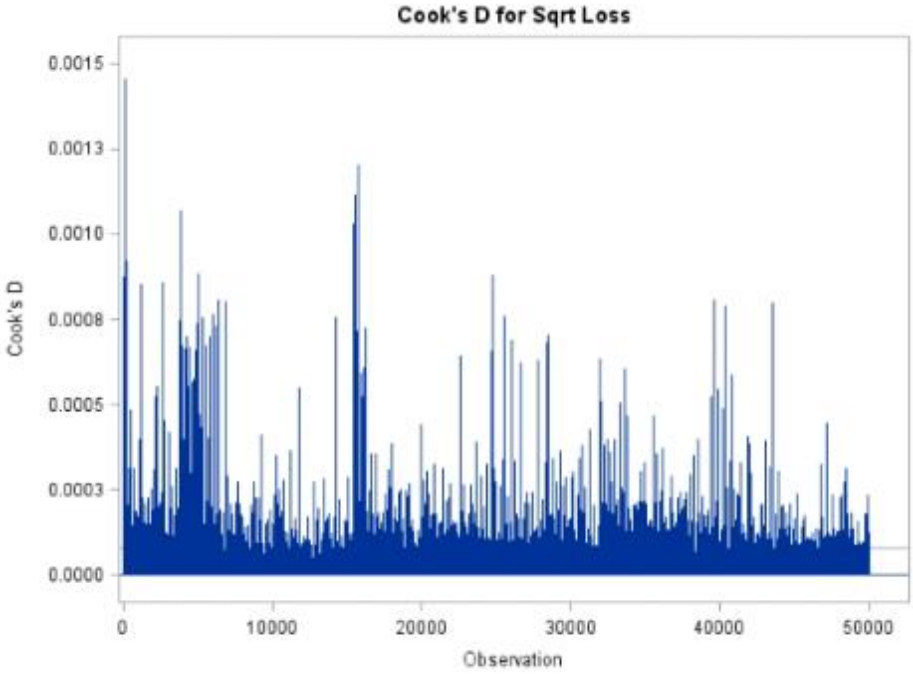


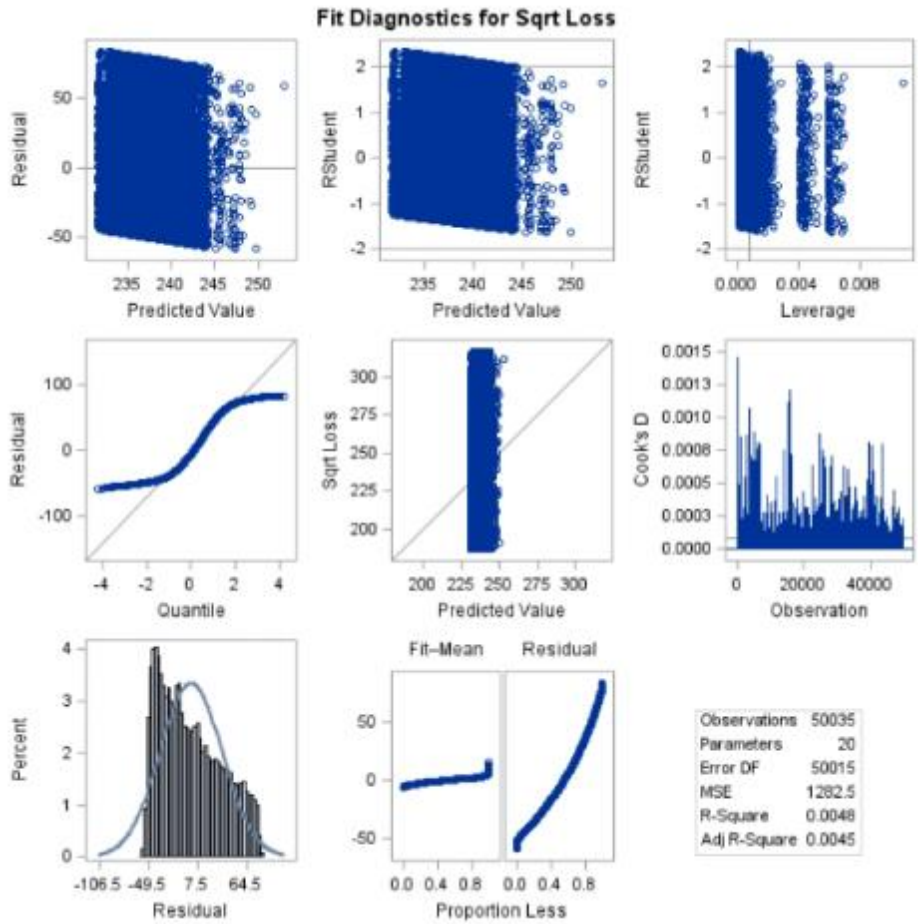
Appendix 3: residuals examination of the models

Small events (EUR 35000-99999)

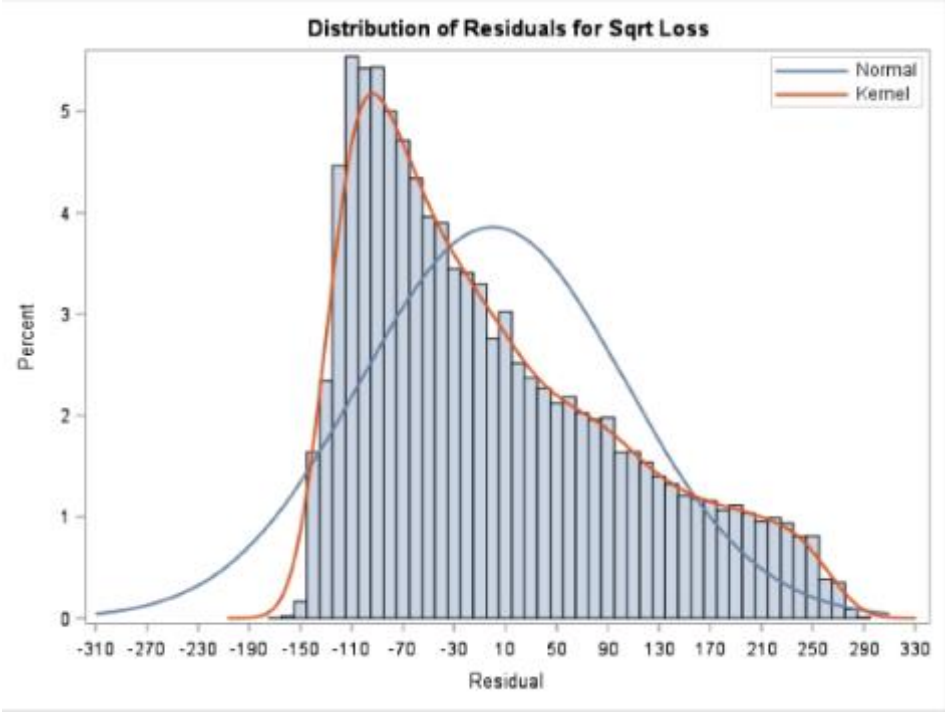


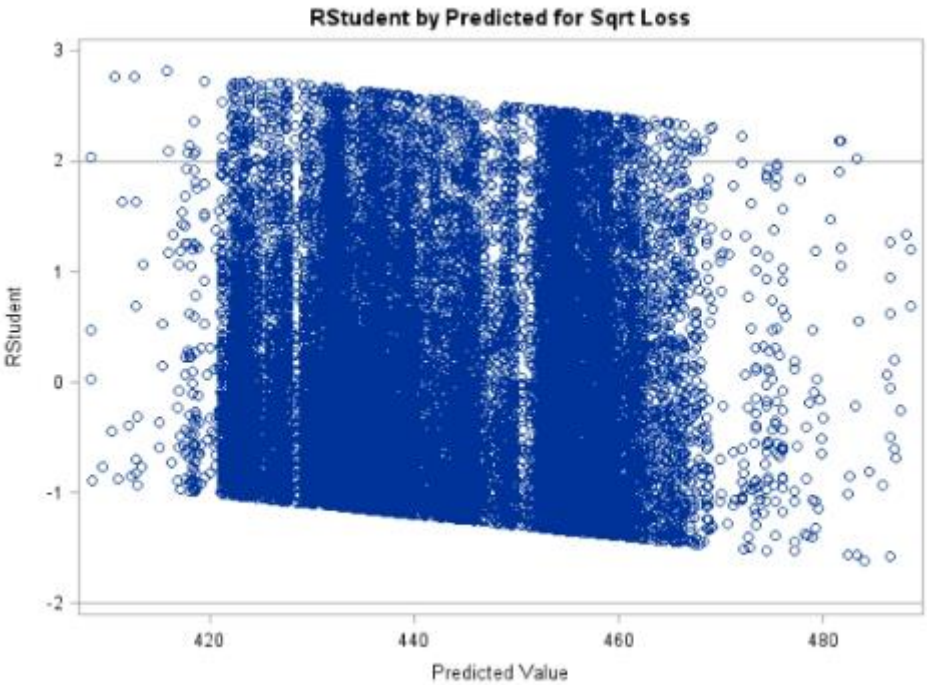


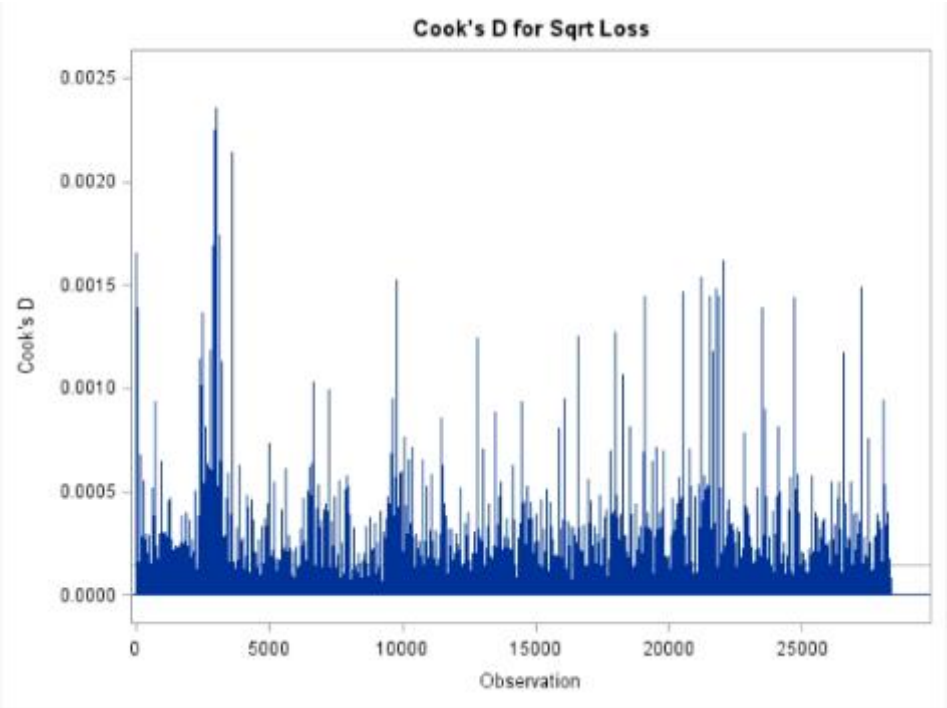

Cook's D for Sqrt Loss
Cook's D
0.0015
0.0013
0.0010
0.0008
0.0005
0.0003
0.0000
0
10000
20000
30000
40000
50000
Observation

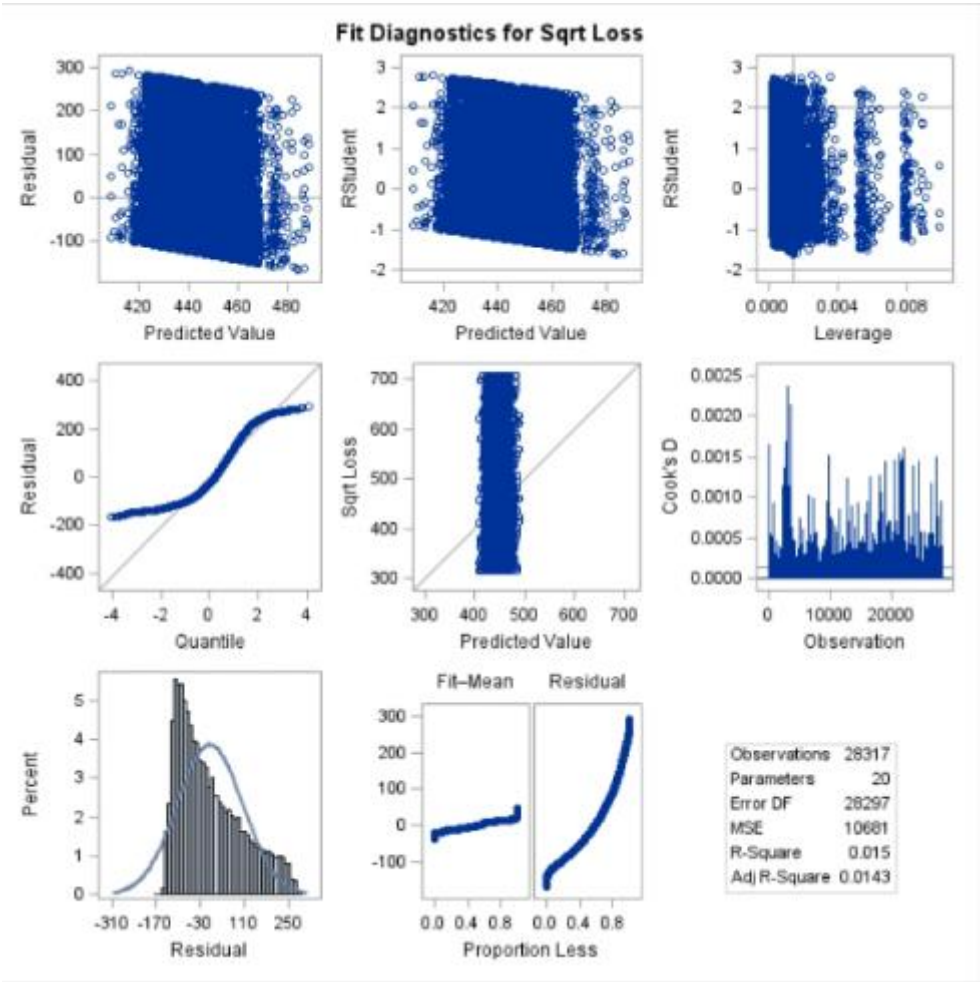

Fit Diagnostics for Sqrt Loss
Residual
Predicted Value
RStudent
Leverage
Quantile
Sqrt Loss
Cook's D
Observation
Percent
Residual
Fit–Mean
Proportion Less
Observations 50035
Parameters 20
Error DF 50015
MSE 1282.5
R-Square 0.0048
Adj R-Square 0.0045

Medium events (EUR 100000- 499999)

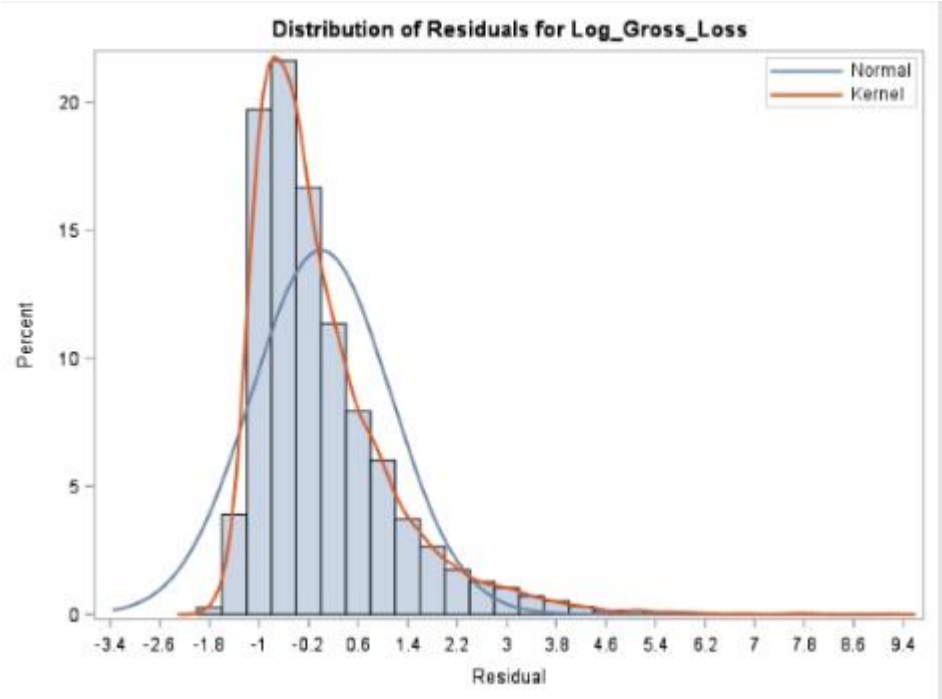


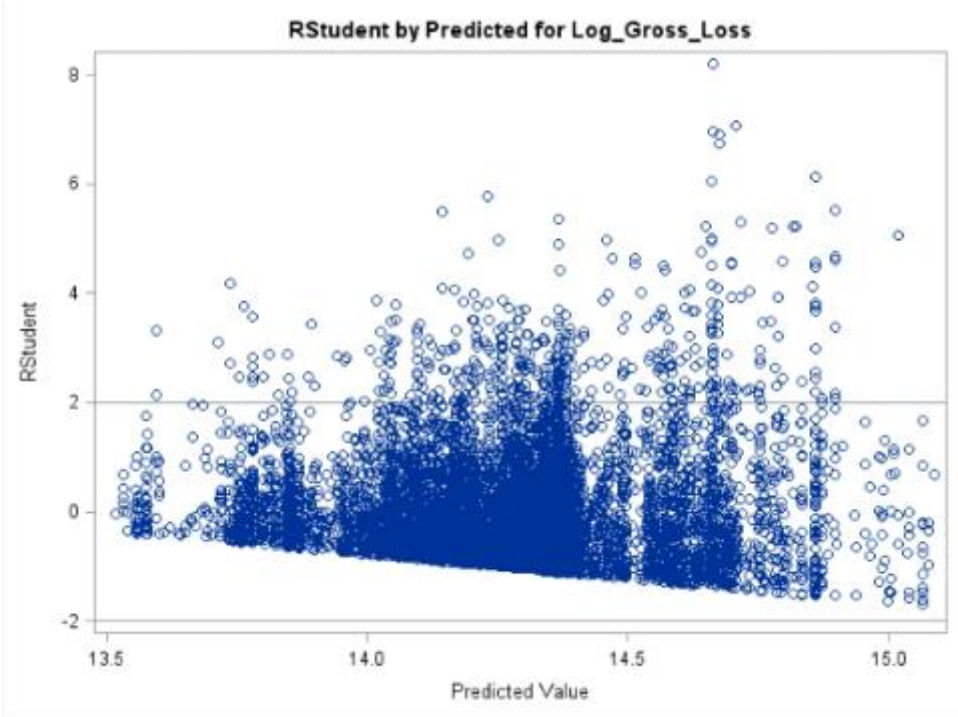


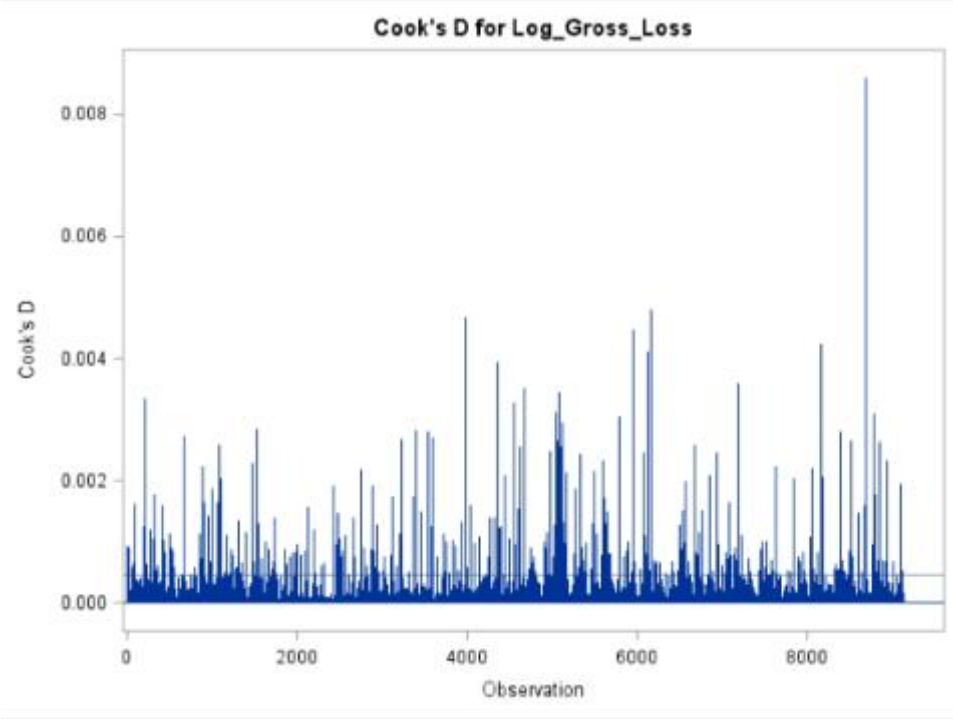

Cook's D for Sqrt Loss
Cook's D
0.0025
0.0020
0.0015
0.0010
0.0005
0.0000
0
5000
10000
15000
20000
25000
Observation

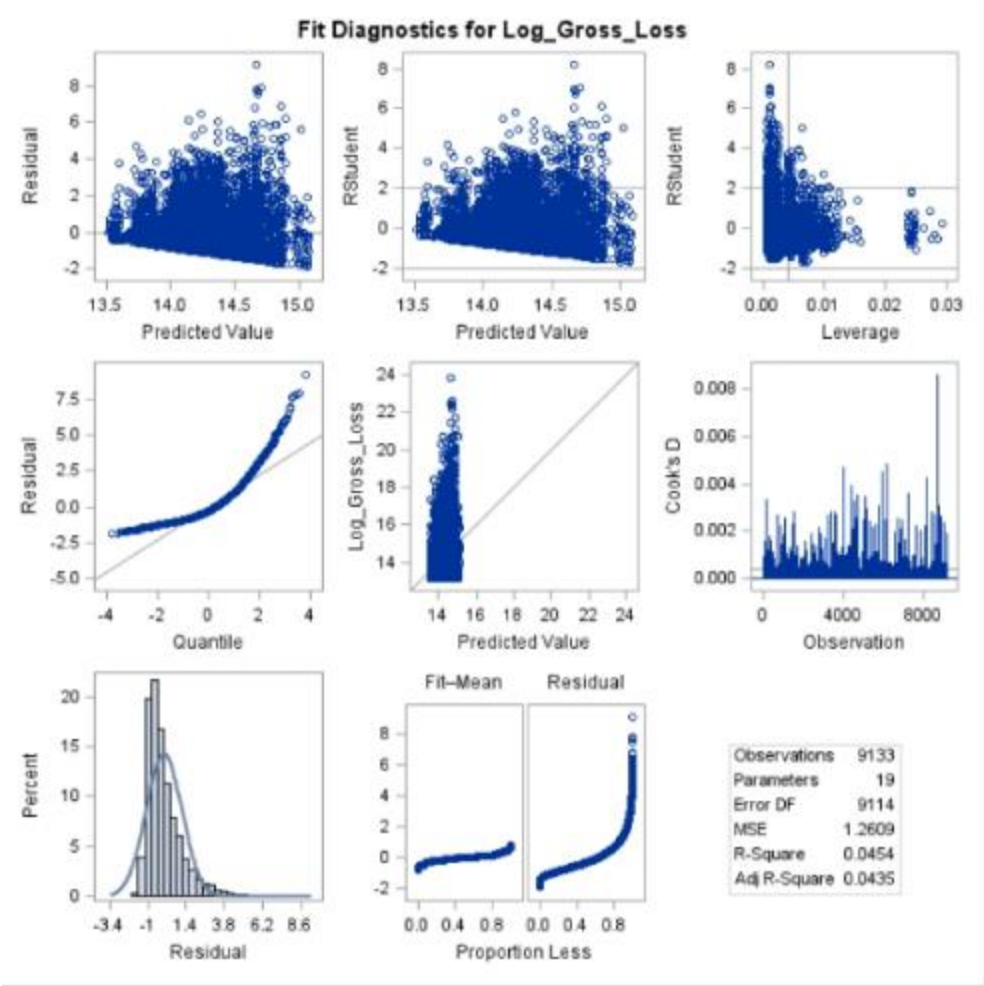

Fit Diagnostics for Sqrt Loss
Residual
Predicted Value
RStudent
Predicted Value
RStudent
Leverage
Residual
Quantile
Sqrt Loss
Predicted Value
Cook's D
Observation
Percent
Residual
Fit–Mean
Residual
Proportion Less
Observations 28317
Parameters 20
Error DF 28297
MSE 10681
R-Square 0.015
Adj R-Square 0.0143

Large events (EUR 500000 →)






Cook's D for Log_Gross_Loss
Cook's D
0.008
0.006
0.004
0.002
0.000
0
2000
4000
6000
8000
Observation


Fit Diagnostics for Log_Gross_Loss
Residual
Predicted Value
RStudent
Leverage
Quantile
Log_Gross_Loss
Cook's D
Observation
Percent
Fit–Mean
Residual
Proportion Less
Observations 9133
Parameters 19
Error DF 9114
MSE 1.2609
R-Square 0.0454
Adj R-Square 0.0435