INVESTIGATING THE SIGNIFICANCE OF REPUTATIONAL RISK IN BANKS' FINANCIAL PERFORMANCE

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"*Research is to see what everybody else has seen, and to think what nobody else has thought.*"

Albert Szent-Gyorgyi

DECLARATION

I hereby solemnly declare that this thesis is a representation of my original work and has not been presented for the award of a degree in this or any other university. All materials, ideas, and findings derived from the work of other authors or published sources have been appropriately acknowledged and cited within this thesis.

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ABSTRACT

The field of organizational studies, particularly in the financial sector, has increasingly acknowledged the importance of effective risk management. This consensus is pivotal for the stability and health of the global financial system and is supported by studies showing the positive impact of managing key risks like credit, market, operational, and liquidity on a bank's overall performance. Despite these advancements, gaps remain, especially concerning nonfinancial risks like reputational risk.

Reputational risk in banking is complex, with current research offering fragmented insights, particularly regarding its impact on financial outcomes. Many studies have focused on short-term market reactions, neglecting the long-term financial impact on banks, and often overlooking key financial metrics like Return on Assets (RoA) (Cummins et al., 2006; Eckert & Gatzert, 2017; Fiordelisi et al., 2013; Gillet et al., 2010; Perry & de Fontnouvelle, 2005). Heidinger & Gatzert (2018) and Gillet et al. (2010) contributed significantly to understanding the dynamics between reputational risk and RoA, but their research did not explore the direct impact of reputational events on RoA, leaving a crucial aspect unexplored. Furthermore, there's a notable lack of research directly linking the severe reputational damage stemming from operational risks, and especially internal frauds to a bank's financial well-being, specifically in terms of deviations in returns (mainly RoA). Also, most reputational research is confined to U.S. and European regions, lacking a global perspective.

The aim of the research was to address these shortcomings by examining the diverse effects of reputational risk resulting from internal fraud on the financial performance of banks, with a particular emphasis on deviations in RoA. The study employed a comprehensive theoretical framework combining the Resource-Based Theory (RBT) and the Unified Theory of Reaction in Assets Market to analyze the dynamics of reputational risk in banking. In order to align with the aforementioned theoretical foundations, the study employs a positivist research paradigm, emphasizing empirical evidence and logical reasoning for the objective validation and generalization of the relationship

between reputational risk and the financial performance of banks. The utilization of quantitative methodologies within this paradigm guarantees the requisite methodological rigor and objectivity for a comprehensive and detailed examination.

By leveraging reputable data sources like the Global Operational Loss Database (GOLD) by Riskbusiness (UK) for operational loss details, the Bloomberg databases for essential financial metrics, and the World Bank databases for critical macroeconomic indicators, the study ensures it is built upon a foundation of accurate, reliable, and globally recognized data points. Consistent with previous studies, the research used a longitudinal dataset spanning ten years, focusing on commercial and retail banks with operational losses exceeding USD 100,000. The comprehensive and systematic process of identifying operational losses resulted in the selection of 61 instances of internal fraud. These losses are distributed across 18 different currencies, implicating 53 banks situated in 23 countries and 10 distinct geographical regions globally.

Considering that the ultimate goal of managing reputational risk, much like the broader risk management framework within a bank, is to continually minimize its influence on pivotal financial indicators like RoA (Coskun et al., 2019; Wanjohi et al., 2017), this research considered adjusting the traditional "event study" methodology and the "market reaction" paradigm commonly employed in reputational research (Cummins et al., 2006b; Eckert & Gatzert, 2017; Fiordelisi et al., 2013b; Gillet et al., 2010b). Instead of focusing on market reactions within an "event window," the study used a panel longitudinal analysis. The estimation of reputational loss was based on the analysis of trends in RoA for a period of three years prior to and following each operational loss event. This was conducted using the Generalized Least Square (GLS) Random Effects model. The rigorous application of multicollinearity, heteroskedasticity, and autocorrelation tests ensures the validity of the random effects model employed. Additionally, the study utilized the Boehmer et al. (1991) test statistic Z, originally developed to detect event-induced volatility in stock returns, to assess the statistical significance of the mean abnormal returns (AR) associated with reputational loss. The collective results of these tests provide substantial evidence that the findings derived from the model are robust and reinforce the credibility of the conclusions drawn from the analysis.

The study's findings revealed a substantial negative impact of internal fraud disclosures on banks' RoA, with an average reputational loss of around $54 million. The finding challenges the RBT, which suggests that larger banks (tangible and intangible assets) are better equipped to mitigate reputational crises. Instead, the study found a high positive correlation between the size of the bank and the intensity of the operational loss. Moreover, the research highlighted the importance of a global perspective, revealing significant regional variations in the impact of reputational losses.

The study's conclusions contribute significantly to the understanding of reputational risk in the banking sector, offering both theoretical and practical insights. The rejection of the null hypothesis (H_{01}) for banks with at least one negative AR post-event confirmed the critical impact of reputational events on financial outcomes. The study also challenged the assumption that the size of operational losses predicts the extent of reputational damage. Smaller banks were found to be more susceptible to reputational damage, supporting the alternative hypothesis (H_3). Additionally, significant regional variations in the impact of reputational losses were confirmed, emphasizing the need for region-specific risk management strategies.

This research not only advances academic discourse but also has substantial implications for real-world banking practices. It contributes to a deeper understanding of reputational risk dynamics, challenging existing theories, and offers banks crucial insights for tailoring their risk management strategies based on size and regional factors. Future research should focus on expanding the sample size for a more comprehensive analysis and investigate the integration of a capital charge for reputational risk in banking regulations.

KEYWORDS AND JEL CLASSIFICATION

Research keywords

- Reputational risk
- Operational risk
- Internal frauds
- Banks
- Resource-based theory (RBT)
- Unified theory of reaction in assets market
- Financial performance
- Return on assets (RoA)

JEL Classification

G32, G21, L25, E58, C12.

DEDICATION

This thesis is dedicated to God Almighty, whose divine guidance and blessings have been essential in my journey.

With heartfelt gratitude and love, I dedicate this work to my family: my dear wife, Nonfon, and our beloved children, Efanam, Kafui, Elonm, Senam, and Akpe-Situ. Their endless support, profound love, and incredible patience have been my pillars of strength and inspiration throughout this academic pursuit.

I extend my dedication to my mother, Marie, and to Father Narcisse for their unwavering presence, prayers, support, and boundless genuine love. Their faith in me fueled my self-confidence, bolstering my resolve to overcome the rigors of higher education. Their role in my life has been pivotal in envisioning and achieving this milestone.

With God's grace, they have all been a guiding light in every step of this journey, and it is to them I attribute the completion and success of this work.

ACKNOWLEDGMENTS

Completing this PhD thesis has been a transformative journey, and it would not have been possible without the support and encouragement of many people.

First and foremost, I extend my deepest gratitude to my supervisor, Prof. Janine MUKUDDEM-PETERSEN, for her unwavering guidance, patience, and invaluable advice throughout this research. Your expertise and insight have been pivotal in shaping both this work and my growth as a scholar.

I am also deeply thankful to Mr. Mike Finlay, CEO of RISKBUSINESS (UK) and editor of the GOLD databases (Global Operational Losses Database), for graciously providing me with complimentary access to the operational risk databases. His contribution has been pivotal to my research. Additionally, I am thankful for Mr. Finlay's insightful reflections on corporate reputation challenges, shared through his working paper, which significantly enriched my understanding of the subject.

My heartfelt thanks go to the University of Cape Town Graduate School of Business, and its Library Team for providing a stimulating academic environment and the necessary resources to conduct my research.

I am indebted to EMERG Group (Econometric Modelling and Economic Research Group) members who shared their time and experiences with me. This thesis would not have been possible without your valuable contributions.

Lastly, I would like to thank my friends for all the moments of relief and laughter amidst the pressures of PhD life.

This journey has been one of growth, learning, and self-discovery, and I am grateful to everyone who has been a part of it.

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ACRONYMS AND GLOSSARY

Key Acronyms

No	Acronyms	Definition
	CAPM	Capital Asset Pricing Model
	CAR	Capital Adequacy Ratio
	COPRAS	COmplex PRoportional ASsessment
	GDP	Gross Domestic Product
	GLS	Generalized Least Square
	MCDM	Multi-Criteria Decision-making Method
	MVRM	Multivariate Regression Model
	NIM	Net Margin Interest
	OLS	Ordinary Least Square
	RBT	Resource-Based Theory
	REM	Random Effects Model
	RoE	Return on Equity
	RoA	Return on Assets
	SAW	Simple Additive Weighting

Glossary of key terms

No	Terms	Definition
1	Bank fraud	"Bank fraud offenses under 18 U.S.C. § 1344 range from relatively non-complex theft or embezzlement of money by a bank employee to complex schemes designed to defraud, such as the over valuation of property, or false loan applications and improper use of loaned money" (uscode.house.gov)
2	Bank size	The study defines bank size by its total assets. "Bank size" by its total assets refers to the scale or magnitude of a bank, measured by the total value of everything the bank owns. These assets are a variety of components such as income-generating assets, cash reserves, amounts owed by other banks, properties acquired through foreclosure, capital assets, goodwill, other intangible assets, assets related to current taxes, deferred tax assets, assets from operations that are discontinued, and miscellaneous assets.
3	Corporate reputation	"Observers ' collective judgments of a corporation based on assessments of the fi nancial, social, and environmental impacts attributed to the corporation over time" (Barnett et al., 2006b).
4	Gross Domestic Product	"Gross domestic product (GDP) represents the sum of value added by all its producers. Value added is the value of the gross output of producers less the value of intermediate goods and services consumed in production, before accounting for consumption of fixed capital in production" (World bank, databank.worldbank.org)
5	Inflation	Inflation as measured by the consumer price index reflects the annual percentage change in the cost to the average consumer of acquiring a basket of goods and services that may be fixed or changed at specified intervals, such as yearly. The Laspeyres formula is generally used (World bank, databank.worldbank.org).
6	Internal frauds	"Internal fraud occurs when a director, an employee, a former employee, or a third party engaged by the bank commits

		fraud, colludes to commit fraud, or otherwise enables or contributes to fraud" (Office of the Comptroller of the Currency, 2019)
7	Operational risk	"Risk of loss resulting from inadequate or failed internal processes, people and systems or from external events. This definition includes legal risk, but excludes strategic and reputational risk" (Basel Committee on Banking Supervision, 2017)
8	Reputational risk	"Risk arising from negative perception on the part of customers, counterparties, shareholders, investors, debt-holders, market analysts, other relevant parties or regulators that can adversely affect a bank's ability to maintain existing, or establish new, business relationships and continued access to sources of funding (eg through the interbank or securitization markets)." (Basel Committee on Banking Supervision, 2009)
9	Resource Based Theory	Also referred to as the Resource-Based View (RBV), this managerial approach is utilized to identify the strategic assets at a company's disposal. It proposes that the foundation of a competitive edge is largely rooted in how effectively a company utilizes its collection of valuable resources (Barney, 1991; Fombrun, 2012)

I. INTRODUCTION

"Adventure is the life of commerce, but caution is the life of banking."

Walter Bagehot

This opening chapter offers a snapshot of the study's context, delineates the research issues at hand, and sets forth its aims, objectives, and queries. It also spotlights the primary outcomes of the study and their significance from both theoretical and practical viewpoints. Chapter one, Introduction, concludes by presenting an outline of the thesis structure.

I-1. Research background

I-1.1. *Overview of risk management in banking*

The fundamental structure of the banking industry has endured over an extended period without substantial alteration. Throughout the years, irrespective of the economic climate, fluctuations in currency, organizational structures, or the scale of operations, risk management has remained a critical and constant element for banks globally (Choudhry, 2018). Diverse categories of banks exist, encompassing among others commercial, retail, investment, development, and central banks. Of these, commercial and retail banks play pivotal roles in the economic landscape. Serving as financial intermediaries, these banks primarily engage with the general public and enterprises, accumulating deposits and extending credit. The activities of commercial and retail banks are particularly subject to oversight and regulation by central banks, adhering to both local and international protocols (Apostolik et al., 2009).

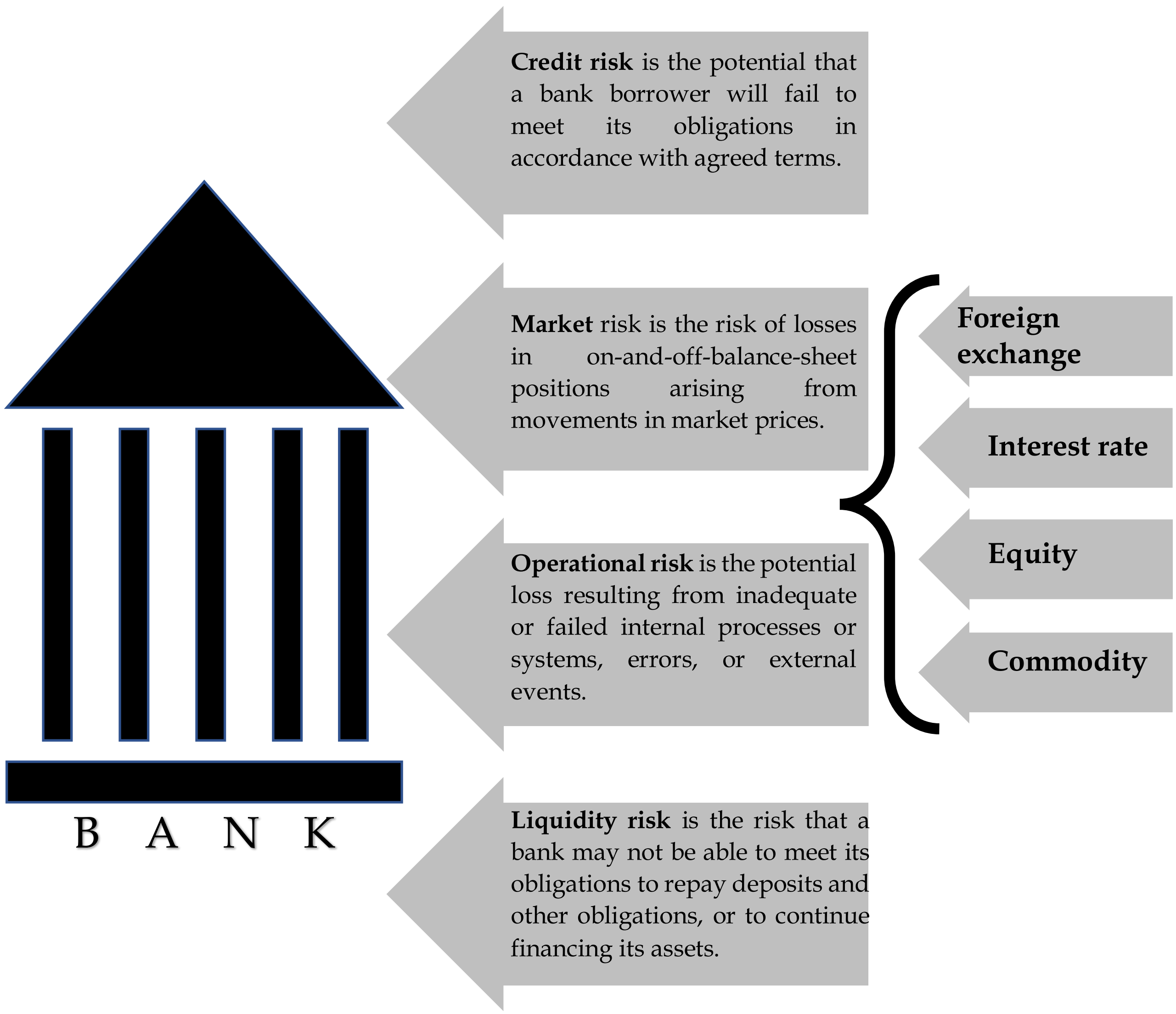
In the field of organizational studies, particularly in the financial sector, risk management has ascended to prominence. A consensus prevails among banks, policymakers, regulators, and scholars worldwide that effective risk management holds paramount significance due to its far-reaching implications for the global financial system (Apostolik et al., 2009; Rampini et al., 2020; Skoglund & Chen, 2015). The Banker's 2020 edition, which ranks the world's top 1000 banks, underscores the heightened necessity for precise banking risk assessment and the discernment of opportunities (The Banker, 2020). This pressing need has culminated in the formulation and continual refinement of a framework of guidelines known as the Basel Accords by international banking regulators, which draws from best practices in risk management (Apostolik & Donohue, 2015). These accords assume a pivotal role as regulatory foundations, directing financial risk management endeavors.

At the heart of the Basel Accords lie four principal categories of risk that underpin the fabric of risk management in banking: credit risk, market risk, operational risk, and liquidity risk (Apostolik et al., 2009; Basel Committee on Banking Supervision, 2011; Van Veventer et al., 2013).

Liquidity risk for example is an area of study that has attracted various viewpoints from researchers and financial analysts. Apostolik et al. (2009) stress the significance of liquidity risk by defining it as the potential inability of a bank to fulfill its financial commitments. Specifically, it encapsulates the possibility that a bank might face challenges in repaying depositors and meeting other financial obligations or in sustaining the financing of its assets. Their stance underscores the pivotal nature of liquidity in ensuring a bank's smooth functioning and, by extension, its reputation and trustworthiness in the market. In contrast, Ghosh (2012) presents a more nuanced understanding. While not dismissing the importance of liquidity risk outright, Ghosh (2012) places it in a broader context, weighing it against other banking risks. The author regards credit risk, market risk, and operational risk as the primary triad of banking risks, each possessing distinct attributes and consequences. In Ghosh's assessment, liquidity risk doesn't command the same level of prominence as these three risks. Instead, it is viewed as a component of market risk, nested among various other subsidiary risks. This perspective suggests a more layered approach to risk assessment, where liquidity risk, though essential, is seen as part of a larger tapestry of financial risks that banks must navigate. Such differences in viewpoints highlight the complexity of risk assessment in the banking sector and underscore the importance of continuous research and debate in this area.

Building on the perspective presented by Apostolik et al. (2009), Figure I-1 offers a visual representation of their viewpoint on the hierarchy and interrelation of banking risks.

Figure I-1: Core banking risks (Apostolik et al., 2009)



Banking risks are categorized into two main groups: financial risks and non-financial risks. The intricate landscape of these risks, along with their corresponding sub-risks and ensuing impacts, is visually depicted in

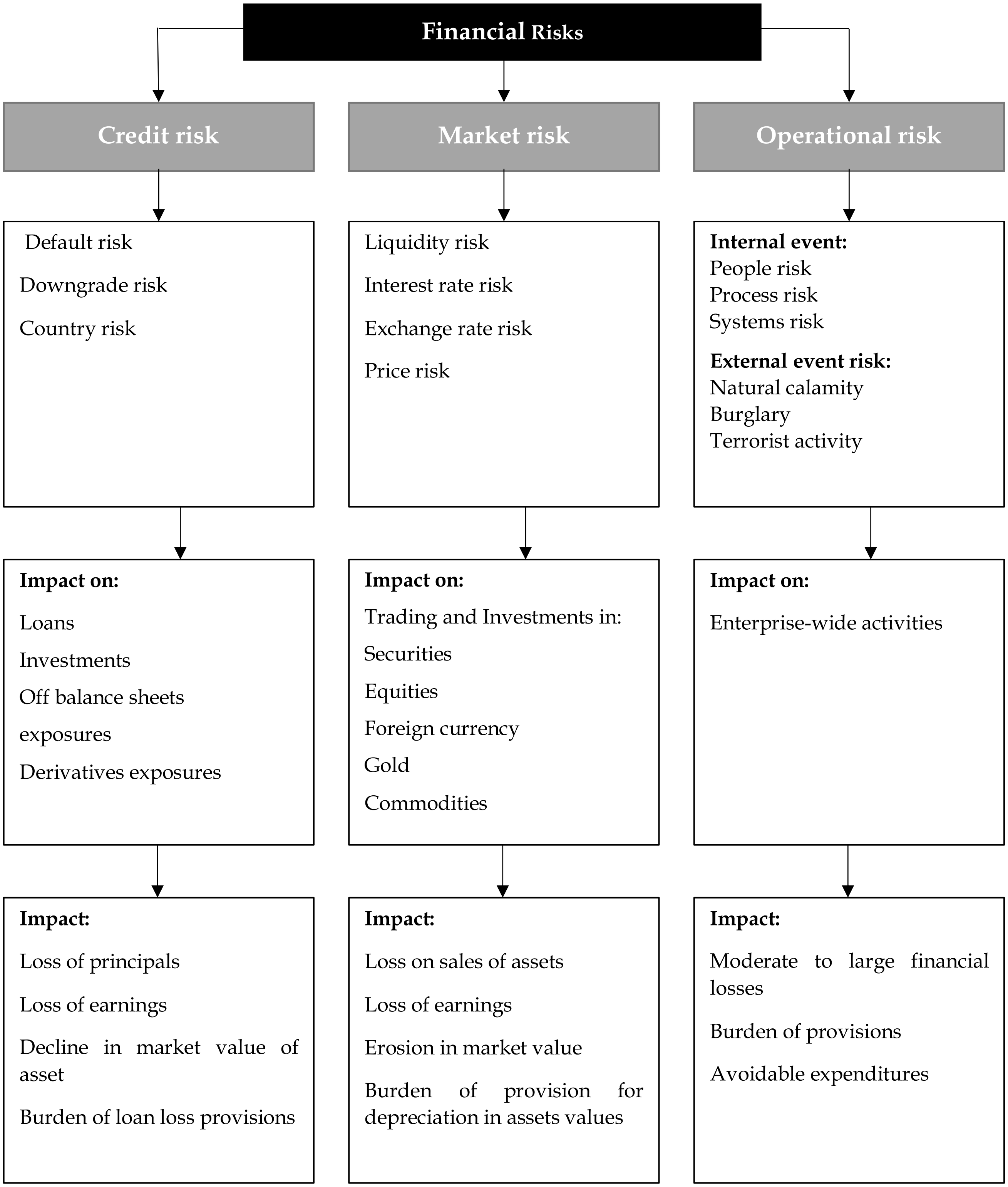
Figure *I-2* and Figure I-3 (Ghosh, 2012).

In

Figure *I-2*, Ghosh (2012) identifies Credit risk, Market risk, and Operational risk as the primary types of financial risks. Credit risk can lead to direct financial consequences such as the loss of principal, reduced earnings, a decrease in asset market value, and the necessity for loan loss provisions (Apostolik et al., 2009). Market risk can manifest in the form of losses from asset sales, diminished earnings, devaluation of market value, and the need for provisions against asset value depreciation. Operational risk affects activities across the entire enterprise and can result in moderate to severe financial losses, additional provisions, and unnecessary expenses (Basel Committee on Banking Supervision, 2011).

The reason Ghosh (2012) categorizes these as financial risks is due to their direct and significant impact on a bank's financial performance. These risks can affect the bank's income statement through increased costs or decreased revenue, and the balance sheet through changes in asset values. Effective management of these risks is then deemed crucial for maintaining financial stability and achieving long-term profitability in the banking sector (Apostolik et al., 2009; Skoglund & Chen, 2015; Svoronos, 2015; Van Veventer et al., 2013).

Figure I-2: Impacts of financial risks (Ghosh, 2012)



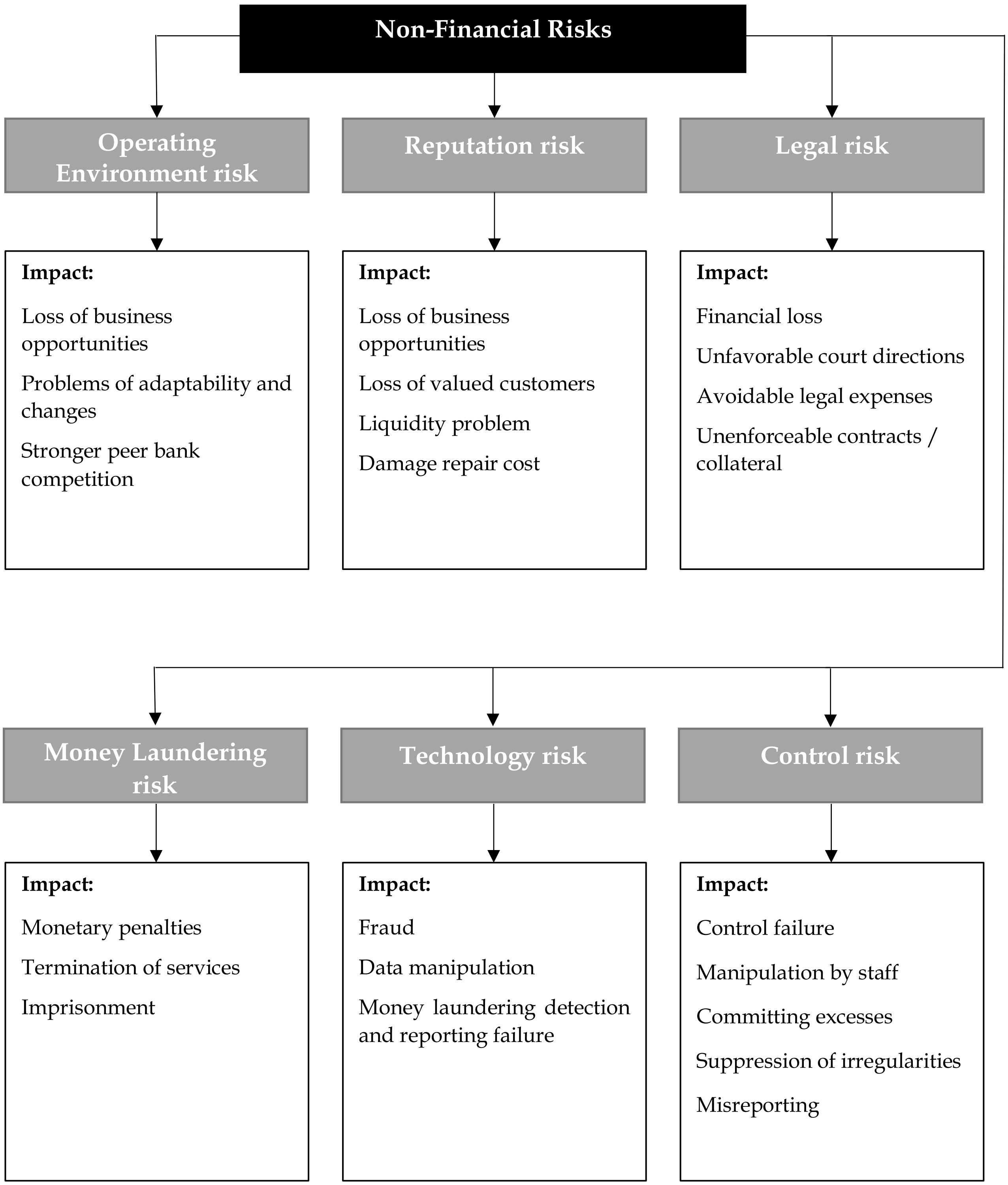
While empirical evidence has substantiated that adept administration of these risks yields a favorable influence on overall banks' performance as demonstrated by a range of studies (Kravec et al., 2020; Li, 2018; Skoglund & Chen, 2015; Sun & Chang, 2011; Van Veventer et al., 2013; Walter et al., 2013), inquiries persist regarding the pivotal nature, significance, and concomitant contribution of other risks, delineated as nonfinancial risks.

As illustrated by Ghosh (2012) in Figure I-3, nonfinancial risks encompass Operating environment risk, reputational risk, legal risk, Money laundering risk, Technology risk, and Control risk. As posited by Ghosh (2012), the ramifications of reputational risk, are commonly linked with, though not restricted to, the erosion of business opportunities, attrition of valued clientele, liquidity challenges, and the costs associated with remedial measures. It is pertinent to recognize that the erosion of business opportunities, attrition of valuable clientele, liquidity challenges, and the expenses incurred in rectification efforts may indeed wield an influence on the financial performance of a bank, thereby potentially impinging upon its assets and capital.

Hence, it becomes evident that the four core banking risks do not exclusively stand as solitary precursors to direct capital losses, profit diminutions, and asset contractions. Further substantiating this perspective, the Basel Committee on Banking Supervision (2009) contends that "Reputational risk can lead to the provision of implicit support, which may give rise to credit, liquidity, market, and legal risk – all of which can have a negative impact on a bank's earnings, liquidity, and capital position".

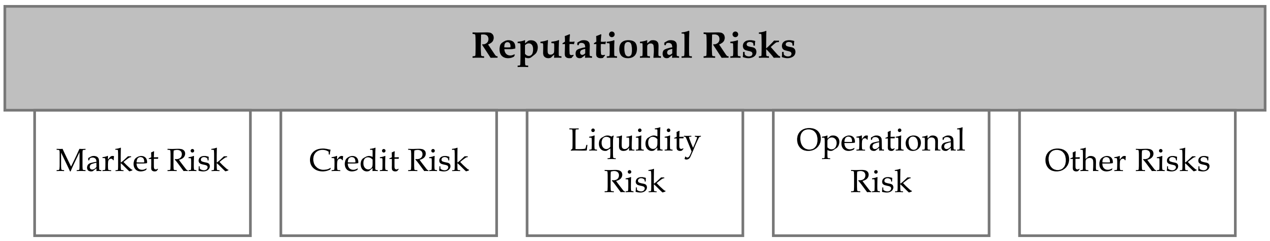
Despite being classified as a non-financial risk, reputational risk seems to exert an implicit influence on a bank's financial performance.

Figure I-3: Impact of nonfinancial risks (Ghosh, 2012)



Highlighting the paramount significance of reputational risk in the financial sector, Soprano et al. (2009) asserted that among the various risks financial institutions face, reputational risk stands out as the most detrimental. These researchers not only emphasize its importance but also illustrate its overarching influence that permeates through all primary banking risks. This conceptual framework is visually depicted in Figure I-4 that follows.

Figure I-4: Reputation risk model (Soprano et al., 2009)



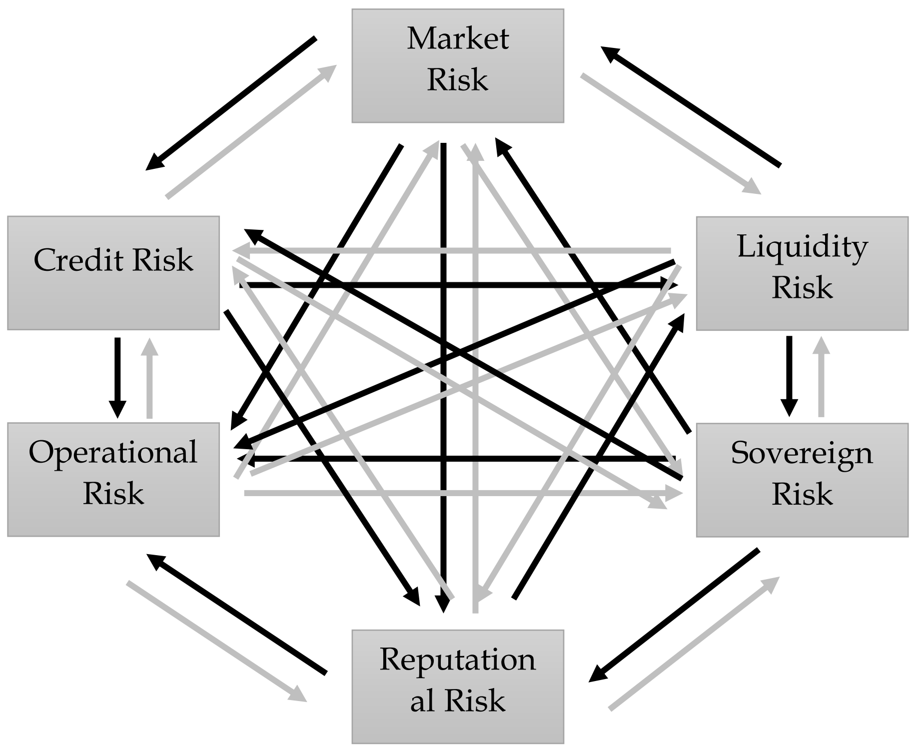
I-1.2. *Financial crises, contagion effect, and reputational risk*

The phenomenon of contagion has been a recurring theme in the examination of financial crises, representing the rapid spread of market disturbances from one segment or country to other regions and sectors. The 2008 global financial crisis (GFC) offered a severe example of contagion in action, as the initial shockwaves originating from the U.S. subprime mortgage market crisis reverberated across global financial markets, affecting economies, asset classes, and financial institutions worldwide (Walter, 2016). The crisis was impaired by the inadequacies in mortgage loan securitization, wherein the failure to adequately hedge against underlying risks highlighted the banks' lack of foresight and contributed to the subprime mortgage crisis. The bankruptcy of Lehman Brothers has been attributed to its substantial exposure to the subprime market (Petersen et al., 2012). The loss of private client funds and the resulting financial impacts led to a significant decline in reputation, especially evident in the case of Lehman Brothers, affecting the entire financial industry (Walter et al., 2013). This created a sense of panic and changed how stakeholders view financial institutions on a global scale (Dowling & Gardberg, 2012; Madhani, 2009).

Though the notion of "reputation" has been a focal point of interest for many years, the global financial crisis especially heightened its relevance, capturing the attention of regulators, banking professionals, and academics. (Fiordelisi et al., 2013; Walter et al., 2013). Empirical analysis by Kottasz & Bennett (2016) unveils the profound and deleterious ramifications of the financial tremors of 2008 upon the reputation of the banking sector in the United Kingdom. Infused with a deep sense of intensity, collective public sentiment rebukes the entire banking realm, attributing infractions, and governance frailties to a broad spectrum, regardless of the variegated levels of involvement in the inception of the crisis.

Figure I-5, as elucidated by Walter et al. (2013), stands as an illustrative schema, depicting the intricate stratification of risks intrinsic to financial intermediaries, delineating six discrete risk domains interconnected through an intricate lattice of thirty-six interconnections. A perceptive observation proffered by the authors outlines that, the upper three risks, encompassing credit, market, and liquidity risks, are more manageable relative to the three risks highlighted at the bottom, which are operational, sovereign, and reputational risks. Within this intricate context, the interwoven dimensions with reputational risk surface as particularly intricate to ascertain and navigate, conferring challenges of profound complexity concerning the realms of assessment and amelioration.

Figure I-5: Hierarchy of banking risks (Walter, 2013)



The crisis has not only brought to the fore the limitations in global banking risk management, but it has also served as a distressing reminder of the intricate interconnectedness of risks that were once regarded in isolation (Aebi et al., 2012). What becomes evident is the potential for any given risk to engender the emergence of other risks. An evident example emerges from the significant surge of depositors, catalyzed by regulatory announcements, fines, or allegations of internal fraud, which could swiftly precipitate liquidity shortages within the bank. This, in turn, may precipitate a potentially drastic decline in asset valuation or even culminate in the bank's collapse. The consequential erosion of trust subsequently sets the stage for a contagion effect that ripples across the broader financial industry (Choudhry, 2018; Walter et al., 2013).

The aftermath of the 2008 upheaval necessitates a prudent recalibration of risk management practices by banks, particularly with respect to the incorporation of reputational risk into their risk management systems, while also comprehending its intricate interplay with other risks (Basel Committee on Banking Supervision, 2009, p. 17).

*I-1.3. **Banking's reputational risk and its sources***

I-1.3.a Defining reputation and reputational risk

The definition of corporate reputation continues to pose a challenge, given the myriad perspectives it encompasses. Barnett et al. (2006) undertook a comprehensive examination of the definitional landscape, cataloging no fewer than 49 distinct sources that proffered insights into the concept of "corporate reputation." Within this purview, the authors spotted a tripartite classification of definitional formulations, demarcating them into three distinct categories: "state of awareness," "assessment," and "asset." They explicated upon the essence of corporate reputation, characterizing it as the "collective judgments of a corporation held by observers," emanating from evaluations of the financial, social, and environmental ramifications attributed to the corporation across temporal dimensions. The premise of this definition stipulates that "corporate reputation" solely attains substance when these collective judgments by observers exhibit a favorable tenor, thereby implying the latent possibility of an adverse outcome, commonly referred to as reputational risk.

The Basel Committee on Banking Supervision (2009) has furnished its own delineation of reputational risk, encapsulating it as the risk stemming from adverse perceptions harbored by customers, counterparties, shareholders, investors, or regulatory entities. These perceptions have the potential to impede a bank's ability to both perpetuate existing and initiate novel business relationships, while concurrently hampering sustained access to essential funding sources, including interbank or securitization markets.

The spectrum of impacts associated with reputational risk, as elucidated by Ghosh (2012), harmoniously resonates with the formulation furnished by the Basel Committee on Banking Supervision (2009), encompassing impediments to the perpetuation or initiation of business relationships, customer disillusionment, and impediments in securing continued funding access.

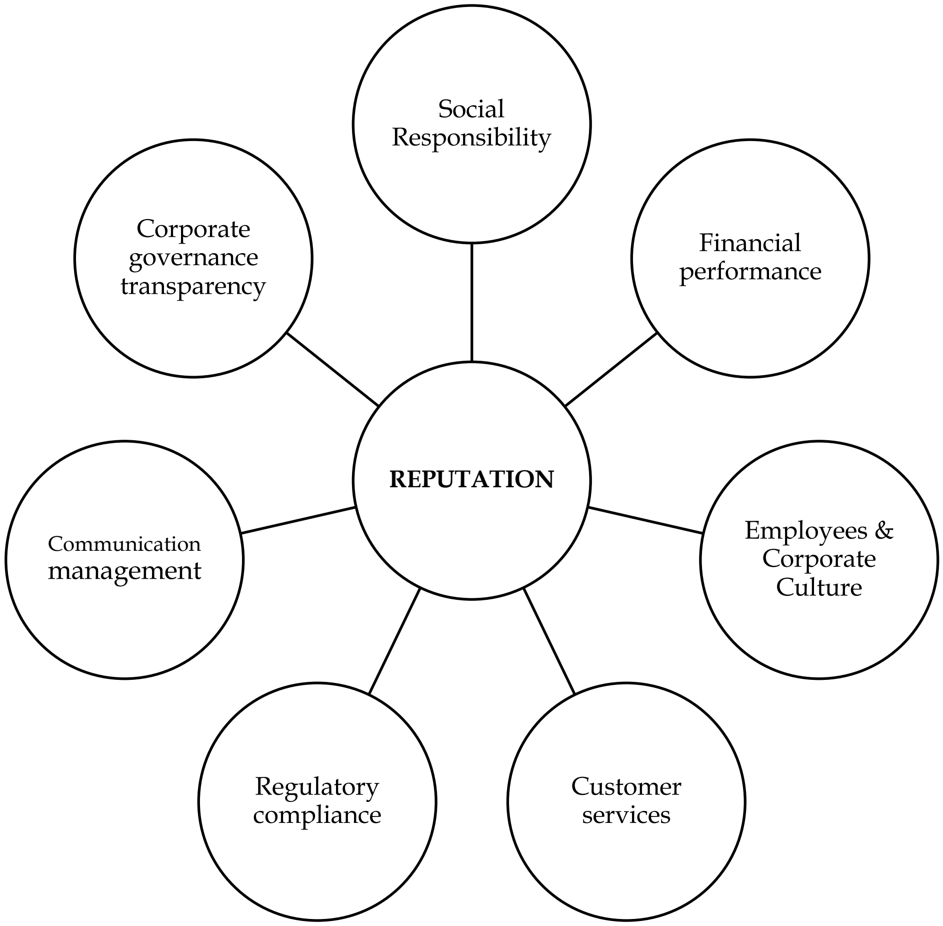
I-1.3.b Origins of reputational risk

The concept of reputational risk has its roots in both corporate governance and crisis management, but it has gained increased prominence in the banking and finance sectors over the past few decades (Fiordelisi et al., 2013; Perry & de Fontnouvelle, 2005). In the banking industry, reputation holds extra weight because it can contribute to systemic risk. This is attributed to information asymmetry, the transformative actions banks take on assets, and their functions in payment and risk management services (Allen & Santomero, 1998; Fiordelisi et al., 2013).

Often perceived as a consequence rather than a standalone risk, reputational risk can emanate from various channels such as operational failures, non-compliance with regulations, ethical lapses, or even negative public perception (Barnett et al., 2006). While the idea of reputation management dates back to ancient civilizations where merchants relied on their standing for business credibility, the modern, institutional understanding of reputational risk solidified with the advent of mass media and, more recently, the digital revolution (Deephouse, 2000; Finlay, 2014; Heidinger & Gatzert, 2018).

Zboron (2006) delineated a compendium of seven plausible origins from which reputational risks can emanate, as depicted in the visual representation provided below in Figure I-6.

Figure I-6: Reputational risks – potential sources (Zboron, 2006)



While Gatzert (2015) appears to tightly associate reputational risk with operational risk, Zboron (2006) yet adopted a broader perspective, encompassing additional variables such as customer experience and financial performance that can potentially erode a company's reputation.

One of the foremost challenges in comprehending reputation (risk) pertains to the diverse array of stakeholder groups involved. Notably, investors and customers do not share homogeneous viewpoints or anticipations. Consequently, they adopt distinct perspectives to evaluate a bank's reputation (Barnett et al., 2006; Barnett & Pollock, 2012; Gatzert, 2015; Gunawardena et al., 2019). The lens used in comprehending reputational risk, therefore, holds considerable significance.

I-1.3.c Banking's reputational risk conceptual frameworks

In a recent study, Adeabah et al. (2022) conducted an exhaustive inquiry akin to Fombrum's (2012) methodology, which entailed the comprehensive cataloging and analysis of a corpus of thirty-five publications spanning the years 2010 to 2020, all focusing on the intricacies of reputational risk within the banking sector. The findings of Adeabah et al. (2022) reveal the emergence of twenty-six distinct research frameworks within the sample literature under scrutiny, encompassing eight theoretical paradigms, six conceptual models, and twelve overarching frameworks. The theoretical underpinnings encompass a spectrum of perspectives, such as the cheap talk theory, theory of behavioral finance, expectancy violation theory, institutional legitimacy theory, pattern recognition theory, theory of blame avoidance, unified theory of reaction in asset markets, and the theory of reputational alignment.

Remarkably, despite a predominant adoption of frameworks across the majority of studies (57%), it becomes evident that each scholarly endeavor adopts a unique conceptual approach toward the understanding and examination of reputational risk. While Fiordelisi et al. (2013) and Fiordelisi et al. (2014) stand as exceptions, both utilizing the "Reputational risks factor-based model," each conceptual framework in the sample is singularly represented by a solitary publication. Eckert & Gatzert (2019) adopt a "portfolio perspective model, Heidinger & Gatzert " (2018) delve into the "reputational awareness-value model," and Gatzert et al. (2016) lean into the "components of risk management" framework. Notably, all these contributions converge on the common objective of delving into the understanding and assessment of reputational risk.

While some of the conceptual avenues toward comprehending bank reputational risk, as spotlighted by Adeabah et al. (2022), may exhibit potential connections with the theoretical framework delineated by Fombrun (2012), it is apparent that a substantive gap persists among the diverse lenses harnessed for the appraisal and understanding of reputational risk. It is noteworthy that a prevailing consensus within scholarly circles acknowledges the central role of Charles Fombrun in the contemporary discourse on reputation. As noted by Gatzert et al. (2016), Fombrun's (1996) publication serves as an indispensable reference for scholars, with their establishment of the journal Corporate Reputation Review (CRR) serving as a vital conduit for the dissemination of a substantial body of research in this domain.

The seminal work of Fombrun (2012) has yielded a collection of seven theoretical frameworks that have indelibly shaped and informed a considerable portion of the discourse within the realm of reputation literature. These frameworks encompass a broad array of perspectives, each contributing to a nuanced comprehension of the multifaceted dimensions that underlie the concept of reputation. Fombrun's theoretical orientations comprise:

1. Institutional Theory: Rooted in the sway of social pressures and the aspiration for legitimation, this theoretical strand delves into the mechanisms through which organizations strive to be recognized as legitimate entities within their societal contexts.

2. Agenda-Setting Theory: This framework pertains to the strategic deployment of mass media to direct public attention toward particular entities or subjects, thus influencing perceptions and priorities.

3. Stakeholders' Theory: Underpinning this theoretical framework is the notion that the outcomes resulting from a company's actions are shaped by diverse stakeholder groups, each possessing a vested interest in the organization's activities.

4. Signaling/Impression Theory: This perspective revolves around the strategic orchestration of corporate communication, lobbying endeavors, and socially conscious initiatives, all aimed at capturing stakeholders' attention and shaping favorable impressions.

5. Identity Theory: An inquiry into the fundamental question of "Who are we?", this theoretical vantage point delves into the core identity of organizations, probing the nuances of self-perception and how it resonates with external stakeholders.

6. Resource-Based Theory: Situated within the parameters of this framework is the notion that specific resources wielded by an organization serve as pivotal conduits for constructing a competitive edge and bolstering reputation.

7. Social Construction Theory: Encompassing a reciprocal interplay between managers and stakeholders, this theoretical framework examines the dynamic process through which notions of reputation are collaboratively constructed and mutually reinforced.

Collectively, these seven theoretical frameworks help understand reputation from different angles and contribute to the grasp of this important concept in the field of organizational studies (Fombrun, 2012).

I-1.4. ***Banking risks and financial performance***

I-1.4.a Reputational risk nexus with operational risks

Although different disciplines have their own lenses for examining reputation, a significant portion of research in the financial sector aims to comprehend reputational risk in the aftermath of operational losses (Eckert & Gatzert, 2017, 2019; Fiordelisi et al., 2013; Gillet et al., 2010; Perry & de Fontnouvelle, 2005). Notably, even though reputational risk is often considered distinct in its impact, it frequently follows operational losses (Eckert & Gatzert, 2017; Ferreira et al., 2016; Soprano et al., 2009). The Basel Committee on Banking Supervision (2017) defines operational risk as “the risk of loss resulting from inadequate or failed internal processes, people and systems or from external events. This definition includes legal risk, but excludes strategic and reputational risk”.

The interplay between reputational risk and operational risk has been the subject of increasing scrutiny in both academic literature and industry practice. While operational risk primarily focuses on the potential for loss resulting from inadequate or failed internal processes, people, and systems, or from external events (Basel Committee on Banking

Supervision, 2011), reputational risk emerges as an amplifying consequence that extends the ramifications of such operational failings (Fiordelisi et al., 2013; Perry & de Fontnouvelle, 2005). For instance, an operational loss event like a data breach could not only lead to financial penalties but also cause significant damage to a bank's reputation, thereby affecting its customer base and market share (Caldwell & Karri, 2005).

Negative perception arises as a result of reputation-damaging events. Most of these events result from operational risk events. They include: "frauds lawsuits, regulatory sanctions, fraudulent earnings, restatements, environmental violations, downsizing, layoffs, negative earnings surprises" (Gatzert, 2015).

Among the myriad of operational losses, internal frauds stand out as particularly insidious, often inflicting profound damage to a bank's reputation. Numerous empirical studies (Biell & Muller, 2013; Fiordelisi et al., 2013; Gillet et al., 2010; Perry & de Fontnouvelle, 2005) have substantiated that the reputational harm arising from internal fraud incidents is significantly more severe than that from other types of operational events. Internal fraud, by its very nature, suggests a breach of trust and integrity within an organization. When employees, who are the custodians of the institution's values and operations, engage in fraudulent activities, it signals a fundamental breakdown in the organization's ethical fabric. This breakdown is not merely a reflection of individual malfeasance but often points to systemic weaknesses that could allow such behavior to go undetected or unaddressed (Office of the Comptroller of the Currency, 2019).

The repercussions of such events are manifold and extend beyond the immediate financial implications. The tarnishing of a company's reputation can lead to a loss of customer confidence, which is far more difficult to quantify and rectify than direct financial loss. Customers and clients begin to question the reliability and safety of their investments and transactions with the institution, which can lead to a withdrawal of funds or the termination of business relationships (Jureviien et al., 2020).

Furthermore, the impact on the company's brand image can deter new customers and partners, potentially stifling growth and market expansion. The cost of internal fraud also includes increased regulatory fines, legal fees, and the expenses involved in implementing corrective measures and strengthening controls to prevent future incidents. Additionally, in the current climate of instant communication and social media, news of internal fraud can spread swiftly and widely, exacerbating the reputational damage (Bălan, 2015; Barakat et al., 2019; Heidinger & Gatzert, 2018). The long-term effects of such reputational damage can be observed in diminished stock prices, loss of competitive advantage, and challenges in attracting quality talent, as prospective employees may be reluctant to associate with a tarnished brand (Singh et al., 2020).

As a result, the reputational losses stemming from internal frauds can often surpass the immediate financial implications, underscoring the critical need for robust internal risk management strategies (Eckert & Gatzert, 2017; Fiordelisi et al., 2013).

Given the pervasive occurrence of operational events globally and especially internal frauds, it becomes imperative to comprehend the ensuing reputational losses and their subsequent influence on financial performance, aiming to enhance risk management practices. Notably, data from the Operational Risk data Exchange Association (ORX), representing a cohort of 100 banks, reveal an aggregate of 383,652 unique operational loss events reported between 2014 and 2019, amounting to an average annual gross loss of EUR24.1 billion (Astill & Basmer, 2020). Evidently, this multitude of losses has the potential to culminate in reputational damages, which may, in turn, exert underappreciated ramifications on the financial performance of banks (Bălan, 2015; Eckert & Gatzert, 2017; Gatzert, 2015). Nonetheless, a limited corpus of scholarship, including the work of Fiordelisi et al. (2013), posits that capital and intangible assets may serve as mitigating factors, ameliorating the extent of reputational damage and thereby reducing the adverse impact on financial performance.

I-1.4.b Assessment of bank's financial performance

Financial performance in banking holds paramount importance not only for the individual bank's stakeholders but also for the larger economy. A bank's financial robustness is directly linked to its ability to weather economic downturns, maintain trust among its depositors, and continue its lending activities, which are pivotal for economic growth and development (Akhigbe & McNulty, 2005). A sound financial footing ensures that banks can effectively play their role in monetary transmission, channeling funds from savers to borrowers, thereby facilitating capital formation and supporting economic activities. Moreover, the financial health of banks is intricately tied to the broader financial system's stability (Basel Committee on Banking Supervision, 2011). Financially weak banks are more susceptible to crises, which can have cascading effects on other financial institutions and the economy at large. Thus, ensuring the strong financial performance of banks is essential not just for their survival, but for the resilience and growth of the entire economy (Berger & Bouwman, 2013; Schaeck & Cihak, 2014).

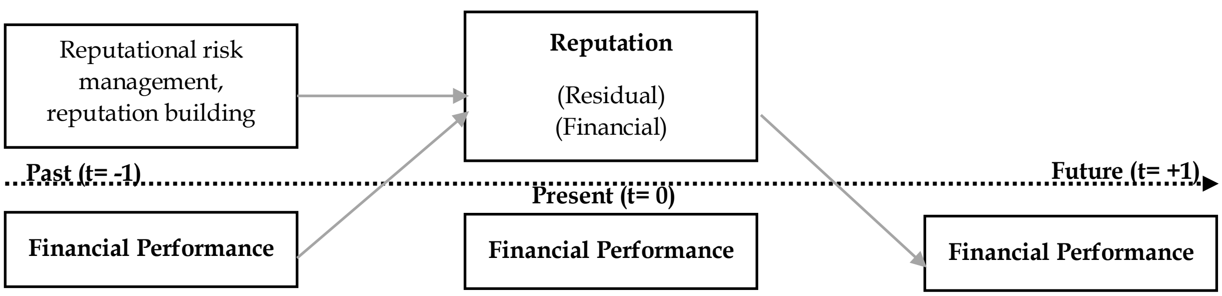
Evaluating the financial standing of commercial and retail banks demands the deployment of precise and meaningful metrics. Foremost among these is the Return on Assets (RoA), a cornerstone measure that illuminates the bank's ability to generate profits from its assets. The preeminence of RoA in banking analyses cannot be overstated: it offers a direct lens into how effectively a bank's management is utilizing its asset base to drive earnings. RoA, in essence, measures the efficiency of the bank's operations in relation to its total assets (Akhigbe & McNulty, 2005; Terraza, 2015). Complementing RoA, other pivotal metrics like Return on Equity (RoE) - which gives insight into the bank's profitability from shareholders' perspectives, Net Interest Margin (NIM) - reflecting the core earnings generated from bank's lending activities, Cost-to-Income Ratio - signifying operational efficiency, and Capital Adequacy Ratio (CAR) - indicating the bank's financial strength and resilience against risks, are all indispensable in painting a comprehensive picture of a bank's financial health (Choudhry, 2018). Together, these metrics form the backbone of rigorous financial analysis in the banking sector, ensuring stakeholders have a clear and holistic understanding of performance, efficiency, and risk (Molyneux et al., 2015).

I-1.4.c Effects of Reputational risk on banks' financial performance

Few scholars have addressed the reputational risk and financial performance nexus in banking (Eberl & Schwaiger, 2005; Heidinger & Gatzert, 2018; Rose & Thomsen, 2004). If it is admitted that reputational damage often results in reduced profitability for the bank (Soprano et al., 2009), the impact might be mitigated when it comes to large corporations. A posited by the resource-based theory (RBT), a robust corporate image or brand name could protect against reputational damage, then against losses in earnings (Fiordelisi et al., 2013; Gillet et al., 2010; Heidinger & Gatzert, 2018).

Bălan (2015) argued that a company's corporate reputation strongly relates to its financial and economic performance. Roberts & Dowling (2002) used a sample of three hundred Fortune ranking firms to investigate the same relationship. Their empirical findings suggested that past reputation management efforts and past financial performance enhance the present and future reputation and financial performance. Figure I-7 below illustrates this relationship.

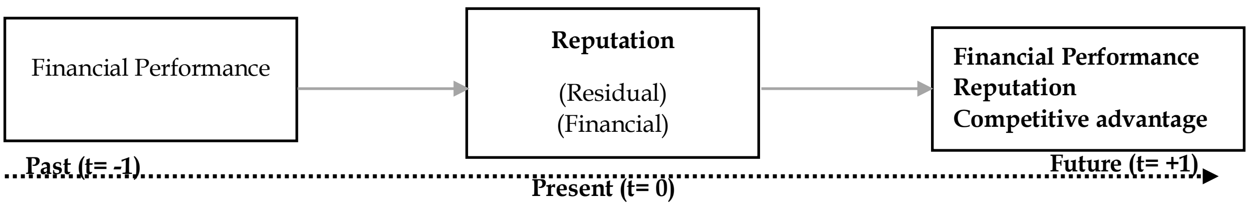
Figure I-7: Effects of Corporate Reputation on financial performance (Roberts & Dowling, 2002)



In an empirical investigation encompassing data from Germany and the US, Raithel & Schwaiger (2015) perceived a constructive linkage between reputation and financial performance. Their findings revealed that an augmented perception of reputation engendered a positive upswing in shareholder value. Conversely, Rose & Thomsen (2004), a decade backward, had articulated an alternate standpoint, contending that financial performance serves as the crucible from which reputation is forged. This reputation, in turn, exerts an influence on future financial performance by amplifying competitive advantage, culminating in an intricate "circular" nexus.

Figure I-8 demonstrates that a firm's financial performance is the starting point of its relationship with corporate reputation. Contrary to Roberts & Dowling (2002), Rose & Thomsen's (2004) research indicates that a company's performance distinguishes it from the public eye, thereby enhancing its corporate reputation and subsequent financial performance. While Roberts & Dowling (2002) propose that corporate reputation originates from a combination of financial performance, reputational risk management, and reputation building, Rose & Thomsen (2004) place greater emphasis on the influence of historical financial performance in cultivating reputation.

Figure I-8: Effects of financial performance on corporate reputation (Adapted from Rose & Thomsen, 2004)



In their empirical study, Heidinger & Gatzert (2018) explored the relationship between reputational risk management and bank performance, using RoA as the dependent variable. However, their findings did not reveal a significant effect of reputational risk management on the bank's RoA. This suggests that the management of reputational risk may not have a substantial impact on the bank's RoA.

Gillet et al., (2010) examined the influence of reputational damage stemming from operational losses on RoA and found a significant relationship. They tested RoA alongside the number of employees (scaled by ten thousand) and found both factors to significantly impact the losses. Interestingly, their findings also indicate that RoA has a varying effect on reputational damage depending on the timing and geographic location. Specifically, more profitable firms in the United States appear to be less affected by an operational loss, whereas, in Europe, these firms experience greater reputational damage on the second and third event dates.

Potentially, it is admitted that there is a central relationship between operational losses, reputational risk, and financial performance. To dissect the dynamic interplay between reputational risk and financial performance, a predominant majority of scholars have undertaken the estimation of reputational losses consequent to operational events using the "event study" approach (Cummins et al., 2006; Fiordelisi et al., 2013, 2014; Gillet et al., 2010; Perry & de Fontnouvelle, 2005).

In a distinct vein, Kravec et al., (2020) undertook a study to assess how reputation affects the performance of commercial banks, employing the expert evaluation approach. The research unfolded in a two-stage process: initially, unstructured (informal) interviews were utilized to identify relevant factors; subsequently, multi-criteria decision-making (MCDM) techniques, including Simple Additive Weighting (SAW), COmplex PRoportional ASsessment (COPRAS), and the geometric mean method, were applied to evaluate these factors. Gunawardena et al. (2019) leveraged the concept of "trust" as a mediating agent between corporate reputation and financial performance. However, the study underscored the imperative of validating the contextual framework of the country and the profile of stakeholders. Gatzert (2015) also introduced "stakeholder behavior" as a mediating factor between reputation and performance.

Furthermore, Fiordelisi et al. (2013) have estimated the reputational loss of 215 operational events (Europe & US) from IBM Algo OpData. The authors suggested that the bank size and profit increase are correlated to a rise in reputational losses. Nevertheless, they found that reputational damage is likely to be minimized by the bank intangible assets and capital. In another study with a larger sample (430 operational events), the authors found reputational losses are not correlated to the size of the operational loss but differ among various event types (Fiordelisi et al., 2014).

I-1.5. *Cases of reputational losses in Banking*

Fiordelisi et al. (2013) found that “a higher level of capital invested and intangible assets reduce the probability of reputational damage”, which means that the size of the bank may serve as a key determinant of reputational risk management. Among the several approaches to sizing a bank, total assets appear to be the most accepted indicator looked at by regulators and academics. Despite its limits, it fully captures the gross nominal volume of a bank's activities (Schildbach, 2017). Many organizations, including Forbes and Standard & Poor's (S&P), categorize banks into different sizes based on their total assets (Horton, 2023; Khan et al., 2023).

It is not uncommon for reports to emerge from around the globe concerning instances of bank failures as a result of potential reputational damage. In the United States, the Federal Deposit Insurance Corporation (FDIC) has documented five instances of bank failure only in the course of 2023 (FDIC, 2023).

In March 2023, Silicon Valley Bank (SVB) was among the banking institutions that experienced a failure. With total assets of US $209 million, SVB is among the most significant financial institutions in the United States. The bank was subjected to a sudden and substantial withdrawal of deposits, amounting to over US $42 million in a single day. This was in response to a liquidity crisis that had a significant impact on the general public's trust and resulted in the largest bank failure since the 2008 financial crisis (French et al., 2023). Similarly, in 2015, in Africa, a comparable scenario was experienced by Chase Bank Kenya (Africa), with smaller size, approximately a decade earlier (Olingo, 2017). Notwithstanding the considerable operational deficit that has had a deleterious effect on its reputation (Corkery, 2016), Wells Fargo Bank has managed to evade a collapse. With different sizes and different locations, the effects of the reputational loss could potentially result in different magnitudes of losses.

I-1.5.a The fall of Chase bank Kenya (Africa)

In 2015, Chase Bank Kenya's total assets amounting to US$1.428 billion (equivalent to KES:142 billion), stood as a prominent banking institution within Kenya. However, a mere rumor that swiftly circulated across social media channels precipitated the rapid downfall of this well-established bank. Despite determined denials from Chase Bank regarding allegations of a missing sum of 15 billion Kenyan shillings (KES) from its financial records, the ensuing massive wave of withdrawals proved unstoppable. The bank urged its customers to disregard the disparaging messages and assured its strength, solidity, and transparency, yet it was placed under receivership in early April 2016 (BBC NEWS, 2016).

Subsequent investigations conducted by the Central Bank of Kenya (CBK) indicated that the bank's collapse was catalyzed by rumors propagated through social media, which triggered an overwhelming rush of depositors (Nyabola, 2019). This panicked exodus of deposits propagated to other banks within Kenya, leading to the failure of twelve banks to adhere to banking regulations, chiefly in terms of breaching the liquidity ratio. Additional concerns were raised among other banks regarding potential violations of prudential guidelines pertaining to capital adequacy. In 2016, a dozen Kenyan banks did not meet regulatory standards for liquidity ratios, following the wave of deposit withdrawals triggered by the fall of mid-tier lender, Chase Bank. This was disclosed in a report by the Central Bank of Kenya (CBK), although the specific banks in question were not identified (Olingo, 2017).

The reputational damage suffered by Chase Bank extended beyond its own operations, turning into a systemic risk that impacted the entire financial landscape in Kenya and sparked a domino effect. Ultimately, the State Bank of Mauritius emerged as the acquirer, securing 75% of Chase Bank Kenya's assets and deposits (Agutu, 2018). This marked the end of a once-powerful banking brand in Kenya with good development prospects. The reputational loss of the bank counts as the main reason for its downfall.

Internal fraud, as evidenced by the case of embezzlement allegations, can severely tarnish a bank's reputation. The repercussions of such allegations are profound and widespread, impacting not just the bank in question but also sending ripples across the broader financial landscape. The mere hint of internal fraud can erode trust, demonstrating the fragile nature of a bank's reputation and the catastrophic consequences when that trust is compromised.

I-1.5.b Wells Fargo Bank: the journey to reputational risk management (USA)

Wells Fargo Bank (WFC) is one of the world's most prominent organizations, among the top three banks in the USA with $1,930.2 billion of total assets in 2016 (Horton, 2023). In its 2016 annual report, WFC argued: "There can be no assurance that continued protests or negative publicity for the Company specifically, or large financial institutions generally will not harm our reputation and adversely affect our business and financial results" (Wells Fargo, 2017). Wells Fargo made that declaration subsequent to an operational loss that inflicted considerable harm upon its reputation. The events unfolded in September 2016 when regulatory authorities imposed a fine of $185 million on Wells Fargo for its involvement in the creation of approximately 2 million fraudulent accounts and cards (Corkery, 2016).

The repercussions of this operational incident reverberated through the bank's reputation, inducing a precipitous decline of over 10% in the value of its stock (WFC) within a mere span of ten days. Influential analysts within the banking domain were quick to characterize the resulting reputational impairment as notably severe (Egan, 2016). Remarkably, as illustrated in Figure I-9, within three months following the incident, the value of WFC stocks rebounded, surpassing the share price that had prevailed prior to the disclosure of the loss (refer to the ensuing trend analysis).

Figure I-9: WFC stock price trend 2016 (Source: macrotrends.net, 2021)

I-1.5.c Comparative examination: Chase Bank Kenya vs. Wells Fargo Bank (US)

The narratives of Chase Bank Kenya and Wells Fargo present a captivating study in contrasts, particularly in the aftermath of operational lapses and allegations of internal fraud. While both institutions faced serious threats to their reputations, their subsequent trajectories were markedly different.

Chase Bank Kenya, once a luminary in the Kenyan banking scene, was toppled by mere rumors, demonstrating the swift and catastrophic power of perceived internal fraud. The bank's inability to counteract the rumors effectively led to an uncontrollable outflow of deposits, pushing the bank into receivership. The repercussions of this event were not only confined to Chase Bank but also echoed throughout Kenya's banking landscape, causing systemic risk and widespread concern.

On the other hand, Wells Fargo, despite its significant operational misconduct, showcased the robustness and resilience often associated with banking giants. The bank weathered a sharp decline in stock value and managed to rebound impressively within a few months. However, even such a recovery was not without its shadows. The 4% dip in net income by the end of 2016, trailed by modest increases over the next two years, prompts in-depth examination. One must probe beyond the surface figures to discern the multifaceted reasons behind this financial trend. Could it be attributed solely to the operational loss? Were external market forces in play? Or, more intriguingly, did the less tangible but potent specter of "reputational loss" play a defining role?

The contrasting impacts of reputational losses observed in Chase Bank Kenya and Wells Fargo highlight the necessity for more thorough research. Questions arise as to why Chase Bank Kenya might have experienced more severe consequences from operational losses. Was it the nature of operational loss, and internal frauds, or did the bank's smaller size fail to provide a sufficient buffer against the reputational damage? Conversely, did Wells Fargo potentially endure less reputational harm due to its larger size or the specific type of operational losses it encountered? These considerations suggest that the nature of the operational event (internal frauds) and the size of the bank are critical factors in assessing the extent of reputational loss.

Furthermore, the situation of Wells Fargo serves as a poignant example. Marked by a rapid decline of over 10% in its stock value (WFC) within just ten days of the incident, followed by a significant rebound within three months, the stock prices even exceeded the pre-disclosure levels. This rebound occurred despite a 4% dip in net income by the end of 2016. This case illustrates the complexity of reputational risk and its impact on financial performance. It highlights that while immediate financial responses, such as stock price fluctuations, are important indicators, they don't always fully encapsulate the long-term effects of reputational damage. This underscores the necessity of considering both immediate and extended impacts when evaluating the consequences of reputational risks in the banking sector.

I-2. Research problem

The exploration of banking research reveals a critical focus on the interconnectedness of reputational risk and bank financial performance. This relationship is pivotal in understanding how banks maintain their market standing and profitability. However, a review of the existing literature reveals a tapestry of divergent findings, creating an overarching sense of uncertainty around key financial behaviors and results. While many scholars' findings (Fiordelisi et al., 2013; Gunawardena et al., 2019; Heidinger & Gatzert, 2018; Kravec et al., 2020) have shed light on various facets of this relationship, the lack of consensus remains striking.

I-2.1. Beyond immediate market reactions: The long-term financial implications

Predominant literature has frequently anchored its assessments on "market reactions" post a reputational event (Fiordelisi et al., 2013; Gillet et al., 2010; Perry & de Fontnouvelle, 2005). While this approach offers immediate insights, it may inadvertently sidestep the enduring and manifold financial ramifications that such events inflict upon a bank's balance sheet.

A notable example of this phenomenon is seen in Wells Fargo's financial performance in 2016. The bank witnessed a 4% decrease in its net income by the year's end, which was potentially a direct consequence of the operational loss and reputational damage incurred (Wells Fargo, 2017). Interestingly, despite an initial plunge in share value following the operational loss, the stock price made a swift recovery, regaining its footing and even surpassing previous levels in a span of less than two months (Egan, 2016). This brisk market response, lasting no more than two months, accentuates the constraints of using stock price recovery as the main metric for assessing the magnitude and aftermath of reputational damage. While immediate market reactions provide valuable insights, they may not always mirror the deeper, long-term financial implications or capture the holistic health of an institution post a reputational debacle. Instances like these underscore the necessity of adopting a more encompassing financial perspective. Within this broader view, RoA emerges as a crucial metric, a sentiment echoed in some reputational risk publications (Gillet et al., 2010; Heidinger & Gatzert, 2018). RoA, with its ability to encapsulate a bank's efficiency in translating assets into profits, becomes indispensable when probing the cascading effects of reputational setbacks on a bank's bottom line. After all, any erosion in reputation can leave lingering traces on end-of-year financials, potentially diluting RoA and signaling deeper systemic concerns (Aebi et al., 2012; Coskun et al., 2019; Walter et al., 2013; Wanjohi et al., 2017).

I-2.2. Reputational risk impact on bank's RoA: Unexplored dynamics

Heidinger & Gatzert (2018) conducted a study focusing on the awareness and management of reputational risk in US and European banks. In their study, they investigated the impact of reputational risk management in banking on RoA. Their findings indicated no significant relationship between these two aspects. However, their research did not delve into the specific effects of reputational risk events on RoA when such events occur. This presents an unexplored area that could yield valuable insights into how reputational incidents directly impact a bank's financial performance.

On the other hand, Gillet et al. (2010) explored the influence of RoA on reputational damage. Their findings revealed a significant relationship, highlighting the impact of financial performance on a bank's reputation. However, like Heidinger & Gatzert (2018), they did not investigate the reverse scenario – the effect of reputational damage on RoA. This leaves a gap in understanding the potential impact of reputational crises on a bank's financial health as measured by RoA.

Furthermore, Gillet et al. (2010) identified that the impact of RoA on reputational damage varies depending on timing and geographical location. This finding suggests that the relationship between financial metrics and reputational risk is complex and influenced by external factors such as time and region.

To comprehensively address the relationship between reputational risk and financial performance, especially RoA, it will be beneficial, if not imperative to investigate the effects of reputational risk events on various financial metrics, rather than solely focusing on how these metrics might influence reputational risk. This approach would provide a more rounded understanding of the causal effects and dynamics between a bank's reputational standing and its financial performance.

I-2.3. Impact of internal frauds on RoA: An uncharted territory

The phenomenon of internal fraud in the banking sector, although recognized for its potential to generate substantial reputational damage, remains less explored in terms of its tangible impact on banks' financial metrics, especially the RoA. Fiordelisi et al. (2011) emphasized the gravity of reputational losses that ensue following the announcements of "pure" operational losses. Within the spectrum of these losses, their research highlighted "fraud" – notably internal frauds – as the leading event type eliciting the most severe reputational harm. However, while the literature does shed light on the immediate repercussions of such events in terms of market reactions and the intangible tarnishing of reputation, there is a glaring absence of empirical analyses connecting these occurrences directly to the bank's financial health as measured by year-end financial metrics like the RoA.

RoA, as a critical metric, represents the efficiency with which a bank utilizes its assets to generate profit (Akhigbe & McNulty, 2005; Molyneux et al., 2015). Thus, understanding the implications of internal fraud events on RoA can offer valuable insights into the deeper, lasting financial impact of these operational incidents. This is pivotal as it moves the conversation from abstract perceptions of damage to concrete financial consequences, providing stakeholders with a clearer understanding of the aftermath of internal frauds on a bank's overall financial health.

Considering the significance of RoA in reflecting a bank's operational success and the potent reputational implications of internal frauds, it becomes imperative to address this gap. Investigating the direct impact of internal frauds on RoA will not only enrich the existing body of knowledge but will also assist banks and regulators in crafting more effective risk management and mitigation strategies.

I-2.4. Gaps in global understanding of reputational risk

The landscape of reputational risk research, predominantly anchored in the U.S. and European banking systems, often exhibits a limited lens. Notably, findings suggest a nuanced distinction in how banks in Europe, compared to their U.S. counterparts, grapple with reputational losses (Cummins et al., 2006; Fiordelisi et al., 2013). Such disparities in outcomes across continents underscore the exigency of expanding the research horizon. However, the majority of existing studies fall short of adopting a holistic, global purview. This narrow focus omits the rich tapestry of market peculiarities, regulatory nuances, and cultural dimensions present in varied geographical regions (Adeabah et al., 2022; Fiordelisi et al., 2013; Gatzert, 2015; Heidinger & Gatzert, 2018; Kravec et al., 2020; Zaby & Pohl, 2019).

A truly comprehensive understanding of reputational risk demands a broader exploration, one that transcends the confines of U.S. and European contexts to embrace and appreciate the multifaceted intricacies of global banking ecosystems. Only through such an expanded vantage can we hope to address and mitigate the challenges posed by reputational risks effectively.

I-2.5. Synthesis of the research problem: comprehending reputational risk

The banking sector's relationship with reputational risk is complex, especially when considering its impact on financial outcomes. Current research offers fragmented insights, leading to key gaps:

- Most studies focus on short-term market reactions to assess reputational damage, overlooking the long-term financial impact on banks. The use of other financial metrics like the RoA – a crucial measure of a bank's profitability – is often neglected.
- Heidinger & Gatzert (2018) and Gillet et al. (2010) made significant contributions to understanding the relationship between reputational risk and RoA, yet notable gaps persist. Heidinger & Gatzert (2018) concentrated on how reputational risk management influences RoA, whereas Gillet et al. (2010) examined RoA's effect on reputational damage. However, neither study delved into how direct reputational events affect RoA, leaving an important aspect unexplored.
- Despite the common understanding that internal frauds lead to more severe reputational damage compared to other operational risks, there seems to be a scarcity of empirical studies explicitly connecting this damage to a bank’s financial health, specifically regarding financial indicators like RoA (Flammer, 2015; Gillet et al., 2010).
- Most research on reputational risk is limited to the U.S. and European banks, ignoring the diverse dynamics of global banking. A wider perspective encompassing different regions is necessary.

In light of the above gaps, the overarching problem statement crystallizes as: ***How can the banking sector, through rigorous empirical research, achieve a more nuanced, holistic,***

and globally inclusive understanding of the multifarious impacts of reputational risk – subsequent to operational events, mainly internal frauds - on its financial performance, specifically concerning the ROA metric? Addressing this quintessential query is pivotal, not just for academic enrichment but for forging robust, informed strategies that shield banks from the turbulent tides of reputational adversities.

I-3. Research aims, objectives, and questions

The focal point of this research was to conduct an empirical investigation into the significance of reputational risk within the global banking sector, with particular emphasis on its correlation with financial performance indicators, mainly the RoA.

The primary aim of this research is twofold:

1. to contribute theoretical insights that deepen the understanding of reputational risk in the banking sector and
2. to set foundations for actionable recommendations that can be universally applied across the industry.

By synthesizing key theories, models, and empirical data, this study addresses the research questions and objectives, providing a comprehensive view of how reputational risk impacts financial performance. The findings and recommendations are framed in such a way that they not only contribute to academic discourse but also serve as a practical guide for banks, regulators, and policymakers. Thus, this research aligns closely with both academic literature and real-world requirements, aiming to make a meaningful impact on the management of reputational risk in commercial and retail banks globally.

I-3.1. *Research aims*

The global research aim is to thoroughly examine the interplay between reputational risk and the financial performance of commercial and retail banks of varying sizes and geographical locations. This investigation seeks to shed light on the enduring consequences and secondary effects on RoA, set against the backdrop of the diverse global banking landscape.

The specific research aims include:

Aim 1: To quantity and assess how the reputational damage, stemming from internal frauds, influences the long-term financial health of banks, with a specific focus on changes in RoA over extended periods.

Aim 2: To examine the relationship between the severity of reputational loss and the size of the bank.

Aim 3: To broaden the scope of existing studies by incorporating diverse banking landscapes outside of the predominant U.S. and European focus.

By achieving these specific aims, the research hopes to offer a holistic view of the implications of reputational risk on the banking sector's financial performance, shedding light on areas previously overshadowed in the literature.

I-3.2. *Research objectives*

The interrelated research objectives are:

Objective 1: To conduct a longitudinal analysis of internal frauds incidents that have damaged the reputation of commercial and retail banks between 2007 and 2016, and to critically examine their subsequent effects on their RoA.

Objective 2: To evaluate how the intensity of reputational losses varies among banks of different sizes, utilizing Pearson correlation analysis.

Objective 3: To compare the magnitude of reputational losses in banks across various global regions, highlighting the financial disparities and commonalities that arise due to regional market dynamics, cultural influences, and regulatory frameworks. This will be achieved through an Analysis of Variance (ANOVA) complemented by a Tukey HSD Post Hoc test.

I-3.3. Research questions

The significance of reputational losses in banks goes beyond mere numbers; it has the power to shape strategies and drive future decisions. To truly understand this complex interplay, it's essential to anchor our inquiries in clear research aims and objectives. Our research questions are designed to align with these aims, ensuring that each inquiry directly contributes to fulfilling our broader objectives. Here are the research questions that will guide our exploration:

Research question 1: How does an internal fraud disclosure affect the RoA of commercial/retail banks as reputational loss in terms of quantifiable monetary value?

Research question 2: How does the size of an operational loss due to internal fraud relate to the quantified monetary value of the subsequent reputational loss?

Research question 3: In what ways might the size of a bank influence the intensity of reputational loss experienced?

Research question 4: How does the impact of reputational losses stemming from internal fraud disclosures differ across banks situated in various global regions?

By systematically addressing these questions, this study aspires to provide a comprehensive perspective on the dynamics of reputational risk and its intricate ties with banking performance across the globe.

I-4. Key findings and research significance

I-4.1.a Key findings

The comprehensive study encompassing four distinct research questions provides a deep dive into the multifaceted relationship between internal fraud disclosures, operational losses intensity, bank size, and regional dynamics in the context of reputational losses within the banking sector.

Research Question 1 focused on the relationship between internal fraud disclosures and the RoA of commercial and retail banks, emphasizing the quantification of reputational loss in monetary terms. This approach diverged from traditional studies that primarily examined immediate market reactions, instead exploring the long-term impact on financial metrics. The empirical evidence revealed an average reputational loss of approximately $442 million following internal fraud disclosures, with a significant number of banks experiencing negative impacts (66%), particularly in subsequent years. The findings, supported by a statistically significant Z value, led to the rejection of the null hypothesis, confirming that affected banks experienced significant deviations in returns (Cummins et al., 2006; Fiordelisi et al., 2013; Gillet et al., 2010; Heidinger & Gatzert, 2018; Perry & de Fontnouvelle, 2005).

Research Question 2 explored the correlation between the magnitude of operational losses due to internal fraud and the subsequent reputational loss. The hypothesis was that larger operational losses might lead to increased media attention and reputational damage. However, the empirical analysis, indicated by a Pearson correlation coefficient of -0.0115, suggested a negligible relationship between these variables. This finding challenges the notion that the size of operational losses is a strong predictor of reputational damage (Cummins et al., 2006; Perry & de Fontnouvelle, 2005), highlighting the complexity of reputational risks and operational losses.

Research Question 3 investigated the link between the intensity of reputational loss and bank size, measured by total assets. Contrary to the Resource-Based Theory's suggestion that larger banks are better shielded against reputational damage (Barney, 1991; Barney

& Clark, 2007), the study found a strong positive correlation between bank size and reputational loss intensity. This indicates that larger banks might face escalating reputational losses as they grow, confirming Fiordelisi et al. (2013) findings that indicated there is a probability of an increase in reputational damage as profit and size increase. The empirical results showed a nuanced scenario where smaller banks experienced more significant reputational damage as their assets decreased, while larger banks also faced increased reputational loss intensity. This highlights the vulnerability of smaller banks and the non-immunity of larger banks to reputational challenges, emphasizing the need for effective reputational risk management strategies across all bank sizes.

Research Question 4 aimed to understand how the impact of reputational losses from internal fraud disclosures varies across global regions. The study filled a gap in existing research by examining regional differences in the banking sector. The empirical analysis, using ANOVA and the Tukey HSD post-hoc test, revealed significant regional variations in reputational loss impacts. For instance, Eastern Asia experienced higher mean reputational losses compared to Central America and Eastern Africa, while Eastern Europe's mean was lower than Eastern Asia's. These findings led to the rejection of the null hypothesis, confirming significant regional differences in the impact of reputational losses (Fiordelisi et al., 2013; Heidinger & Gatzert, 2018). This underscores the importance of a region-specific approach in managing reputational risks in the banking sector.

In summary, the study provides a comprehensive analysis of the complex interplay between internal fraud disclosures, operational losses, bank size, and regional dynamics in the context of reputational losses in the banking sector. The findings highlight the nuanced nature of these relationships and the need for tailored strategies to manage reputational risks effectively. The study's insights are crucial for banking institutions globally, as they navigate the challenges of maintaining financial stability and reputation in an increasingly interconnected and scrutinized financial landscape.

I-4.1.b *Significance of the study*

The significance of this research lies in its multidimensional approach to understanding the complex interplay between reputational risk and financial performance in the banking sector. In an era where reputation is increasingly becoming an intangible yet critical asset, (Ladipo & Adeosun, 2013) there is a growing need for rigorous academic studies that can offer in-depth insights into how reputational risk affects year-end financial metrics like RoA.

Organizational scholars keep questioning the significance of reputational risk and its relationship with financial performance (Bălan, 2015; Eberl & Schwaiger, 2005; Gunawardena et al., 2019; Kravec et al., 2020; Rose & Thomsen, 2004). Globally, there is a lack of empirical data that adequately substantiates the significance of reputational risk in banking (Barnett et al., 2006; Walter, 2016). Walter, 2016 argues that limited theoretical development on reputation is the source of these insufficiencies.

The study's theoretical significance lies in its innovative approach to understanding reputational risk in the banking sector. By focusing on the RoA as a measure of reputational loss, it diverges from traditional analyses that predominantly consider immediate market reactions. This approach enriches the theoretical framework by providing a more comprehensive understanding of the long-term financial impacts of operational events, mainly internal fraud disclosures on banks' financial health. It challenges and extends existing reputational risk theories, particularly those related to the dynamics between operational losses and reputational damage.

Moreover, the global scope of the study adds a new dimension to the theoretical discourse, as it explores the effects of reputational losses across diverse banking systems and regulatory environments. This worldwide perspective contributes to a more nuanced understanding of reputational risk, considering the influence of regional factors. The study's findings also engage with and contribute to the Resource-Based Theory, particularly in the context of how a bank's tangible and intangible assets influence its resilience against reputational challenges.

Practically, the study offers significant insights for both banking institutions and regulatory bodies. Quantifying reputational loss in relation to RoA provides banks with a more tangible metric to assess the impact of internal frauds, guiding them in enhancing their risk management and internal control mechanisms. This approach helps banks in not only addressing the immediate financial implications of fraud but also in understanding and mitigating the broader, long-term reputational impacts.

For regulators, the study underscores the importance of incorporating reputational risk into banking risk management frameworks. It suggests that operational losses due to internal fraud have far-reaching consequences that extend beyond their immediate financial value, advocating for the inclusion of capital charges to account for reputational risks. The reputational loss capital charge suggestion could be formed as an average percentage of the operational loss incurred by the bank. This recommendation could lead to more accurate and comprehensive risk assessments, ultimately contributing to the stability and integrity of the financial system.

Additionally, the study's global perspective is particularly relevant for banks operating in multiple jurisdictions and for international regulatory bodies. It highlights the need for region-specific strategies in managing reputational risks, acknowledging the unique challenges and dynamics of different global regions. This insight is crucial for developing more effective global risk management policies and for fostering a deeper understanding of the interconnected nature of the global financial system.

I-5. Thesis structure

Chapter One, Introduction, lays the groundwork for this study. It commences by addressing the research's contextual background and subsequently pinpoints the existing research gap or problem. This identification serves as the basis for formulating the research's objectives, aims, and questions. Additionally, the chapter delves into the pivotal findings and the broader significance of the undertaken study.

The subsequent sections of the thesis are structured as follows:

- Chapter two provides an in-depth exploration of the Theoretical Framework and Literature Review. It begins by introducing the perspective adopted for evaluating reputational risk. This chapter then proceeds to examine various theories related to reputational risk and assesses empirical evidence. The focus areas include the consequences of reputational harm stemming from internal frauds, approaches to comprehend and evaluate reputational risk, and the effects of reputational damage on financial performance. Additionally, the chapter discusses regional variations in the severity of losses and the relationship between these losses and the size of the banks.

- Chapter three, labeled Research Methodology, delves into the methodological choices made for the study. It elucidates the adoption of the positivist philosophical stance and rationalizes the application of a quantitative approach. This chapter also outlines the research design, encompassing elements such as strategies, time horizons, data sources, variables, analytical techniques, and data management plan.

- Chapter four, titled Empirical Results and Discussions, showcases and critically examines the empirical findings. It starts with descriptive analysis before addressing each research question, and then verifying each of the study’s four hypotheses. An overall summary and discussion of the findings conclude the chapter.

- Chapter five, titled "Conclusions," wraps up the research by detailing the findings related to each research question. It attempts to align these outcomes with the existing literature, pointing out both disparities and commonalities. This chapter emphasizes the theoretical and practical contributions derived from the study. Additionally, it addresses the strengths and limitations of the research and provides essential recommendations for future studies in this field.

II. THEORETICAL FRAMEWORK AND LITERATURE REVIEW

"In a market system based on trust, reputation has a significant economic value"

Alan Greenspan

This chapter begins by laying out the theoretical underpinnings of reputational risk, followed by an exploration of its historical context within the banking sector. Building on this theoretical base, the framework for the study is outlined. The chapter then delves into theories and reviews empirical evidence, focusing on topics such as the aftermath of reputational damage caused by internal frauds, methods for understanding and assessing reputational risk, and the impact of reputational damage on financial performance. Regional differences in the intensity of losses and how theses losses correlate with the size of the banks are also discussed. The chapter concludes with a summary of the literature review and an identification of the gaps in existing research.

II-1. Theoretical foundations of reputational risk

Reputational risk is grounded in the corporate reputation literature. Various disciplinary viewpoints have been employed to comprehend corporate reputation. Fombrun (2012) highlighted seven major theoretical frameworks that have significantly shaped the landscape of reputation literature. These include institutional theory, agenda-setting theory, stakeholders' theory, signaling/impression theory, identity theory, social construction theory, and resource-based theory. Similarly, Walker (2010) found that institutional theory, resource-based theory, and signaling theory were the most prevalent among the utilized theories.

Feldman et al. (2014) outlined diverse perspectives like "institutional theory, financial theory, economic theory, organizational behavior theory," among others. Notably, they emphasized "signaling theory, strategy theory, and the resource-based value theory" as the most frequently referenced ones.

II-1.1. Institutional theory

“Institutional theory is a theoretical framework for analyzing social (particularly organizational) phenomena, which views the social world as significantly comprised of institutions – enduring rules, practices, and structures that set conditions on action.” (Lawrence & Shadnam, 2008). Organizations attempt to build their legitimacy by abiding by the most established institutional rules. These organizations are regarded as conforming to the social order and consequently gain social support that enhances their legitimacy, performance, and reputation (Suchman, 1995). The institutional theory states that a firm that conforms to the context in which it is operating, following the existing norms and regulations, becomes more prosperous and mitigates reputational losses (Meyer & Rowan, 1977).

With the institutional theoretical framework, organizations are driven by social pressure as they do not want to be found violating social norms and regulations while being able to continuously develop their competitive advantage (Fombrun, 2012). In this context, stakeholders view the firm favorably. The firm then uses the proven legitimacy to attract more customers, and increase its performances and reputation (Fombrun, 2012; Meyer & Rowan, 1977).

II-1.2. *Agenda-setting theory*

Agenda-setting theory assumes a significant mass-media influence over the general public discussion and attention. It stands that the general public forms its opinion about a firm based on what the media are disseminating (Carroll & McCombs, 2003; Wartick, 2002). The media play a central role in the community and particularly in the process of creating corporate reputation. In fact, media control the information and technologies of dissemination. Informing the large audience about events and issues shapes the way people see the world and influences stakeholders' image of organizations (Deephouse, 2000).

Consequently, organizations that are frequently present in media are likely to increase brand awareness, trial, and eventually loyalty. This helps the brand remain in the minds of customers and the general public. The more favorable the media coverage is, the more stakeholders assess positively the organization. Also, the more specific characteristics of a company are underlined by the media, the more the general public connects them to the organization's corporate identity (Carroll & McCombs, 2003; Deephouse, 2000).

II-1.3. ***Stakeholders' theory***

Stakeholders' theory looks at the groups of individuals directly or indirectly involved in the organization's operations. Stakeholders are then the target groups of the firm communications or actions to increase revenue, and profit and attract resources (Fombrun, 2012). Many scholars have attempted to define corporate reputation in the stakeholders' perspective. Barnett et al. (2006, p. 30) defined corporate reputation as: "Observers' collective judgments of a corporation based on assessments of the financial, social, and environmental impacts attributed to the corporation over time." Basel Committee on Banking Supervision (2009, p. 19) defined "reputational risk as the risk arising from negative perception on the part of customers, counterparties, shareholders, investors or regulators that can adversely affect a bank's ability to maintain existing, or establish new, business relationships and continued access to sources of funding (e.g. through the interbank or securitization markets)". Stakeholders, in this theoretical view, are pivotal for an organization to build a competitive advantage and mitigate reputational risk. The confusion arises from the variety of views from different types of stakeholders. For example, customers' perception differs from investors' perception, suppliers' views are not the same as the ones of the shareholders and the same for the regulators. As such, an organization may have quite a lot of reputations instead of only one. Consequently, in the stakeholders' theory, reputation is a collective and multidimensional construct. Stakeholders are separated into two (02) major groups. Employees and investors are considered primary stakeholders as they have a direct influence over the firm while the other stakeholders are viewed as secondary (Fombrun, 2012).

II-1.4. *Signaling theory*

The signaling theory was formulated primarily to reduce information asymmetries in the labor market. Job applicants utilize their educational background as a means of signaling their skills to potential employers (Spence, 1973). In their study, Connelly et al. (2011) delineated a signaling timeline that typically involves a "signaler" and a "receiver." The "signaler" transmits a signal to the "receiver," who observes and interprets the signal and responds. In the context of corporate reputation, signals may be intentionally crafted by an organization to align with its anticipated return on investment. A recent bibliographic network analysis of keywords by Connely et al. (2024) showed that "reputation" is among the top three major themes within the signaling research, along with "corporate governance" and "human capital". This further reinforces the importance of this theory in reputational studies.

The organization made efforts to influence its stakeholders' groups and seek their support for its projects (Fombrun, 2012). The efforts are regarded as strategic signals or impressions and include corporate communication, sales promotions, lobbying, sponsoring, and social activities. These signals or impressions are then marketing communications to stakeholders' groups to recommend them with the expected perceived firm value (Deephouse, 2000). On the other hand, stakeholders eventually consider a set of signals from the organization to form their assumptions about the firm position on the market, and consequently shape the perceived corporate reputation (Basdeo et al., 2006).

II-1.5. *Identity theory*

Identity theory examines the interconnections between individuals' roles, self-concepts, and social behaviors, emphasizing how identities influence and are influenced by social interactions. Rooted in symbolic interactionism, identity theory proposes that individuals internalize role expectations associated with social positions, which guide behavior to maintain consistency with those roles (Stryker & Burke, 2000). Over time, organizations develop attributes that are specific to them, and which eventually distinguish them from their competitors in the market, or just stand them out in their community (Leiva et al., 2016). Attributes are specific, stable, coherent, and genuinely identifiable characteristics giving a clear answer to the question: “Who I am” (Fombrun, 2012). The organization's identity is reflected in how employees and executives behave, the corporate values and set of beliefs, vision, and mission, and the organizational structure, practices, processes, and procedures, that are broadly considered central in the firm (Ashforth & Mael, 1989). In the Identity view, these characteristics help the organization build a better reputation.

II-1.6. *Social construction theory*

The reputational concept as a social construct is less cited in the literature and is a more sophisticated view where organizations and all their stakeholders “co-create shared understandings of their respective roles and involvements as they participate in social and informational exchange” (Fombrun, 2012; Schwaiger, 2004). Fombrun (2012) identified five (05) characteristics of interpretations in the relational exchange: "(1) a widespread exchange of information and interpretations among firms and constituents; (2) varying degrees of knowledge and understanding about the industry and the firms inside it; (3) a multiplicity of interpretations, many of which are of a persuasive, self-serving nature; (4) some degree of agreement about standards of performance in an industry; and (5) evaluations of firms relative to these standards and their rivals that give content to their reputations".

Empirical studies demonstrated the social construction (socio-cognitive) perspective enables a good understanding of the way reputation is created or damaged from the processes key stakeholders use to assess a company (Kravec et al., 2020; Mpofu, 2019; Zaby & Pohl, 2019). Both the organization and all its stakeholders participate in a social and informational exchange which reflects on its overall reputation.

II-1.7. *Resource-based theory (RBT)*

At an early stage of Resource-based theory, Wernerfelt (1984) suggested the "resource-based view", theorizing competitive advantage using the resources a firm involves in developing a market strategy. Other streams of competitive advantage research were developing theories that were strongly related to the resource-based perspective: "theory of invisible assets" and "competence-based theories of corporate diversification" are among the most significant streams (Barney & Clark, 2007). The resources that are foundational for the competitive advantage can be classified into four (4) broad categories: (1) "physical capital resources" cover the tangibles assets, the geographical location, and raw materials access of the organization; (2) "financial capital resources" include the organization's income, equity and debts; (3) "Human capital resources" comprise the background, experience and skills of employees and executive board of the organization; "Organizational capital resources" include organization's key attributes that stand it out in the marketplace (Barney & Clark, 2007).

RBT stretches out to identify the most relevant resources for an organization to build a robust and durable competitive advantage in its business sector (Barney, 1991). RBT investigates reputation as the origin of sustained competitive advantage for its value and scarcity (Walker, 2010). From an RBT theoretical view, "reputation is a valuable and rare intangible resource because it is difficult to imitate and highly causally ambiguous, which in turn, leads to a sustained competitive advantage" (Deephouse, 2000; Roberts & Dowling, 2002; Walker, 2010). It is easier for an organization to outperform its competitors when it has valuable and unique resources.

Resource-based theory is referred to as one of the most prominent lenses to assess corporate reputation (Barney & Clark, 2007; Feldman et al., 2014; Walker, 2010; Wernerfelt, 1984).

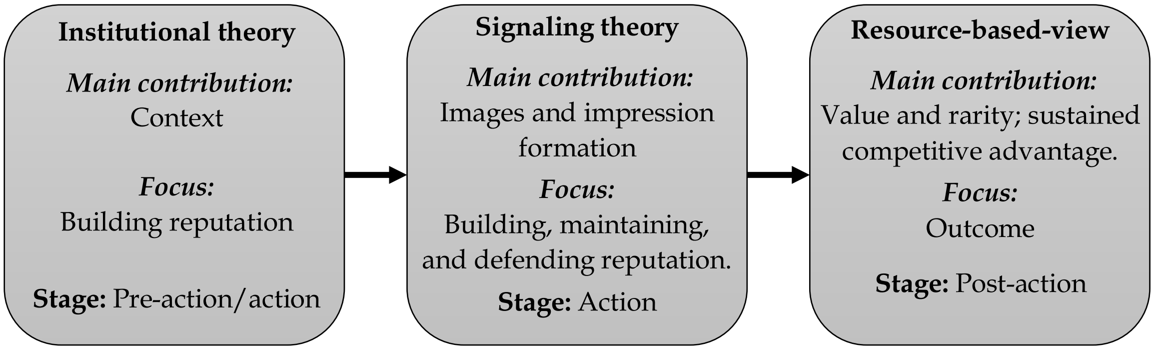
II-2. Historical perspective on reputational risk in banking

Reputational risk in banking has been a subject of theoretical exploration, particularly in understanding its origins, impacts, and management strategies. The theoretical perspectives on reputational risk in banking have evolved over time, reflecting the changing dynamics of the banking industry and the broader economic environment (Fiordelisi et al., 2013, 2014; Gatzert et al., 2016; Heidinger & Gatzert, 2018; Trostianska & Semencha, 2019; Walter, 2016; Zaby & Pohl, 2019). Yet, the field of reputational risk within the banking sector remains underdeveloped. It largely leans on a global understanding of corporate reputation, whereas a more comprehensive body of literature exists for non-financial industries (Fiordelisi et al., 2013).

From a global perspective, Walker (2010) conducted a comprehensive review of reputation literature covering over twenty-seven years (1980-2006) of publication in multiple management disciplines. The final sample of 54 journal articles consists of the most cited and high-quality papers, from the most relevant scholarly journals. From all the theories used in the literature, the author created an analysis model to focus on the three most prominent: institutional theory (used in five papers) resource-based theory – RBV (used in five papers) and signaling theory (used in three papers).

Walker (2010) classified these three main theories according to the relevant stage. The author presented the stages moving from pre-action to post-action as illustrated in Figure II-1.

Figure II-1: Pre-action to post-action of reputation (Walker, 2010)



Walker (2010) posits that "institutional theory" is at the first stage (pre-action), contributing to the context of reputation by focusing on building reputation. In contrast, "signaling theory" (stage two: Action) pertains to the creation of images and impressions with an emphasis on constructing, sustaining, and safeguarding reputation based on the most desirable corporate image. According to this view, "signaling theory" is applicable to corporate reputation as it elucidates how a company's strategic decisions serve as signals, which stakeholders then interpret to form opinions about the company (Basdeo et al., 2006; Fombrun, 1996; Walker, 2010).

Conversely, the "resource-based theory," which characterizes the final stage (post-action), concentrates on the outcomes of reputation management. This theory significantly contributes to comprehending and evaluating reputation as a valuable intangible asset that generates a competitive advantage leading to enhanced financial performance (Deephouse, 2000; Roberts & Dowling, 2002).

While the three prominent theories previously discussed address reputation from a broad, global standpoint, the financial industry has seen the emergence of a few specialized theoretical perspectives. In a systematic literature review, Adeabah et al. (2022) examined research on reputational risk within the banking sector, reviewing thirty-five papers published from 2010 to 2020. The authors presented a distinctive, if not unique, exploration of the theoretical frameworks surrounding reputational risk in the banking industry. Their findings, however, reveal a lack of consensus in the field, as each theory, model, or framework identified is typically represented by a single paper. This diversity highlights that scholars often approach reputational risk from their individual perspectives. Notably, their "Unified Theory of Reaction in Assets Market" has garnered considerable attention from researchers (Cummins et al., 2006; Fiordelisi et al., 2013, 2014; Gatzert, 2015; Gillet et al., 2010; Heidinger & Gatzert, 2018; Perry & de Fontnouvelle, 2005), a point that seems underrepresented in Adeabah et al.'s classification. For instance, they categorize the works of Fiordelisi et al. (2013) and (Fiordelisi et al., 2014) under the "Factor-Based Model". However, these studies also delve into the market's reaction to reputational damage, suggesting a closer alignment with the "Unified Theory of Reaction in Assets Market" than Adeabah et al. (2022) initially suggest. This discrepancy underscores the complexity and multifaceted nature of reputational risk research in the banking sector, indicating a field that is still evolving and open to diverse interpretations and methodologies. Table II-1 presents a summary of the theoretical approaches.

Table II-1: Summary of reputational risk theoretical approaches (Adeabah et al., 2022, summary)

No	Theories	Definition
1	Cheap Talk Theory	This theory is used to understand how banks communicate and manage information, especially in situations where their actions might not align with their words.
2	Theory of Behavioral Finance	This theory examines how psychological influences and biases affect the financial behaviors of individuals and institutions, including banks
3	Expectancy Violation Theory	This theory is employed to study the effects of operational risk announcements by banks and how these announcements violate or meet stakeholders' expectations
4	Institutional Legitimacy Theory	This theory is used to understand how banks maintain legitimacy in the eyes of stakeholders, especially after reputational damage
5	Pattern Recognition Theory	This theory helps in identifying patterns in reputational risk events and their impacts.
6	Theory of Reputational Alignment	This theory focuses on aligning a bank's reputation with its stakeholders' expectations and perceptions
7	Unified Theory of Reaction in Assets Market	This theory is used to understand market reactions to reputational risk events in banks

Adeabah et al. (2022) also identified their study a range of conceptual models and frameworks pertinent to reputational risk research, as summarized in Table II-2:

Table II-2: Summary of reputational risk conceptual models and frameworks (Adeabah et al., 2022)

No	Conceptual models	Definition
1	Stakeholder Reputation Score Model	This model is used for quantifying a bank's reputation among its stakeholders.
2	Reputational Risks Factor-Based Model	This model helps in identifying and analyzing various factors contributing to reputational risk
3	Reputational Index Point Model	This model is used for measuring a bank's reputation at a given point in time
4	Portfolio Perspective Model	This model views reputational risk as part of a bank's overall risk portfolio
5	Information Asymmetry Hypothesis	This hypothesis is used to understand how information asymmetry between banks and their stakeholders can lead to reputational risks
6	Reputational Awareness-Value Model	This model emphasizes the importance of awareness and valuation of reputation in risk management

Adeabah et al. (2022) also point out several areas that require further attention in reputational risk research, such as the need for more explicit theoretical frameworks specifically addressing reputational risk in banks and the exploration of reputational risk from a global perspective.

II-3. Study's theoretical framework

Reputational risk has been most assessed in the wake of operational loss events researchers (Cummins et al., 2006; Fiordelisi et al., 2013, 2014; Gatzert, 2015; Gillet et al., 2010; Heidinger & Gatzert, 2018; Perry & de Fontnouvelle, 2005), and echoes the post-action perspective outlined by Walker (2010) in Resource-Based Theory. This research angle primarily considers the financial impacts following reputational damage, reflecting an approach where RBT posits that a firm's tangible and intangible assets contribute to competitive advantage and potentially mitigate reputational harm. This viewpoint underscores the aftermath and resilience factors in reputational risk as per the RBT framework.

The Resource-Based Theory (RBT) then offers a robust framework for analyzing how a bank's internal resources and capabilities can influence its competitive advantage and performance. In the context of reputational risk, RBT is particularly relevant as it emphasizes the role of intangible assets, of which reputation is a critical component. In the banking industry, where the relationship is based on trust, reputation is seen as one of its most important intangible assets. Indeed, scholars have provided empirical evidence about the role of resources (intangible assets and capital) against banking's reputational damage (Fiordelisi et al., 2013; Gunawardena et al., 2019; Heidinger & Gatzert, 2018; Walter, 2016). Banks with strong reputational capital are often seen as more trustworthy and reliable, which can lead to competitive advantages such as customer loyalty, lower cost of capital, and resilience in times of crisis. Also, the adequate integration of tangible and intangible resources helps build competitive advantage, prevent loss in value, and foster financial performance (Barney, 1991; Wernerfelt, 1984).

This study aims to evaluate the impact of reputational risk on the financial performance of commercial and retail banks. Given that a comprehensive evaluation of sustained competitive advantage necessitates a longitudinal approach, theories lacking this aspect would be inadequate for assessing the impact of reputational risk on financial performance (Barney & Clark, 2007). Notably, among the three major theories discussed, only the resource-based theory has been used in longitudinal studies. This theory has consistently been employed as the exclusive approach to investigating profitability across reputation literature, as observed in Walke's (2010) sample.

Additionally, Walker (2010) found that studies successfully incorporating all the reputational attributes outlined in his research were those employing the resource-based theory. This was not the case for the other theories. Consequently, the resource-based theory emerges as a suitable approach for research on reputational risk. Noteworthy studies that investigate the reputational risk from a resource perspective within the banking sector include Fiordelisi et al. (2013), Gillet et al. (2010), and Roberts & Dowling (2002).

In contrast to institutional theory and signaling theory, the resource-based Theory (RBT) appears to be the most appropriate theoretical framework for reputation research, as well as for the present study's exploration of the impact of reputational risk on the financial performance of commercial and retail banks. Its holistic perspective, emphasis on sustainable competitive advantage, and applicability in longitudinal studies make it an ideal choice for delving into the intricate relationship between reputation and financial outcomes in the banking sector (Walker, 2010). The RBT also offers a perspective that goes beyond mere short-term gains. It acknowledges that a bank’s reputation is not solely built on immediate actions but on a collection of valuable and rare resources that contribute to its competitive position. This resonates with the need to evaluate the long-term implications of reputational risk on financial performance, which is a core focus of our research.

Moreover, RBT applicability in longitudinal studies provides the depth necessary to capture the dynamics of reputational risk and its effects on financial performance over extended periods. Longitudinal approaches allow for the identification of trends, patterns, and causal relationships that might not be evident in shorter-term studies, further reinforcing the significance of this theory for our study's objectives (Easterby-Smith et al., 2015).

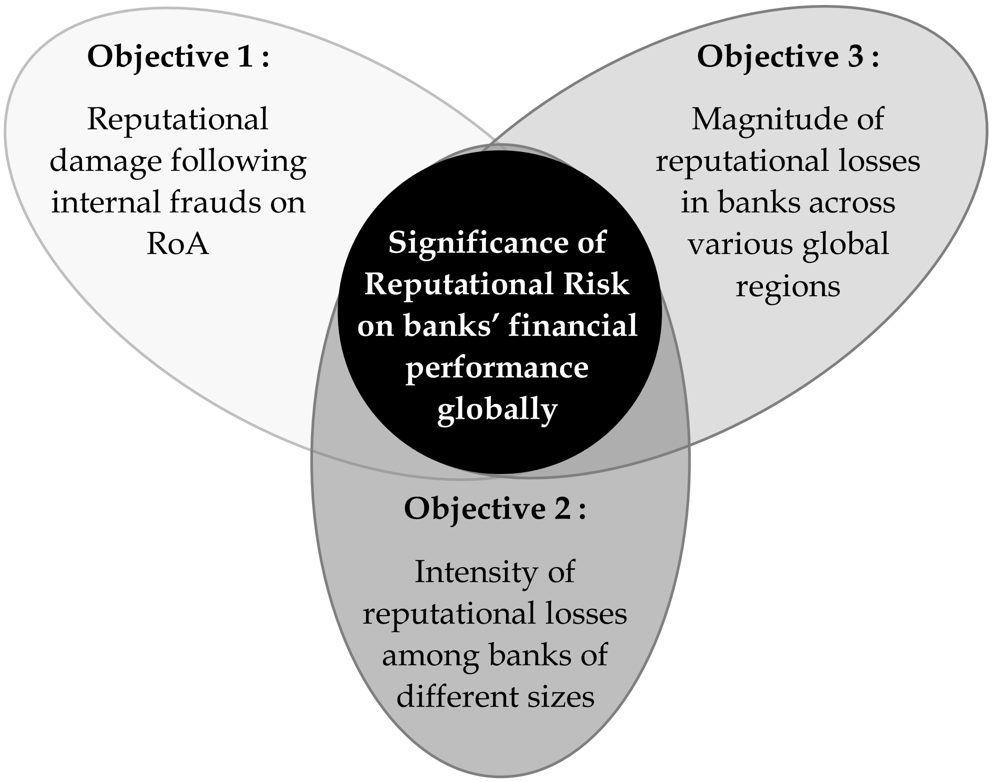
By applying RBT, this research can explore how the intrinsic resources of a bank, notably its reputation, contribute to its ability to manage and mitigate reputational risks in the aftermath of operational losses. This theory allows for a deeper understanding of how banks can leverage their internal strengths to protect and enhance their reputation, thereby ensuring long-term sustainability and profitability.

Consistent with previous studies, the Unified Theory of Reaction in Assets Market, provides a valuable lens for examining how operational risk incidents such as internal fraud, impact a bank's market valuation and investor perceptions (Cummins et al., 2006; Fiordelisi et al., 2013, 2014; Gillet et al., 2010). This theory is particularly pertinent in understanding the immediate and observable effects of reputational damage on a bank's financial performance, as reflected in its asset prices and market behavior. By incorporating this theory, the research can dissect the dynamics of market reactions to reputational events, offering insights into how these reactions affect the bank's financial performance, especially the RoA across different banks, sizes, and regions. This perspective is crucial for comprehending the broader financial implications of reputational risk and for developing strategies that can mitigate the adverse effects of such risks on a bank's market standing.

Together, the Resource-Based Theory and the Unified Theory of Reaction in Assets Market provide a comprehensive theoretical framework for this research. RBT allows for an in-depth exploration of the internal mechanisms through which banks can build and maintain reputational capital, while the Unified Theory offers a macro view of how reputational events influence market perceptions and financial outcomes. This dual-theoretical approach enables a holistic understanding of reputational risk in the banking sector, encompassing both the internal resource-based capabilities of banks and the external market reactions to reputational events. This synergy of theories is instrumental in developing a nuanced and multi-dimensional understanding of reputational risk, making it a well-justified choice for the theoretical foundation of this research.

Adopting the RBT and the Unified Theory of Reaction in Assets Market as the theoretical framework, the study addressed global research aim as follows:

Figure II-2: Study's framework to assess the significance of reputational risk on financial performance.



As applied to the study, the chosen framework holds that:

1. A bank's tangible and intangible assets help the bank build a competitive advantage and serve as a buffer against reputational losses (Barney, 1991; Barney & Clark, 2007; Fombrun, 2012). On the other hand, a good reputation built on resources may foster financial performance (Rose & Thomsen, 2004). The rationale behind this expectation is that the bank's tangible and intangible assets may influence its financial performance (Heidinger & Gatzert, 2018). The subsequent favorable perception and adoption will create a robust competitive advantage mitigating reputational risk because the bank's resources favor a positive interpretation from the stakeholders.

2. There is a discernible and immediate market reaction following the disclosure of operational losses. This reaction is not merely confined to the direct financial implications of the loss itself but extends to encompass the broader, more nuanced aspects of the bank's overall health. It encompasses a significant reputational component, which, although intangible, has tangible consequences on the bank's

market valuation, and financial metrics like the RoA. This reputational loss is a distinct and measurable entity, separate from the direct financial loss.

The definition of reputational risk for the present study is the Basel Committee on Banking Supervision (2009) understanding as "the risk arising from negative perception on the part of customers, counterparties, shareholders, investors, or regulators that can adversely affect a bank's ability to maintain existing or establish new business relationships and continued access to sources of funding (e.g., through the interbank or securitization markets)."

Also, the study, following the Basel Committee on Banking Supervision definitions, considers reputational risk as a distinct risk in the context it follows an operational risk. In fact, the Basel Committee on Banking Supervision (2017) defined operational risk as "the risk of loss resulting from inadequate or failed internal processes, people and systems or from external events. This definition includes legal risk, but excludes strategic and reputational risk".

II-4. Reputational risk consequences of internal frauds

Reputational risk in the banking sector, particularly in the context of internal frauds, is intricately linked to operational risk (Gatzert, 2015; Gillet et al., 2010). Operational risk, as defined by the Basel II Framework, encompasses the risk of loss resulting from inadequate or failed internal processes, people, and systems, or from external events. This definition, however, explicitly excludes strategic and reputational risks (Basel Committee on Banking Supervision, 2011). Despite this exclusion, reputational risks often emerge as a direct consequence of operational risks, especially in cases involving internal frauds.

"Internal fraud occurs when a director, an employee, a former employee, or a third party engaged by the bank commits fraud, colludes to commit fraud, or otherwise enables or contributes to fraud" (Office of the Comptroller of the Currency, 2019). When disclosed, the reputation of the bank is questioned by various stakeholders and may result in adverse financial outcomes (Gillet et al., 2010).

Empirical studies in the field have been instrumental in shedding light on the consequences of reputational losses stemming from internal frauds, offering valuable insights that are particularly distinct when compared to other types of operational risks:

- **Magnitude of Reputational Losses:** Empirical research consistently demonstrates that reputational losses can substantially surpass the initial operational losses. For instance, studies have shown that internal fraud events can significantly increase their share of total mean loss when reputational losses are considered (Fiordelisi et al., 2014; Perry & de Fontnouvelle, 2005).
- **Distribution of Losses:** The inclusion of reputational losses alters the distribution of losses among different operational risk event types. Internal and external fraud events, in particular, become more prominent in terms of total losses, underscoring their critical importance in risk management (Gillet et al., 2010).
- **Severity of Reputational Losses:** The severity of reputational losses is often correlated with the size of the operational loss. Larger operational losses are more likely to lead to significant reputational damage, highlighting the need for effective measures to mitigate large-scale operational risks (Cummins et al., 2006).
- **Risk Management Implications:** Empirical findings suggest that risk management strategies should particularly focus on preventing and mitigating internal and external fraud events due to their substantial impact on reputational losses. This includes implementing robust risk measures and conducting integrated scenario and sensitivity analyses (Heidinger & Gatzert, 2018).

Despite the limited theoretical perspective on reputational losses due to internal frauds in banking, the empirical evidence highlights the complex and multifaceted nature of reputational risk. These perspectives underscore the importance of integrating reputational risk considerations into the broader operational risk management framework. A common theme in the literature is the challenge of data availability and the need for more research in this area. Many studies are based on limited samples and there is no primary focus on internal fraud events, indicating a gap in the literature that future research could address (Fiordelisi et al., 2013). This theoretical foundation is essential for developing effective strategies to manage and mitigate reputational risks in the banking sector.

II-5. Awareness, assessment, and management of reputational risk

II-5.1. Awareness of reputational risk

Reputation is seen as a strategic asset (Ladipo & Adeosun, 2013). Awareness of reputational risk, therefore, becomes a crucial starting point for strategic resource allocation in banks (Barney, 1991). The 2008 global financial crisis served as a watershed moment for the banking sector, marking a paradigm shift in the awareness and management of reputational risk. Post-crisis, there has been a noticeable shift towards increased awareness of reputational risks.

Theories of organizational learning and adaptation, such as the "Punctuated Equilibrium Model," support the idea that major crises can stimulate rapid learning and change (Romanelli & Tushman, 1994). In the banking sector, the 2008 crisis acted as such a punctuation mark, leading to an evolution in reputational risk awareness and management strategies. The crisis led banks to reconsider their business models, ethical frameworks, and risk assessment processes, among other elements, to protect and rebuild their reputational capital (Walter, 2016). As a matter of fact, Heidinger & Gatzert (2018) conducted a text-mining analysis of annual reports from 2006 to 2015 and found a more than threefold increase in the use of terms like "reputation," "reputational risk," and "reputational risk management." This trend indicates an increasing emphasis and awareness of reputational issues, which is likely a direct aftermath of the experiences of the 2008 financial crisis. Moreover, their study indicates that not only did the frequency of mentions increase in absolute terms, but also relative to the total number of words in these reports. This points to a genuine growth in awareness and not just an artifact of longer annual reports. It's essential to note that this trend was more pronounced in larger firms and those located in Europe, suggesting that certain segments of the banking industry may be more attuned to reputational risks.

Further empirical work by Fiordelisi et al. (2013a) reinforces the growing attention to reputational risk by linking bank size and profitability to reputational damage, adding another layer of urgency for large and profitable banks to be acutely aware of such risks in the post-crisis environment. Walter (2016) also contributes to the empirical literature, specifically focusing on large international banks. According to Walter (2016), these banks possess considerable reputational capital that demands acute awareness given the complexity and scale of their operations.

II-5.2. Measurement of Reputational risk

Measuring reputational risk has been a challenging endeavor in the banking industry, primarily due to the intangible nature of reputation as an asset. In non-financial sectors, many approaches have been developed, mostly to measure corporate reputation, rather than measuring reputational risk indices (Fombrun, 1996). Measuring corporate reputation and assessing reputational risk serve distinct but interconnected purposes in the realm of corporate governance.

Measuring corporate reputation aims to gauge the current or historical state of how a company is perceived by various stakeholders, using methodologies ranging from customer satisfaction surveys to brand equity indices (Fombrun, 1996). On the other hand, assessing reputational risk is a forward-looking exercise that identifies and quantifies potential events or vulnerabilities that could adversely affect a company's reputation (Perry & de Fontnouvelle, 2005). While the former focuses on outcome-oriented indicators like brand value or customer satisfaction, the latter is more concerned with risk-oriented metrics that aim to proactively manage potential threats to reputation. Both concepts are critical for a comprehensive approach to reputation management (Gatzert, 2015; Walker, 2010).

Various frameworks like Fortune's World's Most Admired Companies (WMAC), Reputation Quotient (RQ), and the RepTrak system are commonly used for assessing corporate reputation (Barnett & Pollock, 2012; Chun, 2005; Wartick, 2002). However, Trotta & Cavallaro (2012) argue that these generalist models may not adequately capture the unique characteristics of the banking sector, given its strict regulatory environment. To address this, Trotta & Cavallaro (2012) introduced a specialized model for financial institutions, known as the Five "R's" Model, which focuses on Relationships (with both internal and external stakeholders, including other banks and regulatory bodies), Results, Responsibility, Role, and Regulatory compliance. This model emphasizes the need to identify key stakeholder groups as a crucial step for accurately measuring a bank's reputation. Despite its focus on outcomes, Trotta's model does not offer a risk-oriented approach to assessing reputational risk.

From a risk management perspective, a blend of theories and empirical research has emerged over the years to guide and refine the measurement of reputational risk in the banking industry. Theoretical approaches to assessing reputational risk include:

1. **Event Study Methodology:** Stemming from financial economics, the Event Study Methodology is widely used to measure the immediate financial impact of an event on a bank's stock prices, thereby gauging reputational damage (Mackinlay, 1997). Numerous academics have employed event study methodology as a primary framework for measuring reputational risk (Cummins et al., 2006; Fiordelisi et al., 2013; Gillet et al., 2010; Perry & de Fontnouvelle, 2005). This empirical approach allows researchers to scrutinize the impact of specific events, such as operational losses or regulatory sanctions, on a company's stock price and other financial metrics. By observing the stock price behavior before and after the event, researchers quantitatively assess the financial implications of reputational damage (Cummins et al., 2006; Fiordelisi et al., 2013; Gillet et al., 2010; Perry & de Fontnouvelle, 2005).

2. **Sentiment analysis:** Sentiment analysis, often used as part of Natural Language Processing (NLP) applications, is a method that mines text data to identify and categorize opinions or sentiments expressed toward a bank or financial institution.

This method is particularly useful in gauging public perception and therefore helps in identifying and quantifying reputational risk. A study by Pak and Paroubek (2010) shows that sentiment analysis techniques can effectively categorize consumer opinions into positive, negative, or neutral, with an accuracy rate of up to 80% when applied to social media content. Likewise, sentiment analysis could capture rapid shifts in public opinion following critical events, such as financial scandals or data breaches, which traditional surveys or studies might not be able to detect quickly. Exploring how these changes in public sentiment towards a bank correlate with its financial health presents an intriguing opportunity to reveal insights that other methods may overlook.

3. **Multi-Criteria Decision Making (MCDM):** This theory advocates for a multi-dimensional approach to evaluate reputational risk, incorporating both quantitative and qualitative measures. Especially pertinent in situations where the facets of reputational risk are diverse, this approach is an extension of Multi-Criteria Decision Analysis (MCDA) as presented by Belton & Steward (2002). It has found applications in multiple scholarly works focused on themes of "trust" and "reputation" (Chang et al., 2014; Pasi et al., 2019).

Empirical research employing event methodology has yielded significant insights into the dynamics of reputational losses in the financial sector. Gillet et al. (2010) highlighted that operational loss events disproportionately impact firms with higher Tobin's Q ratios, indicating that companies with robust growth prospects are most vulnerable. On a related note, Fiordelisi et al. (2013) found that the likelihood of reputational damage escalates with increases in bank risks, profits, and size, yet declines with a rise in equity capital and intangible assets. In an empirical investigation, Biell & Muller (2013) found that while market reactions to operational loss events are fairly prompt—typically manifesting within 25 days—they are swifter in bull markets and delayed in bear markets. Sturm's (2013) research shows that the stock market reacts negatively not just to the initial news release but also to subsequent settlement announcements, which confirm the scale of the losses. This pattern of negative cumulative abnormal returns continues past both the initial news and the settlement, highlighting the enduring impact on a company's reputation following an operational loss. Moreover, the study's multivariate regression analysis reveals that the severity of reputational damage is influenced more by the firm's own characteristics than by the details of the operational loss event itself. For instance, companies with a higher liabilities-to-assets ratio are found to suffer greater reputational harm following operational losses than those with a more robust equity standing. Furthermore, Perry & de Fontnouvelle (2005b) work demonstrates that significant reputational events impact not only the stock prices but also the deposit flows in banks, thereby indicating that multi-dimensional measures are essential.

The evolving methodologies for measuring reputational risk in banking are underpinned by a solid combination of theoretical frameworks and empirical research. Yet, these studies are not without their limitations. A notable issue is the variation in event windows used to calculate Cumulative Abnormal Returns (CAR) across different studies. This inconsistency creates challenges in making cross-study comparisons. Also, there is a need to look at long-term perspectives based on year-end financial metrics. Addressing these discrepancies is crucial for advancing the accuracy and reliability of reputational risk assessment in the sector.

II-5.3. Management of reputational risk

The banking sector has been an epicenter of reputational risk, necessitating the development and application of adequate approaches to manage this form of risk effectively. Reputation management theory posits that an organization's reputation is a critical asset that can impact its long-term success or failure. This asset needs to be managed proactively to maintain stakeholder trust and confidence (Fombrun, 1996). The literature underscores various approaches to managing reputation. In the banking sector, Proactive management of reputational risk is often rooted in transparency, ethics, and compliance (Gatzert & Schmit, 2016); Stakeholder Engagement posits that communication with key stakeholders like customers, shareholders, and regulatory bodies is crucial. Regular updates on risk management processes and financial statuses can mitigate reputational risks (Senft, 2019). Reputation management theory also advises the use of specific key performance indicators (KPIs) to monitor reputation (Eckert, 2017).

The growing body of literature on reputational risk management in the banking sector underscores the importance of proactive approaches. For instance, Kottasz & Bennett (2016) observed that banks that had taken anticipatory steps to manage their reputation suffered less from public anger in the aftermath of the 2008 financial crisis. This suggests that having a preemptive reputational management strategy can act as a buffer against large-scale negative public sentiment. Similarly, a case study by Mukherjee et al. (2014) on the European Investment Bank found that active management of its reputation led to fewer reputational risks in comparison to other financial institutions. This empirical evidence strengthens the argument for proactive reputation management, aligning with the findings by Kottasz & Bennett (2016).

Further, Trostianska & Semencha (2019) point out that proactive reputation management efforts can actually fill credibility gaps, thereby playing a preventive role in reputational risk. This adds another dimension to the argument, suggesting that reputation management not only defends against negative sentiments but can also build trust among stakeholders.

In terms of practical applications in banking, several recommendations emerge from scholarly works. Senft (2019) strongly advocates for the development and implementation of crisis management plans that are grounded in reputation management theory. This provides a structured and theoretically-backed approach to managing crises that could negatively impact a bank’s reputation. Moreover, an increasing number of banks are focusing on Corporate Social Responsibility (CSR) initiatives as a way to proactively manage reputation. This approach, as highlighted by Gatzert & Schmit (2016), can be particularly effective as it resonates well with contemporary societal expectations of corporate behavior. In summary, both theoretical insights and empirical evidence advocate for a proactive approach to managing reputational risk, emphasizing comprehensive crisis management plans and CSR activities as practical steps for implementation.

II-6. Effects of reputational risk on financial performance

The Basel Committee on Banking Supervision (2009) defines reputational risk as "the risk arising from negative perception on the part of customers, counterparties, shareholders, investors, or regulators that can adversely affect a bank's ability to maintain existing or establish new business relationships and continued access to sources of funding (e.g., through the interbank or securitization markets)." Failure to maintain current business relationships or establish new ones, as well as difficulties in securing funding, can result in financial losses for the bank, which directly impacts its financial performance.

In the context of the RBT, reputational capital is considered a strategic asset that has direct and indirect effects on a bank's financial performance. The complex interplay between reputational risk and financial performance in the banking sector is an area that remains relatively under-studied, despite its critical importance (Dowling, 2016; Feldman et al., 2014; Fiordelisi et al., 2013; Heidinger & Gatzert, 2018; Roberts & Dowling, 2002; Rose & Thomsen, 2004).

II-6.1. Theories

Waddock & Graves (1997) pioneered research in the field of reputational risk nexus with financial performance, emphasizing the connection between social performance and financial outcomes. Even though their research does not delve directly into reputational risk, it crucially underscores the influence of intangible assets, such as reputation, on financial metrics. This aligns seamlessly with the principles of the RBT, which emphasizes the strategic significance of non-tangible assets in organizational performance (Barney, 1991).

Dierickx & Cool (1989) further elucidated the concept, articulating that building reputation, akin to other strategic resources, is a long-term endeavor and one that can witness decline over time. This perspective resonates strongly within the banking realm, where sustaining consumer trust is paramount. Consequently, the notion of "reputational capital" emerges as a vital facet, insinuating that robust reputational standing can counterbalance financial adversities over extended durations.

Schnietz & Epstein (2005) conducted a research in the wake of the Seattle World Trade Organization protests, showing that firms with higher reputational rankings faced smaller declines in stock value in response to social risk events. The banking sector can take a cue from these insights. This can be corroborated by Deephouse & Carter (2005) who suggested that a firm's conformity to industry norms, or legitimacy, may reduce reputational risk, and thus indirectly safeguard financial performance.

Contrarily, Barnett & Salomon (2012) warn that a good reputation might sometimes be a "double-edged sword". Firms with excellent reputations may be scrutinized more intensely during crisis situations, potentially leading to significant reputational and financial damage. This serves as a cautionary note for banks, which often find themselves at the epicenter of public and regulatory attention.

II-6.2. Empirical evidence

With the lenses of the market model, the "Unified Theory of Reaction in Assets Market", empirical studies have consistently highlighted the immediate impact of reputational damage on market value (Dowling, 2016; Feldman et al., 2014; Fiordelisi et al., 2013; Heidinger & Gatzert, 2018; Roberts & Dowling, 2002). For instance, research focusing on corporate scandals and ethical breaches has demonstrated significant negative impacts on market capitalization (Roberts & Dowling, 2002). These studies reveal that events causing reputational damage can lead to immediate declines in stock prices, reflecting investor perceptions and market sentiment. Furthermore, the long-term financial repercussions of reputational damage are evident in profitability, revenue growth, and return on assets, often measured over several years following a reputational crisis (Deephouse, 2000; Rindova et al., 2005).

Soprano et al., (2009) demonstrated that reputational damage often directly leads to diminished profitability for banks. However, scholars like Fiordelisi et al. (2013), Gillet et al. (2010), Heidinger & Gatzert (2018) posit a layer of complexity by arguing that the impact of reputational risk may be nuanced based on the size and brand strength of the corporation. Their studies imply that established and larger corporations may have reputational resilience, which acts as a buffer against financial loss, supporting the view from the RBT that certain internal assets, such as a strong corporate image, can serve as strategic resources.

Bălan (2015) emphasized the significant relationship between a company's corporate reputation and its economic performance. The findings resonate with the empirical work of Roberts & Dowling (2002), who investigated the reputational and financial performance of 300 Fortune Ranking firms. Their results revealed a cyclical relationship: historical reputation management efforts and past financial performance bolster current and future reputational and financial metrics. The empirical evidence thus provides a quantifiable dimension to the RBT's conceptual frameworks.

The banking sector, with its unique challenges and public scrutiny, serves as a compelling backdrop for evaluating the implications of reputational risk on financial performance. The extant literature, although limited, highlights that while a damaged reputation often leads to financial loss, the magnitude of the impact can be modulated by various factors, including the strength of the corporate brand and the effectiveness of past and current reputation management efforts importance (Dowling, 2016; Feldman et al., 2014; Fiordelisi et al., 2013; Heidinger & Gatzert, 2018; Roberts & Dowling, 2002; Rose & Thomsen, 2004).

The Unified Theory of Reaction in Assets Market, while providing valuable insights into the immediate market reactions following operational losses, presents key limitations when it comes to accurately assessing the long-term financial implications of reputational losses. This theory primarily focuses on the immediate response of the market, typically observed through changes in stock prices or market capitalization. However, such a narrow focus on immediate market reactions can obscure the more profound and enduring financial consequences that a bank faces in the aftermath of reputational damage.

End-of-year metrics such as Return on Assets (RoA), Net Income, and Return on Equity (RoE) are crucial for a comprehensive evaluation of a bank's financial performance (Akhigbe & McNulty, 2005). These metrics seem indicative of a more accurate reflection of the bank's overall financial stability and health, beyond the short-term fluctuations in market perception. Furthermore, the immediate market reaction may fail to account for the gradual and cumulative impact of reputational damage on a bank's operational efficiency, customer loyalty, and strategic opportunities. The long-term perspective is essential to understanding the full spectrum of reputational loss implications, which can manifest over several years and significantly alter a bank's financial trajectory.

In conclusion, while the empirical evidence supports the effects of reputational risk on financial performance, and the Unified Theory of Reaction in Assets Market offers a useful framework for understanding immediate market responses to reputational events, there seems to be a need to provide a holistic view of the long-term financial repercussions. Future research and risk management approaches should integrate end-of-year financial metrics and adopt a longer-term perspective to more accurately assess and address the consequences of reputational losses in the banking sector.

II-7. Variations in reputational loss intensity

II-7.1. Regional difference in Reputational damage

The regional disparities in the reputational impact of operational losses in the banking sector can be understood through a blend of theoretical foundations and empirical evidence. These disparities are potentially influenced by cultural, regulatory, and economic factors that vary significantly across different global regions.

Cultural Dimensions Theory posits that cultural values significantly influence organizational behavior and public perception. In the context of banking, this means that the cultural backdrop of a region can dictate how operational losses are perceived and, consequently, the extent of reputational damage. For instance, in cultures with high uncertainty avoidance, such as in many Western countries, operational losses might lead to greater reputational damage due to a lower tolerance for ambiguity and risk (Hofstede, 1984).

Discussing the corporate reputation theories, Fombrun (2012) suggested that the structures of society, including regulations, norms, and traditions, shape the actions of organizations. Institutional theory states that a firm that conforms to the context in which it is operating, following the existing norms and regulations, becomes more prosperous and mitigates reputational losses (Meyer & Rowan, 1977). Under the lens of Institutional Theory, organizations are influenced by societal pressures, as they strive to conform to prevailing social norms and regulatory standards. This framework posits that organizations are motivated by a desire to maintain legitimacy and avoid the repercussions of deviating from societal expectations. Concurrently, they seek to evolve and enhance their competitive advantage within these established norms and regulations. This theory underscores the balance organizations must strike between adhering to external expectations and pursuing internal strategic objectives for sustained growth and competitiveness (Fombrun, 2012). In regions with stringent financial regulations and governance standards, such as the European Union, operational losses can have a more significant reputational impact due to heightened regulatory scrutiny and public expectations of corporate governance (Fiordelisi et al., 2013).

The Resource-Based Theory argues that a firm's resources, including its reputation, are critical for gaining competitive advantage (Barney, 1991; Barney & Clark, 2007). Larger banks in more developed markets might face greater reputational risks from operational losses due to their more extensive customer base and higher public visibility.

Research focusing on the U.S. and European banks has shown that European banks often suffer more pronounced reputational damage compared to their U.S. counterparts following operational losses. This difference is potentially attributed to various factors, including the level of media scrutiny and public trust in financial institutions (Fiordelisi et al., 2013; Heidinger & Gatzert, 2018).

In Asia, particularly in markets like Japan and China, the reputational impact of operational losses is often mitigated by cultural factors such as a preference for resolving issues internally and a less confrontational media landscape (Yamori & Harimaya, 2013). However, this does not imply that reputational damage is non-existent; rather, it manifests differently compared to Western markets.

In emerging markets, the reputational impact of operational losses is often compounded by the lack of well-established risk management practices and regulatory frameworks. This can lead to more pronounced and long-lasting reputational damage, as seen in cases in Latin America and parts of Africa (Aebi et al., 2012).

In conclusion, the body of research on reputational risk in the banking sector, while extensive and insightful, reveals a significant gap in its geographic focus and scope. The majority of these studies are predominantly sector-specific, with a heavy concentration on U.S. and European financial institutions. This narrow focus results in a substantial underrepresentation of the financial landscapes in other global markets, which may exhibit unique characteristics and face distinct challenges in managing reputational risks. The lack of comprehensive global coverage in existing literature highlights the need for more inclusive research that encompasses a wider array of banking systems across different regions. Such an expanded perspective is crucial for developing a more holistic understanding of reputational risk management in the banking sector, accommodating the diverse regulatory, cultural, and economic contexts that shape banking practices worldwide. Addressing this gap is not only essential for academic completeness but also for providing practical insights that can be applied across the global financial industry.

II-7.2. Reputational losses and banks' size

Theoretically, the RBT offers a foundational perspective in understanding this relationship between the intensity of the reputational loss and the bank's size. RBT posits that a firm's resources, both tangible and intangible, play a crucial role in its competitive advantage and ability to manage risks (Barney, 1991). In the context of banking, larger banks are often presumed to have more extensive resources, which could theoretically buffer against the impact of reputational losses. This assumption is underpinned by the idea that larger institutions possess more robust risk management systems, greater financial resilience, and a more diversified client base, potentially mitigating the impact of any single operational loss event.

However, the visibility theory suggests a counterargument. It posits that larger organizations, due to their higher public profile and greater media attention, might suffer more severe reputational damage when operational losses occur (Deephouse, 2000). This theory aligns with the notion that larger banks are under constant scrutiny from stakeholders, regulators, and the public, making any operational loss event more damaging to their reputation.

Empirical studies have provided mixed insights into this relationship. For instance, Fiordelisi et al. (2013) found a positive correlation between bank size and reputational loss intensity, suggesting that larger banks, contrary to the buffering hypothesis of RBT, might actually face greater reputational damage. This finding aligns with the visibility theory, indicating that the public profile of larger banks amplifies the impact of operational losses on their reputation.

Conversely, other studies have indicated that smaller banks suffer more intensely from reputational losses. The argument here is that smaller banks, with fewer resources and less diversified operations, are more vulnerable to the impacts of operational losses (Perry & de Fontnouvelle, 2005). This vulnerability is exacerbated by their limited capacity to absorb financial shocks and manage public relations effectively in the aftermath of such events.

Despite these insights, there remains a significant gap in the literature. Most studies tend to focus on either large global banks or small local banks, with mid-sized institutions often overlooked. Additionally, the majority of empirical research has been concentrated in specific geographic regions, primarily in the U.S. and Europe, leaving the experiences of banks in other global markets underexplored. This gap highlights the need for more inclusive research that considers a broader range of bank sizes and includes financial institutions from diverse geographic contexts. Such research would provide a more comprehensive understanding of how bank size influences the intensity of reputational losses following operational losses, contributing valuable insights to both the academic field and the banking industry at large.

II-8. Summary and gaps in the reputational risk research

The comprehensive review of literature on reputational risk in the banking sector reveals a multifaceted and complex landscape, marked by a variety of theoretical perspectives and empirical findings. Theories such as the RBT and the Unified Theory of Reaction in Assets Market have been instrumental in framing the discussion around reputational risk. RBT, for instance, emphasizes the strategic significance of non-tangible assets like reputation in organizational performance, while the Unified Theory focuses on the market's immediate reaction to operational losses and their reputational implications.

Empirical studies have provided valuable insights into the immediate impacts of reputational losses on financial performance, particularly in terms of market value, and profitability (Deephouse, 2000; Fiordelisi et al., 2013; Gatzert, 2015; Gillet et al., 2010; Perry & de Fontnouvelle, 2005). These studies highlight the nuanced ways in which reputational damage can affect banks, with factors such as the size of the bank and the strength of its brand playing significant roles in moderating these effects.

However, the literature review also uncovers notable gaps. Firstly, there is a predominant focus on immediate market reactions in existing studies, often at the expense of a more thorough examination of long-term financial health indicators. This emphasis on short-term market responses does not fully capture the prolonged and potentially more damaging financial consequences of reputational losses.

The work of Heidinger & Gatzert (2018) and Gillet et al. (2010) has been instrumental in shedding light on the dynamics between reputational risk and Return on Assets (RoA), but there are still significant areas that remain unexplored. While Heidinger & and Gatzert’s (2018) research focused on the impact of managing reputational risk on RoA, Gillet et al. (2010) investigated how RoA influences reputational damage. However, what is not addressed in either study is the direct effect of specific reputational events on RoA, an area that is crucial for a complete understanding of this relationship.

Thirdly, despite widespread acknowledgment that reputational damage from internal frauds is typically more severe than from other operational risks, there is a noticeable gap in empirical research that directly connects this damage to a bank's financial health. Specifically, there's a lack of studies linking such reputational harm to key financial metrics like RoA. Studying the effects of internal frauds on reputational risk in the banking sector is particularly crucial due to the unique and profound impact these events can have compared to other operational risks. Internal frauds, by their very nature, strike at the core of a bank's trustworthiness and integrity, which are fundamental to its reputation (Biell & Muller, 2013; Gillet et al., 2010; Perry & de Fontnouvelle, 2005). Unlike external threats or systemic failures, internal frauds suggest a breakdown in a bank's internal controls and governance, potentially leading to more severe and lasting damage to its reputation. This erosion of trust can have far-reaching implications, not just in terms of immediate financial losses, but also in long-term customer relationships, investor confidence, and regulatory scrutiny (Office of the Comptroller of the Currency, 2019). In contrast, other operational risks might be perceived as less controllable or more external, and thus might not have the same profound impact on a bank's perceived integrity. Therefore, understanding the specific repercussions of internal frauds on reputational risk is essential for developing more targeted risk management strategies and for maintaining the overall health and sustainability of banking institutions. This gap points to the need for more focused research in this area to understand the financial implications of reputational damage due to internal frauds.

Another significant limitation is a lack of comprehensive studies exploring these dynamics in other global markets, while there is a considerable amount of research on reputational risk in Western banking systems. This identified gap underscores the necessity for research that encompasses a broader geographical scope. Such studies would be invaluable in understanding how regional variances could potentially affect the impact of reputational risk, providing insights into the diverse ways in which different global regions respond to and are affected by reputational issues.

In conclusion, while the existing body of literature provides a solid foundation for understanding reputational risk in banking, it also highlights the need for further research. Future studies should aim to address these gaps by focusing on the long-term financial implications of reputational damage, exploring the effects of internal frauds more directly, and expanding the geographical scope of research to include a wider range of banking systems and markets.

III. RESEARCH METHODOLOGY

"The real purpose of scientific method is to make sure Nature hasn't misled you into thinking you know something you don't actually know."

Robert M. Pirsig

Chapter three details the methodology anchored in the Resource-Based Theory and the Unified Theory of Reaction in Assets Market. It starts with the research paradigm and moves to hypothesis formulation derived from the literature review. The research design is then presented, followed by the sampling strategy. The methods for data collection and analysis are described subsequently. Concerns regarding reliability and validity, and their addressed challenges, are discussed. The chapter concludes with a section on ethical considerations and a data management plan.

III-1. Research paradigm

In the landscape of organizational research, scholars traditionally pivot among quantitative, qualitative, and mixed methods approaches, each with its distinct epistemological and ontological orientations (Creswell & Creswell, 2018; Muijs, 2004). For this study, the objective is to ascertain the extent to which reputational risk impinges upon the financial performance of banks by systematically examining interconnected variables. Rooted in the epistemological stance that a singular objective reality exists, the study upholds the principles of Positivism, which emphasizes that the research environment should be manipulated objectively to glean verifiable data (Adams et al., 2014; Saunders et al., 2019)

The study assumes that there exists a singular, objective reality—in this case, the nature and magnitude of the relationship between reputational risk and financial performance in banks. This premise aligns closely with the Positivist paradigm, which suggests that reality is constant and can be measured objectively (Wahyuni, 2012). The role of the researcher is to remain impartial, ensuring that personal viewpoints do not cloud the rigorous assessment and interpretation of data (Saunders et al., 2019). This objectivity is essential for the credibility and reliability of the findings.

Another cornerstone of the Positivist paradigm is the emphasis on generalizability (Saunders et al., 2009). The research aims to produce findings that are not just applicable to a specific case but can be generalized across the broader banking industry. This ambition dovetails with the study's overarching aim to offer an empirically grounded framework for understanding and managing reputational risks in banking.

The research paradigm of this study is then deeply rooted in positivism, which emphasizes the use of empirical evidence and logical analysis to understand phenomena (Creswell & Creswell, 2018). This paradigm aligns seamlessly with a quantitative research methodology, which is employed to investigate the intricacies of reputational risk in the banking sector. Quantitative methods offer the empirical rigor required for scrutinizing complex relationships between variables, which is critical for examining the interconnected variables of reputational risk and financial performance indicators like the RoA. As Stockemer, (2019) aptly points out, quantitative research is the "primary tool to establish empirical relationships," offering a structured, numerical basis for hypotheses testing, thereby leading to generalized conclusions.

The choice of this methodology is not arbitrary but is intricately linked to the study's theoretical underpinnings, namely the RBT and the Unified Theory of Reaction in Assets Market. The RBT, with its focus on the strategic importance of intangible assets like reputation (Barney, 1991; Wernerfelt, 1984), provides a robust framework for quantifying the impact of reputational risks on a bank's financial performance. Meanwhile, the Unified Theory of Reaction in Assets Market offers a lens to understand market reactions to operational losses (Adeabah et al., 2022), specifically those stemming from internal frauds (Gillet et al., 2010; Perry & de Fontnouvelle, 2005). By leveraging a quantitative approach, the study aims to empirically validate these theories, providing measurable insights into how reputational risks affect banking institutions' financial performance.

This methodology enables a systematic and objective analysis of data, ensuring that the conclusions drawn are firmly rooted in empirical evidence, thus adhering to the positivist tradition of seeking verifiable knowledge through scientific means (Saunders et al., 2009).

In conclusion, the strategic choice of a Positivist research paradigm in this study is meticulously aligned with the objective of empirically validating and generalizing the relationship between reputational risk and the financial performance of banks. This paradigm, emphasizing empirical evidence and logical reasoning, is particularly suited to the study's theoretical foundations in the RBT and the Unified Theory of Reaction in Assets Market. The adoption of quantitative methods under this paradigm ensures the methodological rigor and objectivity necessary for a thorough and comprehensive examination of the intricate dynamics between reputational risks and their financial implications in the banking sector. This approach not only facilitates a deeper understanding of these relationships but also contributes to the broader discourse in financial and risk management literature.

III-2. Hypotheses formulation

To understand and investigate the complex relationship between internal fraud disclosure, reputational loss, and subsequent financial consequences in the banking sector, hypotheses have been formulated as testable propositions. Grounded in academic literature and real-world dynamics, these hypotheses serve as structured propositions that guide the analytical phase of the research, bridging theoretical constructs with empirical validations. By setting clear hypotheses, this research endeavors to uncover insights into the complexities of reputational risk in commercial/retail banking environments.

The following hypotheses have been developed to correspond with the research questions posed in the study. Each of these hypotheses is constructed to provide a structured path for empirical analysis, allowing one to either reject the null hypothesis in favor of the research hypothesis or fail to do so.

III-2.1.a Hypothesis 1: Impact of internal fraud events on RoA

Research Question 1: How does an internal fraud disclosure affect the RoA of commercial/retail banks as reputational loss in terms of quantifiable monetary value?

Hypothesis: An internal fraud disclosure has a negative impact on the RoA of commercial/retail banks.

Null Hypothesis (H_{01}): An internal fraud disclosure has no impact on the RoA of commercial/retail banks.

Alternative Hypothesis (H_1): An internal fraud disclosure has a significant negative impact on the RoA of commercial/retail banks.

Rationale: Many researchers agree that operational losses, especially from internal frauds, can negatively influence a bank's financial health (Eckert & Gatzert, 2017a; Fiordelisi et al., 2013; Gillet et al., 2010). When such frauds are revealed, they can damage a bank's reputation, potentially decreasing trust from stakeholders. This can subsequently affect profitability indicators, such as RoA (Wanjohi et al., 2017).

III-2.1.b Hypothesis 2: Correlation between Operational and Reputational Loss

Research Question 2: How does the size of an operational loss due to internal fraud relate to the quantified monetary value of the subsequent reputational loss?

Hypothesis: The magnitude of operational loss due to internal fraud is directly correlated with the quantified monetary value of reputational loss.

Null Hypothesis (H_{02}): There is no correlation between the magnitude of operational loss and reputational loss.

Alternative Hypothesis (H_2): There is a significant positive correlation between the magnitude of operational loss and reputational loss.

Rationale: The larger the operational loss from internal fraud, the greater the likely media coverage, and public scrutiny, leading to intensified reputational damage and its monetary consequences. Numerous studies support this view. Specifically, Gillet et al. (2010) noted that when internal fraud is revealed, the decline in market value often exceeds the reported operational loss, indicating reputational harm. The adverse effect amplifies when the loss constitutes a sizable portion of the company's net profit. Furthermore, (Eckert & Gatzert, 2017) highlights that reputational losses can often surpass the initial operational loss. Overlooking reputational damages can result in a significant underestimation of certain operational risks, particularly in the case of fraud events.

III-2.1.c Hypothesis 3: Impact of bank size on reputational loss intensity

Research Question 3: In what ways might the size of a bank influence the intensity of reputational loss experienced?

Hypothesis: Smaller banks experience a greater intensity of reputational loss compared to larger banks.

Null Hypothesis (H_{03}): Bank size has no correlation with the intensity of reputational loss.

Alternative Hypothesis (H3): Smaller banks experience a significantly greater intensity of reputational loss compared to larger banks.

Rationale: According to the Resource-Based Theory, a bank's tangible and intangible assets contribute to its competitive edge (Barney & Clark, 2007). By comparing the operational losses incurred by smaller banks like Chase Bank Kenya to larger ones like Wells Fargo, it can be inferred that a bank's size can cushion against reputational loss. While Fiordelisi et al. (2013) suggest that larger profits and size might elevate the risk of reputational harm, they also demonstrate that substantial capital and intangible assets can lessen this risk.

III-2.1.d Hypothesis 4: Regional variation in the impact of reputational losses

Research Question 4: How does the impact of reputational losses stemming from internal fraud disclosures differ across banks situated in various global regions?

Hypothesis: The impact of reputational losses due to internal fraud disclosures varies significantly across different global regions.

Null Hypothesis (H_{04}): There is no regional variation in the impact of reputational losses stemming from internal fraud disclosures.

Alternative Hypothesis (H_4): The impact of reputational losses stemming from internal fraud disclosures varies significantly across global regions.

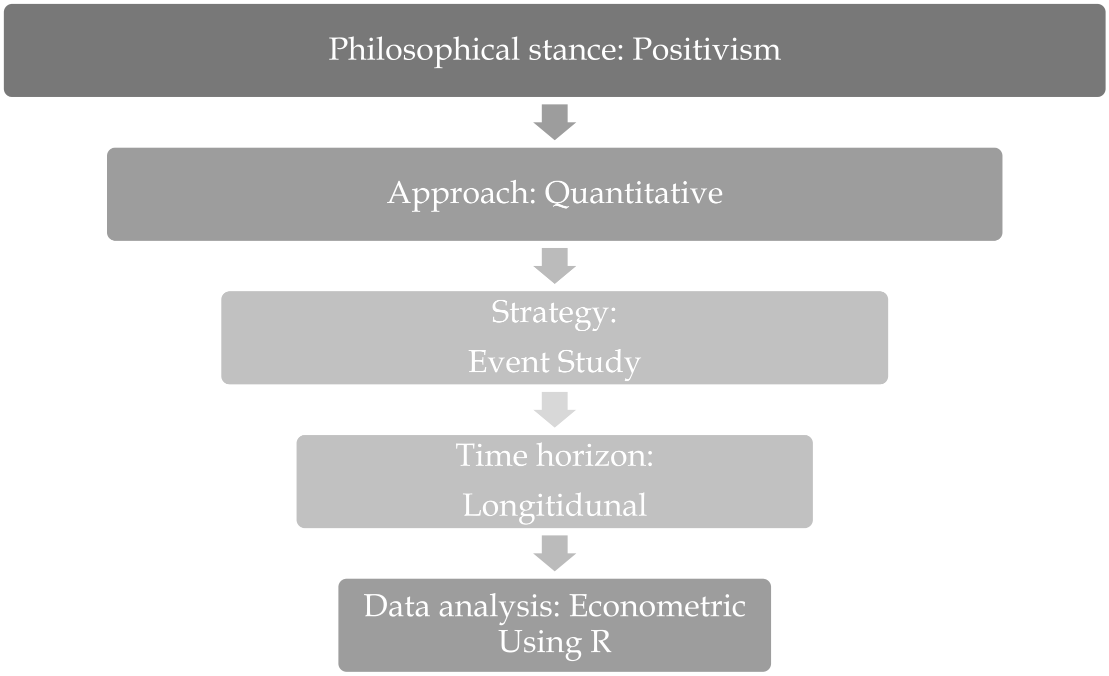
Rationale: Regional factors, such as regulations, customer views, media influence, and culture, can influence the effects of reputational losses. For instance, evidence indicates that banks in Europe face different challenges with reputational losses compared to U.S. banks, with European banks experiencing more significant reputational harm than those in the U.S. (Cummins et al., 2006; Fiordelisi et al., 2013).

III-3. Research design

Research design acts as the architectural blueprint for conducting empirical research, guiding the systematic collection, analysis, and interpretation of data. This blueprint offers a structured, time-sensitive, and resource-optimized plan aimed at rigorously answering specific research questions (Cooper & Schindler, 2014). This plan incorporates elements of theory, data collection methods, analytical approaches, and even ethical considerations, ensuring that the study achieves its objectives in a credible and reliable manner. In essence, the research design serves to align the inquiry process with the research objectives, thereby offering a coherent and efficient roadmap for scholarly investigation.

A brief summary of the research design is outlined below in Figure III-1.

Figure III-1: Summary of the research design



III-3.1. Type of study

The present study is classified as "Applied Research," adopting a "Quantitative Research Design" as its primary methodology. Applied research is problem-oriented and context-specific, aimed at offering practical solutions to real-world issues (Johnson & Christensen, 2019; Yin, 2018). This form of research aligns well with the study's objective of evaluating the impact of reputational risk on key financial metrics in the banking sector. The insights derived from this study are intended to have immediate applicability in enhancing risk management frameworks in commercial and retail banking (Creswell & Creswell, 2018; Maxwell, 2012).

Quantitative Research Design serves as the backbone of this investigation. This type of research emphasizes the measurement and analysis of causal relationships between variables, typically relying on statistical methods (Muijs, 2004; Trochim, 2006). Given the study's focus on understanding the correlation between reputational risks and financial indicators like the RoA, a Quantitative Research Design employing regression analysis offers an objective, empirically grounded approach (Field, 2013; Hair et al., 2019).

The adoption of a Quantitative Research Design is underpinned by the Positivism research paradigm, adhering to the view that reality can be objectively observed and measured (Adams et al., 2007; Saunders et al., 2019; Wahyuni, 2012). This perspective is in line with the methodological assumption that there exists a singular, observable reality, whose properties can be studied in an unbiased manner (Bryman, 2016; Flick, 2018). Consequently, quantitative methods emerge as the most appropriate tools for understanding and interpreting this reality, especially when studying empirical relationships (Cooper & Schindler, 2014; Stockemer, 2019).

Building on the foundation set by recent empirical studies (Fiordelisi et al., 2013; Heidinger & Gatzert, 2018; Sorescu et al., 2017; Walter, 2016), this research primarily employed event study as a quantitative strategy. These methods align with the study's overarching goal: to examine the general relationship between reputational risk and the financial performance of commercial and retail banks.

III-3.2. Study Setting

The setting of this research is the global commercial and retail banking sector, with a focus on institutions that have experienced operational losses and potentially reputational challenges between the years 2007 and 2016 (10 years). The study encompasses both domestic and international banks, providing a comprehensive landscape for analysis. Given that the financial industry operates in a highly dynamic environment influenced by numerous variables such as economic conditions, government regulations, and technological advancements, it is crucial to understand the study setting in depth (Saunders et al., 2019).

Geographically, the study is not limited to a specific region, as the aim is to observe global trends and impacts. All the continents are covered. This approach enables an understanding of the various market factors and locational nuances that may influence the effects of reputational risk on the RoA (Coskun et al., 2019).

The rationale for choosing this setting is threefold. First, commercial and retail banks play an instrumental role in the global economy, irrespective of the region, serving as a conduit for financial transactions, credit provisioning, and savings (Bryman, 2016). Second, the banking sector is particularly susceptible to reputational risks due to its reliance on consumer trust and regulatory compliance (Fiordelisi et al., 2013; Walter, 2016). Lastly, the timeframe between 2007 and 2016 allows for a longitudinal study that can capture the evolving nature of reputational risks and their impacts over time and across multiple regions (Yin, 2018). The decision to focus on a 10-year timeline for this study is driven by three key considerations:

1. To maintain consistency with the timeframes examined in prior studies, thereby allowing for a contextual understanding within the existing body of literature (Sturm, 2013).

2. To circumvent the financial irregularities brought about by the COVID-19 pandemic, which emerged towards the end of 2019. This approach is critical to preserving the integrity of the data and avoiding the skewing effects of these unprecedented global events. It seems evident that the health crisis which began at the end of 2019 has deeply affected the banking sector. Given the extensive effects of this crisis, assessing reputational risk during this time frame becomes less pertinent for the scope of this study.

3. To facilitate an in-depth analysis of the financial performance for a three-year period following each operational loss incident, with the study period deliberately not exceeding 2019. This specific duration is vital to comprehensively assess the financial repercussions in the aftermath of each event, without the influence of post-2019 variables. Using a three-year window before and after an event is a common choice in empirical studies, particularly in finance and economics. This period is often selected due to its ability to capture the immediate short-term effects

as well as some of the medium-term consequences of an event, without being too broad that it loses specificity or too narrow that it misses significant impacts (Agrawal et al., 1992; Altunbas et al., 2012; Flammer, 2015).

This study set aligns well with the research objectives and questions, offering a robust framework for conducting regression analysis and content analysis as the main research methodologies (Field, 2013a; Hair et al., 2019a).

III-4. Sampling strategy

The sampling strategy plays a crucial role in achieving reliable and valid results in research. In this study, the sampling technique is guided by the need to investigate the significance of reputational risks on the financial performance of commercial banks. The strategy aims to create a subset that represents the larger population of banks, thereby providing valuable insights that are generalizable.

III-4.1. Sampling frame

The study focuses on commercial banks that had operational losses of USD 100,000 or more between 2007 and 2016 (10 years). This specific time frame is consistent with previous studies that utilized datasets spanning ten or more years (Biell & Muller, 2013; Fiordelisi et al., 2013; Gillet et al., 2010; Sturm, 2013). Fiordelisi et al. (2013) utilized a dataset comprising 215 instances of operational losses, each amounting to at least USD 1,000,000, spanning a five-year period from 2003 to 2008. Sturm (2013) investigated 136 operational losses spanning 2000 and 2009 (10 years). In contrast, Gillet et al. (2010) analyzed 154 cases of operational losses, with a minimum loss size of USD 10,000,000, covering a fifteen-year timeframe from 1990 to 2004 (15 years). Subsequently, Fiordelisi et al. (2014) examined a broader dataset of 430 operational losses, occurring between the years 1994 and 2008 (15 years).

The average size of operational risk events as reported by ORX members from 2014 to 2019 stands at approximately USD 500,000 (Astill & Basmer, 2020). In aligning with research methods such as those in studies by Sturm, (2013) where losses from EUR 100,000 were considered, and Fiordelisi et al. (2013), incorporating losses from USD 1,000,000, this investigation also opts to delve into operational losses of USD 100,000 or more. This approach contrasts with other studies (Cummins et al., 2006; Gillet et al., 2010), which strictly examine losses exceeding USD 10 million.

Incorporating losses of smaller amounts facilitates a more nuanced analysis, enabling a detailed exploration of the relationship between the magnitude of operational loss and the ensuing reputational damage. This comprehensive approach allows for a more granular understanding of how varying degrees of operational losses impact reputational standing, providing insights that are critical for both academic exploration and practical implications in financial management and risk mitigation strategies.

Fiordelisi et al. (2013) sourced their operational loss data from the IBM ALGO OpData™ database based on a specific set of criteria, which included the parent company being a publicly quoted bank in the U.S. or Europe, the availability of price and market capitalization data at the time of the loss announcement, and a confined time frame from January 1, 2003, to August 1, 2008, among other parameters.

In this study, the selection of operational losses was guided by a carefully curated set of criteria, influenced by Fiordelisi et al. (2013), and adapted to align with this research's specific aims:

1. The operational loss must be publicly disclosed through recognized channels.
2. The disclosed loss should be unmistakably categorized as operational at the time of its revelation.
3. The loss should not have been pre-announced or mentioned in prior communications.
4. Precise financial figures associated with the loss should be made available either on the announcement day or shortly after.

5. The magnitude of the operational loss should meet or surpass USD 100,000.
6. The specific category or nature of the operational loss should be distinctly articulated at its disclosure.
7. The occurrence of any potential confounding events or macroeconomic situation on the same day should be absent.
8. The operational loss announcement's date must be anchored between January 1, 2007, and December 31, 2016.
9. To mitigate the overlapping effects of multiple losses, the bank should register an operational loss during only one year within the defined timeframe, ensuring a clearer impact assessment on the RoA.

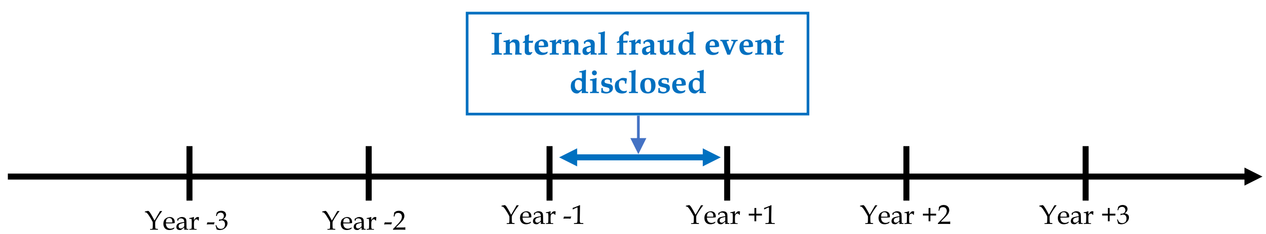
Given that, the study aims to assess the influence of reputational risk stemming from operational losses on the banks' RoA for three years before and after the loss event, the data collection for analysis is limited to the end of the 2019 financial year. This cut-off is intentional, as the pandemic was declared shortly thereafter. As a result, the most current operational losses considered in this study are dated up to the end of 2016, allowing for a comprehensive three-year follow-up financial performance analysis (up to 2019).

Event study methodology, as expounded upon by Mackinlay (1997), is a versatile approach that can be applied across various time frames, ranging from days and months to even years. In implementing this methodology, researchers commonly opt for an event window that surpasses the specific duration they are primarily interested in. Such an expanded window facilitates a more comprehensive analysis by covering periods leading up to and succeeding the event. This means that both the time before the event (anticipatory phase) and the time after (reaction phase) are under scrutiny.

While Mackinlay (1997) does provide insights into the application of the event study methodology using daily data, suggesting that the parameters of a market model can be estimated over a span of 120 days, he doesn't distinctly prescribe a duration for studies using yearly data. This variability in the choice of the event window is further exemplified by Sorescu et al. (2017), who, in their research, employed a concise 3-day event window centered on the announcement day. This diversity in the duration of the event window underscores the adaptability of the event study methodology to cater to the specific nuances and objectives of individual research endeavors.

Figure III-2 showcases how, for an operational loss occurring in a designated year, the financial metrics from both preceding and subsequent years are amassed. Taking, for instance, an operational loss in 2016; the data from the three years leading up to it (2013, 2014, and 2015) would be gathered. Given that the repercussions of this loss are anticipated to be evident in the financial performance at the close of 2016, this year serves as the inaugural post-loss year (Year+1). Following this, 2017 and 2018 helped in observing and gauging the trajectory of the RoA post the incident. Only banks with accessible financial data spanning three years both prior to and following the operational loss are considered.

Figure III-2: Financial metrics sampling frame



Banks are identified through an exhaustive list sourced from the public edition of the Global Operational Loss Database (GOLD).

III-4.2. Sampling method

In light of the specialized focus of this research and the necessity for high-quality, relevant data, this study employs a purposive sampling strategy. Purposive sampling allows for the careful selection of participants—in this case, commercial and retail banks—based on specific characteristics that align closely with the research objectives (Teddlie & Yu, 2007).

Utilizing this method enables the study to target banks that have suffered substantial operational losses, making them ideal subjects for investigating the effects of reputational risk on financial performance.

To ensure that the dataset is appropriate to the research questions, the following methodical steps were taken in curating data from the publicly available operational loss databases GOLD:

1. **Identification of banking-related losses:** Only operational losses that are clearly disclosed and pertain to the banking sector were selected.
2. **Relevance to research objectives:** Only internal frauds losses specifically tied to commercial and retail banking were prioritized to align with the study's aims.
3. **Regional representation:** An overview of the geographic regions represented in the sample was conducted to ensure a balanced and global perspective.
4. **Currency conversion:** For uniformity in analysis, all monetary values were converted to U.S. dollars (USD) using historical exchange rates obtained from www.exchangerates.org and www.ofx.com. All conversions were based on the year-end closing rate (December 31) in which each loss was reported.
5. **Financial threshold filtering:** A filter was applied to the internal frauds operational losses based on their monetary value (in USD), narrowing down to a finalized sample relevant to the study's scope.
6. **Identifying banks:** Banks that experienced these internal frauds operational losses were pinpointed and categorized by year. This approach enabled the formation of an extensive dataset with a longitudinal perspective.
7. **Assembling longitudinal dataset:** In the final step, following the identification of the banks, financial metrics were systematically collected for each bank in alignment with the established sampling frame.

This methodological approach is designed to yield a robust and focused dataset, effectively enabling the study to delve deep into the nuances of reputational risk and its impact on financial performance in the banking sector.

III-5. Data Collection methods

III-5.1. Secondary financial data rationales

The study principally relied on secondary financial data to achieve its research objectives. This approach offers several compelling advantages, particularly in establishing the trustworthiness and real-world applicability of the data. Firstly, the secondary financial data are sourced from well-established and reputable financial databases such as Bloomberg, and the Global Operational Loss Database (GOLD). These databases are recognized for their rigor in data curation and are extensively used in both academia and industry, lending credibility to the data. Secondly, the data represent actual historical financial performances and incidents, as opposed to hypothetical or simulated scenarios. This attribute adds a layer of real-world context that enhances the validity of the study's findings (Yin, 2018).

Furthermore, financial institutions are obligated to adhere to rigorous regulatory standards when disclosing their financial information. Regulatory agencies and auditing firms scrutinize these disclosures, making the data inherently trustworthy and reliable for academic research (Saunders et al., 2019). Lastly, given that these are standardized, publicly disclosed figures, the secondary financial data ensures uniformity and allows for consistent comparative analysis across multiple banks, thereby further solidifying the robustness of the research design (Field, 2013).

III-5.2. Types and sources of data

To address the research objectives and questions adequately, a diverse set of data types needs to be amassed from multiple sources. Below is a structured overview detailing the nature and origin of the required data:

1. **Commercial and Retail Banks' Operational Losses:** To identify the banks that have experienced operational losses leading to reputational risks, data was sourced from the public Global Operational Loss Database (GOLD). GOLD Databases are edited by Riskbusiness (UK) which serves as a global provider of Governance, Risk, Audit, and Compliance (GRAC) solutions. Over 200 financial institutions worldwide are actively using their Software-as-a-Service (SaaS) offerings. The database offers a comprehensive repository of operational loss events in the financial industry that have been publicly disclosed. It is frequently employed in scholarly research that concentrates on risk management issues (Pakhchanyan, 2016; Thirlwell, 2002).

2. **Financial metrics (RoA and total Assets):** For financial metrics like RoA and Total Assets, the study made use of Bloomberg databases. These databases offer a wealth of financial information and are considered highly reliable sources in both academic and professional circles (Hair et al., 2019).

3. **Macroeconomic data:** The primary source of data for GDP growth rate and inflation is the World Bank databases. Recognized globally for its comprehensive and authentic data repositories, the World Bank provides detailed economic, financial, and social indicators for countries worldwide. The GDP growth rate data offers insights into the economic performance of nations over time, capturing the annual percentage growth in the value of all goods and services produced. Similarly, the inflation data, typically measured by the consumer price index, represents the annual percentage change in the cost of acquiring a basket of goods and services (World Bank, 2023). Both these indicators, sourced from the World

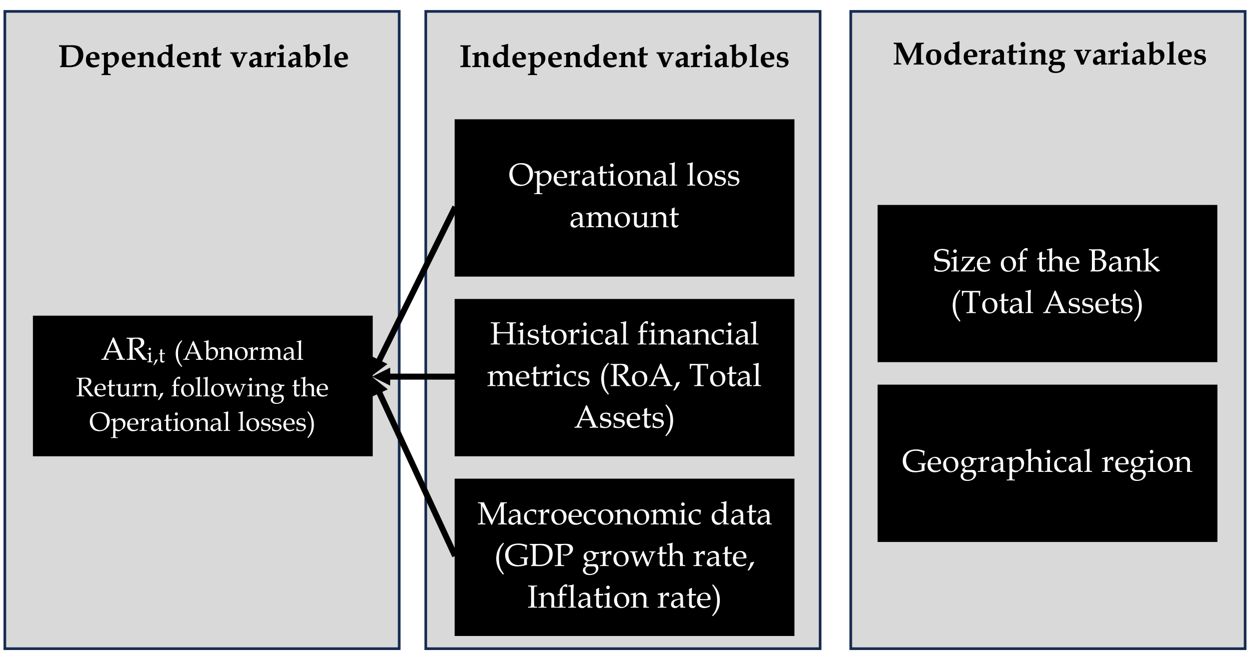
Bank, ensure the study benefits from reliable and consistent metrics, offering an accurate depiction of economic landscapes across the timeline in focus.

In summary, the robustness and integrity of this research greatly hinge on the quality of data procured. By leveraging reputable data sources like the Global Operational Loss Database (GOLD) by Riskbusiness for operational loss details, the Bloomberg databases for essential financial metrics, and the World Bank databases for critical macroeconomic indicators, the study ensures it is built upon a foundation of accurate, reliable, and globally recognized data points. These databases, each with its unique strengths and specializations, collectively provide the comprehensive data landscape necessary for a nuanced exploration of the research objectives and questions at hand.

III-5.3. Study variables

In this study, several key variables are examined to understand their relationship with reputational risk and financial performance as illustrated below:

Figure III-3: study variables



For a nuanced understanding of the dynamics involved in reputational loss within the banking industry, this study adopts the above comprehensive framework to operationalize various dependent, independent, and moderating variables. A concise overview of these pivotal variables is provided below:

III-5.3.a Dependent Variable

Change in RoA as Abnormal Return ($AR_{i,t}$): RoA is an essential metric in banking as it evaluates a bank's capability to generate profits from its assets. Calculated as a percentage, it determines how effectively a bank's management can make earnings from its asset base. Significant and consistent alterations in RoA can act as an indicator of reputational damage which might be an aftermath of operational disruptions. This study focuses on how RoA evolves after the announcement of operational losses.

III-5.3.b Independent Variables

Operational Losses (Ol): This variable encompasses losses emanating from internal fraud incidents. It's segregated based on the area of operation, either a commercial bank or a retail bank, and the monetary scale of the loss. All figures are denominated in millions of USD. Operational loss data are obtained from the open GOLD databases.

Historical RoA ($RoA_{i,t}$): This variable aims to capture the RoA both before and after the occurrence of the operational loss. The metric is provided in percentage terms. Historical RoA for the selected banks are obtained from the Bloomberg databases.

Historical Total Assets ($A_{i,t}$): Reflecting the magnitude of resources controlled by a bank, this variable traces the total assets both pre and post the operational loss incident. The figures are provided in millions of USD. Historical Total Assets for the selected banks are obtained from the Bloomberg databases.

GDP Growth Rate ($G_{i,t}$): A broader economic indicator, this variable considers the GDP growth rate of the country the bank operates. It provides a macroeconomic backdrop, considering data from three years before to three years post the internal fraud disclosure. Figures are denoted in percentages. The GDP Growth Rate for the country of each bank in the sample is obtained from the World Bank economic databases.

Inflation Rate ($I_{i,t}$): Another pivotal macroeconomic metric, the inflation rate gives insights into the purchasing power and the economic stability of a country. For this study, the inflation rate of the country in which the bank operates is considered, spanning from three years before to three years after the internal fraud event, expressed as a percentage. Inflation Rate for the country of each bank in the sample is obtained from the World Bank economic databases.

III-5.3.c Moderating Variables

Bank Size (S): The size of a bank can influence its resilience to operational losses and the subsequent reputational impacts. While Fiordelisi et al. (2013) used market capitalization as a marker for bank size, this study adopts a more direct approach by using total assets. For classification purposes and following Akhigbe & McNulty (2005) and Terraza (2015), banks with assets below 1 billion USD are categorized as small (1); those between 1-10 billion USD as medium (2); and those with assets exceeding 10 billion USD are labeled as large (3).

Geographical Region (g1 and g2): The geographical location can play a pivotal role in moderating the effects of reputational losses. Factors intrinsic to a region or country, such as regulatory environment, media dynamics, and cultural aspects, can influence the extent of reputational damage. For this study, both the country (g1) and the broader geographical region (g2) in which the bank operates are considered as potential moderating influences on reputational loss dynamics. Geographical region data for each bank in the sample are obtained from the open GOLD databases.

In summing up the study variables, the adopted framework serves as a nuanced lens through which the intricate relationship between operational losses, financial performance, and reputational damage has been meticulously explored. By meticulously defining and operationalizing these variables, the intention has been to furnish a comprehensive and multi-dimensional insight into the realms of reputational risk within the banking landscape. This holistic perspective is anticipated to enrich both academic discourse and practical strategies in risk management.

III-5.4. Sample size

Within the timeframe of 2007 to 2016, there were a total of 22,240 reported operational losses sourced from the GOLD public database. A staggering 17,794 (80%) of these losses were specifically attributed to the banking industry, underlining the profound implications of operational risks within this sector.

Of the 17,794 banking-related operational losses, transparency was observed in 7,242 instances where the amount of loss was clearly and publicly disclosed. As the study's focus is keenly set on commercial and retail banking business lines, it's worth noting that out of the entire array of banking operational losses, 3,925 pertained directly to the domains of commercial and retail banking.

Upon closer examination of the 3,925 losses, it was found that only 2,232 losses had their event types thoroughly documented. Of these, 488 events were categorized under internal frauds, ranking it among the top three types of operational losses noted. The predominant type of internal fraud documented was "Embezzlement and Internal Fraud Schemes." Along with "Internal Credit Approval Fraud or Abuse," these two categories made up about 80% of the 488 internal fraud cases. The diverse categorizations of internal frauds can be seen in Table III-1 below.

Table III-1: Defining the sample size: Types of Internal frauds.

No	Event type	Size	%
1	Embezzlement and Internal Fraud Schemes	278	56.97%
2	Internal Credit Approval Fraud or Abuse	110	22.54%
3	Pilferage and Physical Theft	27	5.53%
4	Bribes Accepted by Employee	18	3.69%
5	Fraudulent Internal Credit Application for an Existing Customer	15	3.07%
6	Internal Identity Theft without System Intrusion	15	3.07%
7	Internal Identity Theft Involving System Intrusion	12	2.46%
8	Fraudulent Internal Credit Application for a Fictitious Customer	5	1.02%
9	Identity Misuse	2	0.41%
10	Intentional Disclosure of Confidential Corporate Information	2	0.41%
11	Money Laundering (for personal benefit)	2	0.41%
12	Internal Staff Identity Theft	1	0.20%
13	Profitability and Valuation Manipulation	1	0.20%
	Total	**488**	**100.0%**

Given the prevailing academic consensus, numerous studies have uniformly highlighted the presence of statistically substantial reputational losses stemming from operational failures attributed to internal frauds (Fiordelisi et al., 2013; Gillet et al., 2010; Perry & de Fontnouvelle, 2005). Per the findings of Fiordelisi et al. (2013), internal fraud is identified as the event type exhibiting the highest mean value and standard deviation. Such consistent empirical findings emphasize the substantial repercussions internal fraudulent activities can have on an institution's reputation. Therefore, aligning with these conclusive insights, this study is framed to channel investigative endeavors specifically towards understanding the nuances of internal frauds.

The 3,925 operational losses were expressed in 79 distinct currencies. Recognizing the centrality of the "amount of loss" as a pivotal dependent variable in the study, deliberate measures were taken to ensure uniformity and comparability of data. To this end, amounts denominated in currencies other than the US Dollar were converted to USD, given the US Dollar's predominance as the global trading currency. For accuracy in conversion, the closing exchange rate of the specific year in which each loss took place had been applied, in accordance with the protocols stipulated in our sampling method.

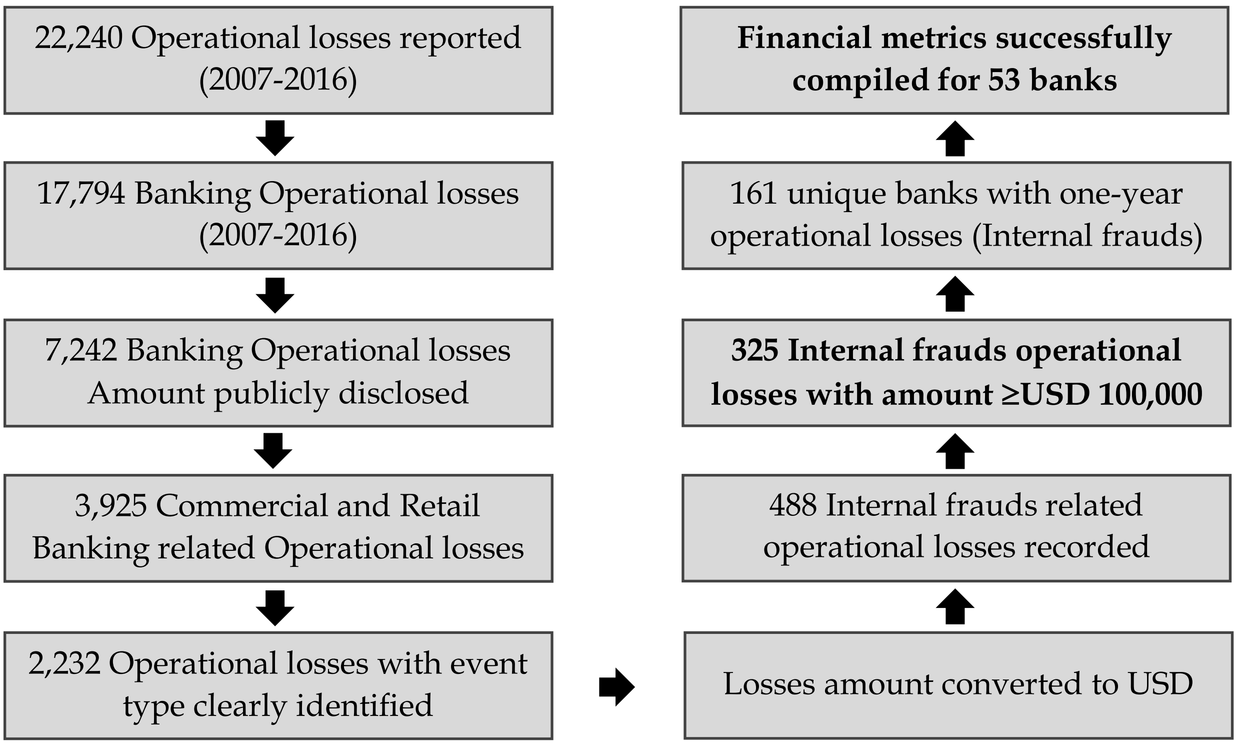
The sample selection for this study involved a careful process to minimize bias and accurately assess the impact of each operational loss. Out of 201 banks with 325 internal fraud events, only those with operational losses exceeding USD 100,000 were chosen. A critical criterion for inclusion was that each bank's operational losses had to be recorded in a specific year within the database. For instance, a bank that experienced multiple operational losses in a single year, like 2012, was included. However, banks with operational losses spanning multiple years, such as incidents in both 2012 and 2015, were excluded. This approach ensured a focus on unique loss events and their individual impacts. As a result, 39 banks with operational events spread over various years were not included, amounting to 148 cases of internal fraud. This methodological choice was made to provide a clearer, undiluted understanding of the consequences of each individual operational loss event.

Financial data for the study was sourced from the Bloomberg Terminal. Out of the 161 banks accounting for 177 internal fraud events, financial metrics were successfully collected for 53 banks. This data covers three years before and after the announcement of their operational losses. It's worth noting that, apart from these 53 banks, financial data for the remaining banks was inaccessible on Bloomberg Terminal. Various reasons account for this: some banks lacked data for the desired period, some were not listed, and others had no available financial information on Bloomberg.

This detailed and methodical filtration process culminated in the ultimate selection of 61 internal fraud-related operational events. These losses span across 18 different currencies, implicating 53 banks situated in 23 countries and 10 distinct geographical regions globally.

A comprehensive visual representation of our sample size can be referenced in Figure III-4.

Figure III-4: Visual representation of the study's sample size definition



III-6. Data analysis methods

This section outlines the specific statistical techniques and tools employed in the study to rigorously investigate the relationship between reputational risk and financial performance in commercial and retail banks.

In line with the overarching goal of reputational risk management, which aligns with the broader risk management objectives within banks to reduce the impact on key financial indicators like RoA (Coskun et al., 2019; Wanjohi et al., 2017), this study proposed a modification to the conventional methodologies used in reputational research. Traditionally, studies have relied on "event study" methods and the "market reaction" paradigm to evaluate reputational risk (Cummins et al., 2006; Eckert & Gatzert, 2017; Fiordelisi et al., 2013; Gillet et al., 2010). However, this research diverged from solely focusing on market reactions within a defined event window. Instead, it employed a panel longitudinal analysis approach, which involved estimating the reputational loss by examining the trends in RoA over a period of three years before and after each identified operational loss event. This method offered a more comprehensive view of the impact of reputational risk on a bank's financial performance over time.

III-6.1. Descriptive statistics

Descriptive statistics provided a comprehensive overview of the fundamental features of the dataset utilized, offering a valuable snapshot of its distribution, central tendency, and dispersion. It acts as the foundation, laying the groundwork for deeper inferential analyses aligned with the research questions posed (Saunders et al., 2019).

The data spans multiple banks from diverse global regions, covering several years. The descriptive analysis mainly covered:

1. **Measures of Central Tendency:** The mean, median, and mode are computed for continuous variables like RoA, Total Assets, and GDP Growth Rate. These measures provided insight into the general trend and central value of the dataset (Trochim, 2006).

2. **Measures of Dispersion:** Standard deviation, variance, and range are calculated to gauge the spread and variability within the dataset. This helped in understanding the consistency or variability of variables such as RoA and Total Assets across banks (Field, 2013).

3. **Distribution Shape:** Skewness and kurtosis metrics are determined to describe the shape of the dataset's distribution. This indicates if variables, for instance, RoA, are normally distributed or if they lean towards a particular direction (Dewberry, 2005).

4. **Frequency Analysis:** For categorical variables like Geographical location and Country, frequency counts and percentages are evaluated. This depicts the distribution of banks across various regions and countries (Saunders et al., 2019).

5. **Correlation Matrix:** A correlation matrix has been constructed to observe relationships between variables. This is especially relevant for Research Question 2, probing the relationship between the size of operational loss and reputational loss's monetary value (Field, 2013).

Descriptive statistics not only offer a preliminary understanding of the dataset but also ensure the subsequent advanced statistical methods are appropriate and meaningful (Hair et al., 2019). By understanding the basic structure, distribution, and relationships within the data, the study can ensure that further analyses are grounded on a solid foundational understanding of the data's characteristics.

The statistical package R has been used for the computational processes, and its 'ggplot2' library for the graphical representations.

III-6.2. Adjusted "Event study" to quantify reputational risk

An event study is a methodological approach that seeks to determine the impact of specific events or announcements on a firm's value or performance. This approach has been popularized in finance to understand how stock prices react to corporate announcements, policy changes, or macroeconomic shocks (Boehmer et al., 1991; Kothari & Warner, 2007). In the domain of organizational studies, event studies have been employed to measure responses to various corporate events, from mergers and acquisitions to announcements of corporate social responsibility initiatives (Binder, 1998; Bloom, 2011; Eckert & Gatzert, 2019; Mackinlay, 1997; Sorescu et al., 2017).

In organizational contexts, event studies have been expanded to analyze a broader array of outcomes beyond stock prices, such as profitability, operational performance, and even employee morale. The focus often lies in understanding the effects, both direct and indirect, of specific events on organizational health and performance. This perspective is essential in both shorter and longer terms because while stock prices might react immediately, other organizational metrics might take longer to show any significant change (Kothari & Warner, 2007).

III-6.2.a Fundamentals of event study: the abnormal return

To address Research Question 1, it is imperative to evaluate the effect of the operational event by quantifying the abnormal return. The abnormal return (AR) represents the difference between the actual return (R) of a security during the event window and its expected or "normal" return (E) during the same period. This normal return is the anticipated return without the occurrence of the specific event (Mackinlay, 1997). For a given firm, denoted as firm *i*, on the event date *t*, the abnormal return can be represented as:

$$\boldsymbol{AR_{i,t}} = R_{i,t} - E(R_{i,t} \mid X_t)$$

With $\boldsymbol{AR_{i,t}}$, $R_{i,t}$, and $E(R_{i,t} \mid X_t)$ being respectively the Abnormal return, the actual return, and the normal (expected) return of firm *i* in period t. X_t represents the conditioning information utilized in the normal return model (Mackinlay, 1997).

Mackinlay (1997) underscores two prevalent methods to conceptualize this normal return: the "constant mean return model", where the return, denoted as X_t, remains consistent, and the "market model", where X_t represents the market return. The former model posits that a security's mean return remains unchanged over time. In contrast, the latter infers a consistent linear relationship between the return of a security and the broader market return.

The event study methodology traditionally models abnormal returns as prediction errors from established models like the market model. However, an alternate approach directly integrates the event into the return equation by extending the sample period to encompass the event and parameterizing the abnormal return. This method, introduced by Izan

(1978), employs dummy variables for each announcement or event period, allowing for the direct estimation of abnormal returns in the regression. When the model is applied to a portfolio return, the coefficient on the dummy variable provides an estimator of the average abnormal return across the stocks in the portfolio (Binder, 1998).

III-6.2.b Adapting models to context

Binder, (1998) highlighted the adaptability of models to incorporate benchmarks like the CAPM or account for trends like the "January Effect." However, when abnormal returns differ across firms, conventional models falter. The multivariate regression model (MVRM) system, introduced by Gibbons (1982) and later adopted by Binder (1998) and others, disaggregates returns for individual firms.

The MVRM approach emphasizes the flexibility to account for varied responses across firms, particularly when abnormal returns show divergent trends. This granularity mirrors the capabilities of the random effects model adopted in this study. By accommodating both observed and unobserved heterogeneities, the random effects model effectively quantifies reputational loss through abnormal returns, underscoring its precision and relevance in the context of event studies (Treiman, 2009). This is particularly relevant for understanding the prolonged impact of reputational losses, allowing the study to isolate the reputational effect from other concurrent events or inherent bank-specific attributes (Hair et al., 2019).

Isolating reputational loss effects from direct operational loss is a complex task (Eckert & Gatzert, 2017; Fiordelisi et al., 2013). This research approach captures the long-term implications of operational losses in commercial and retail banks, potentially leading to sustained reputational damages. The methodology hinges on the annual deviations (Abnormal Return) from a bank's expected RoA trajectory (Normal Returns), suggesting these deviations serve as indicators of lingering reputational loss, consistent with the event study literature (Eckert & Gatzert, 2017; Binder, 1998; Kothari & Warner, 2007; Mackinlay, 1997).

III-6.2.c Predicting the RoA

To accurately measure the repercussions of unexpected events, such as operational losses leading to reputational damages, it's crucial to set a predicted RoA baseline using historical performance data. Through multivariate regression analysis of RoA data from the three years leading up to the operational loss, a projection for the following three years is constructed, painting a picture of the anticipated RoA trajectory had the operational loss not occurred. This approach is embodied in the Generalized Least Square (GLS) Random effects model applied in this study.

The mathematical representation of the Random effects model, in the context of this study, is:

$$\boldsymbol{eRoA_{it}} = \beta_0 + \sum_{j=1}^{3} \beta_j \,(RoA, j)_{it} + \sum_{k=1}^{3} \gamma_k \,(A, k)_{it} + \delta G_{it} + \varepsilon I_{it} + \sum_{l=1}^{N} \theta_l \,(g, l)_{it} + \in_{it}$$

Where:

- $\boldsymbol{eRoA_{it}}$ is the expected RoA (Normal Return) for bank '$\boldsymbol{i}$ ' in year '$\boldsymbol{t}$ '
- β_0 is the intercept.
- β_j are the coefficients for the RoA lags (RoA, j) of 1, 2, and 3 years respectively (prior to the event).
- γ_k are the coefficients for Total Assets (A) lags of 1, 2, and 3 years respectively (prior to the event).
- δ is the coefficient for GDP Growth Rate (G), for bank '$\boldsymbol{i}$ ' in year '$\boldsymbol{t}$ ' (considering the specific country in which the bank is operating)
- ε is the coefficient for Inflation Rate (I) for bank '$\boldsymbol{i}$ ' in year '$\boldsymbol{t}$ ' (considering the specific country in which the bank is operating)
- θ_l are the coefficients for each regional (g) dummy variable (with N representing the number of unique regions).
- $\in_{i,t}$ is the error term for bank '$\boldsymbol{i}$ ' in year '$\boldsymbol{t}$ '

III-6.2.d Computing the Abnormal Return (Rl)

Once the anticipated RoA ($\boldsymbol{eRoA_t}$) is determined, the tangible effect of the operational loss can be gleaned by assessing the discrepancies between the forecasted values and the observed RoA values, Actual Returns ($\boldsymbol{RoA_{+1}}$, $\boldsymbol{RoA_{+2}}$, and $\boldsymbol{RoA_{+3}}$) in the years subsequent to the loss announcement. This difference potentially embodies the financial ramifications of reputational damage (Binder, 1998; Kothari & Warner, 2007).

$$\boldsymbol{AR_{i,t}} = RoA_{i,t} - eRoA_{i,t}$$

A mere percentage deviation in RoA ($\boldsymbol{AR_{i,t}}$), while indicative of performance shifts, might not vividly communicate the financial stakes. By multiplying this deviation with the Total Asset values, the tangible financial implications are highlighted ($\boldsymbol{mAR_{i,t}}$).

$$\boldsymbol{mAR_{i,t}} = AR_{i,t} \times A_{i,t}$$

Where:

$\boldsymbol{A_{i,t}}$ represents the observed value for Total Assets for a specific bank '*i*' in year '*t*' after an operational loss has been registered.

In the empirical analysis of event studies, discerning whether the observed abnormal returns are statistically significant is of paramount importance (Fiordelisi et al., 2013; Kothari & Warner, 2007; Mackinlay, 1997). The significance of these returns can provide insights into the market's reaction to a particular event. In the context of this study, the event in question is the disclosure of internal frauds, and the metric of interest is the RoA.

Following Fiordelisi et al. (2013), the study employed Boehmer et al. (1991) test statistic Z, originally designed to capture event-induced volatility in stock returns, to test the statistical significance of mean AR. The test has been widely recognized for its robustness.

The central tenet of the Boehmer et al. approach is to ascertain if the observed abnormal returns differ significantly from zero. The test does so by gauging the standard deviation of the abnormal returns relative to the number of observations. Under the null hypothesis, the Z statistic adheres to a standard normal distribution.

While the Boehmer et al. approach is primarily tailored for stock returns, this study adapts it to fit the RoA context. The rationale remains consistent: to discern if the RoA post-fraud disclosure significantly deviates from the expected RoA. Given the unique dynamics of RoA, as opposed to stock returns, adjustments were made to account for the different scales and magnitudes.

The standardized abnormal return, SR, for each bank 'i' is calculated as:

$$SR_i = \frac{CAR_i}{\sigma(AR)_i}$$

Where:

$\boldsymbol{SR_i}$ is the Standardized Abnormal Return for bank 'i'.

$\boldsymbol{CAR_i}$ is the Cumulative Abnormal Return for bank 'i'.

$\boldsymbol{\sigma(AR)_i}$ is the standard deviation of Abnormal Returns for bank 'i' over the post-event years.

For each bank, the CAR is standardized by dividing it by the standard deviation of its AR. This process effectively converts the CAR into a z-score, indicating how many standard deviations a bank's CAR is from the mean CAR of the sample.

Subsequently, the Z test statistic is calculated as the mean of the SR divided by its standard deviation, scaled by the square root of the number of observations. This test statistic captures the event-induced increase in return volatility and is employed to test the significance of the CAR. The Z test statistic, as employed in this analysis, is formally defined by the equation:

$$Z = \frac{\frac{1}{N}\sum_{i=1}^{N} SR_{i,t}}{\sigma(SR)/\sqrt{N}}$$

Where:

Z: This is the Boehmer et al. (1991) test statistic. It measures how many standard deviations away the average standardized return (SR) is from zero, considering the sample size. The significance of this statistic will indicate whether the event has a statistically significant effect on returns.

N: This is the total number of banks (N= 53) in the sample. It computes the average standardized return across all observations.

$\sum_{i=1}^{N} SR_{i,t}$: This represents the sum of the standardized abnormal returns (SR) for all banks. It aggregates the impact of the event across all banks in the sample.

$\sigma(SR)$**:** This is the standard deviation of the standardized abnormal returns (SR) across all banks. It measures the dispersion or variability in the abnormal returns after the event.

$\sqrt{N}$ **:** The square root of the sample size, which adjusts the standard deviation for the number of observations. This adjustment is essential to account for the fact that as the sample size increases, the standard error of the mean decreases.

By leveraging this test statistic, the study seeks to ascertain the empirical relevance and significance of the impact of internal frauds on the RoA of the banks in the sample.

III-6.2.e Measuring the Reputational loss (Rl)

To accurately assess reputational loss, it's vital to differentiate the immediate operational loss from the broader financial discrepancies. The operational loss has already impacted the bank's net income, and subsequently, its RoA for the event year. In the years following the event, given no new operational incidents recorded in our sample, there's no direct effect of operational losses on the bank's financial metrics. The formulated approach takes into account the influence of the operational loss amount for each post-event year, ensuring a clear delineation of reputational loss.

The reputational loss $(\boldsymbol{Rl_t})$ is calculated using the proposed formula:

$$\boldsymbol{Rl_{i,t}} = ((RoA_{i,t} \times A_{i,t}) + Ol_i) - (eRoA_{i,t} \times A_{i,t})$$

Where:

$\mathbf{Rl_{i,t}}$ represents the reputational loss for bank 'i' in year 't' post-event.

$\mathbf{RoA_{i,t}}$ is the actual RoA for bank 'i' in year 't' post-event.

$\mathbf{A_{i,t}}$ stands for the total assets for bank 'i' in year 't' post-event.

$\mathbf{Ol_i}$ denotes the reported operational loss for bank 'i'.

In another perspective, the financial impact reflected in the abnormal return can be decomposed into two distinct components: the intensity of the operational loss and the intensity of the reputational loss. By subtracting the reputational loss intensity from the monetary abnormal return, it essentially retrieves the disclosed amount of the operational loss.

$$\boldsymbol{mAR_{i,t}} = Ol_{i,t} + Rl_{i,t}$$

The magnitude of the reputational loss, represented as $Rl_{i,t}$, can manifest in either positive or negative values. A negative value suggests that even after accounting for the disclosed operational event, there's an additional financial setback that the bank endured, potentially hinting at the deeper undercurrents of reputational damages. Positive values for $\mathbf{Rl_{i,t}}$ suggest that the bank has not experienced any reputational damage in light of the operational loss. In fact, its actual RoA surpasses the expected, indicating a resilient financial performance.

For computational processes, the 'plm' library in the R's statistical package was employed. Using R leverages its well-established libraries and functions designed for robust statistical analysis. The decision to use R aligns with its widespread acceptance and reliability in academic and organizational research for quantitative analysis (R Core Team, 2020).

III-6.2.f Model validity and robustness check

Ensuring the accuracy and validity of the selected statistical model is pivotal for drawing robust and reliable conclusions (Saunders et al., 2019). In the context of our research, the Random Effects model was subjected to three key statistical tests to validate its appropriateness for the data and the research questions at hand.

1. **Multicollinearity Test:** To ensure that the independent variables in the model are not too highly correlated, a Variance Inflation Factor (VIF) test was conducted. Multicollinearity can inflate the variance of the regression coefficients, making them unstable and challenging to interpret (Coskun et al., 2019b; Fiordelisi et al., 2013). A VIF value above 10 is usually considered a sign of multicollinearity. In the study's model, all VIF values were well below this threshold, suggesting that multicollinearity is not a concern for the data.
2. **Heteroskedasticity Test:** Heteroskedasticity refers to situations where the variance of the residuals is not constant across observations. This can undermine the

efficiency of the coefficient estimates (Breusch & Pagan, 1979). In the analysis, the presence of heteroskedasticity in the model was initially investigated using the Breusch-Pagan test. However, given potential concerns about the reliability of this test in certain contexts, heteroskedasticity was further assessed using robust standard errors, specifically the heteroskedasticity-consistent standard error estimator. This robust method, often referred to as "White standard errors," offers a more rigorous approach to ensuring that the standard errors remain reliable, even in the presence of heteroskedasticity. By incorporating this robust test, the validity and reliability of the regression results were enhanced, ensuring that any potential heteroskedasticity would not compromise the study's conclusions.

3. **Autocorrelation Test:** Autocorrelation occurs when the residuals in the model are correlated with themselves across different time lags. In panel data, it's essential to ensure that there's no autocorrelation, as it can lead to biased standard errors (Wooldridge, 2015). The Wooldridge test for autocorrelation in panel data was used in this context. The study's model showed no significant autocorrelation, validating the reliability of the coefficient estimates.

In summary, the rigorous application of these tests ensures the validity of the Random Effects model used in this study. Their collective results provide confidence in the robustness of the findings derived from the model and reinforce the credibility of the conclusions drawn from the analysis.

III-6.3. Correlation analysis

Correlation analysis, in the realm of statistics and research, gauges the strength and direction of the linear relationship between two quantitative variables. The essence of this analysis is to discern if fluctuations in one variable are systematically associated with variations in another. In other words, it seeks to determine if an increase or decrease in one variable consistently corresponds with an increase or decrease in another variable. The outcome is represented by a correlation coefficient, typically denoted by 'r'. (Saunders et al., 2009). The value of 'r' can range from -1 to +1; with -1 indicating a perfect negative relationship, +1 indicating a perfect positive relationship, and 0 indicating no relationship (Stockemer, 2019).

For instance, in the context of this study, a positive correlation between the magnitude of operational loss due to internal fraud and the monetary value of reputational loss would suggest that as the operational loss increases, the reputational loss, in monetary terms, also amplifies. Conversely, a negative correlation would indicate an inverse relationship: as one variable rises, the other tends to decrease.

It's crucial to note that while correlation can indicate the presence of a relationship, it does not imply causation. That is, just because two variables move in tandem doesn't mean that changes in one variable cause changes in the other. Correlation analysis provides a preliminary understanding of potential relationships, which can then be further explored using more sophisticated statistical techniques (Hall et al., 2016).

The Pearson correlation coefficient, represented by "r", is frequently used in research to measure how two variables relate linearly. It's a popular statistic in empirical studies for gauging the strength and direction of the association between two variables (Cohen et al., 2003; Hall et al., 2016). The formula for the Pearson correlation coefficient is:

$$r = \frac{\sum_{i-1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i-1}^{n}(x_i - \bar{x})^2 \ \sum_{i-1}^{n}(y_i - \bar{y})^2}}$$

Where:

- "n" stands for the total number of pairs of data points we're looking at.
- "x_i" and "y_i" represent the individual data points, with "i" being an index to specify which data point we're referring to.
- "$\bar{x}$" and "$\bar{x}$" are just the average values of X and Y data sets.

Empirical studies in the realm of organizational research frequently employ correlation analysis as a foundational tool to decipher the relationships between variables. This analytical technique has paved the way for seminal findings across various domains, from human resource management to organizational behavior and strategic management. For instance, studies have used correlation analysis to unearth the relationship between the number of operational losses and reputational damages, bank size, and reputational losses (Eckert & Gatzert, 2017; Fiordelisi et al., 2013; Gillet et al., 2010).

In the context of this research, employing correlation analysis becomes instrumental in addressing Research Questions 2 and 3. Specifically, the analysis will provide insights into the relationship between the size of an operational loss due to internal fraud and the subsequent monetary value of the reputational loss. Further, it will shed light on how the intensity of reputational loss might vary based on the size of the affected bank. These investigations, grounded in correlation analysis, will offer a nuanced understanding of the dynamics at play, echoing findings from prior empirical evidence (Cummins et al., 2006; Fiordelisi et al., 2014; Gatzert, 2015; Gillet et al., 2010).

For the data analysis, the study utilized the R programming language, specifically leaning on its capabilities for correlation analysis. While R's native 'cor.test()' function offers a basic calculation of the Pearson correlation coefficient, the study opted for the 'Hmisc' package. This choice was driven by 'Hmisc's advanced functions, particularly 'rcorr()', which not only computes a detailed correlation matrix but also emphasizes significance levels and provides comprehensive visualizations (R Core Team, 2020). The main reasons for using the "Hmisc" Package are:

- **Versatility:** It can process correlations for many variables at once, which is great for big datasets.
- **Statistical Significance:** Along with the correlation matrix, rcorr(), it gives p-values, which helped in figuring out how reliable the correlations are.
- **Compatibility:** It's good for data that's either numbers or categories.
- **Visualizations:** The package has tools for making graphs, useful for understanding and presenting the data.

III-6.4. Analysis of Variance (ANOVA) and Tukey HSD test

III-6.4.a Analysis of Variance (ANOVA)

To address the fourth research question, "How does the impact of reputational losses stemming from internal fraud disclosures differ across banks situated in various global regions?", an Analysis of Variance (ANOVA) was employed. ANOVA is a statistical method used to test differences between two or more means. It may seem odd that ANOVA is used to test a linear relationship between two variables. However, when one of the variables is categorical and the other is continuous, ANOVA is the appropriate method to determine if the means of the continuous variable differ across the categories (Field, 2013).

In the context of this research, the categorical variable is the global geographical location where the bank operates (e.g., Eastern Asia, Northern America, Western Europe, etc.), and the continuous variable is the reputational loss intensity (Rl). The primary goal was to determine if the mean reputational loss differs significantly across the various global regions.

III-6.4.b Tukey's Honest Significant Difference (HSD) Post-hoc Test

While ANOVA determines if there are any statistically significant differences between the means of the selected groups, it does not specify which groups are significantly different from each other. To identify which specific regions have significantly different mean reputational losses, a post-hoc test was necessary.

For this purpose, Tukey's Honest Significant Difference (HSD) post-hoc test was employed. Tukey's HSD is a method used to perform pairwise comparisons between group means, and it controls for the family-wise error rate, ensuring that the probability of making a Type I error remains at the desired level (usually 0.05) across all comparisons

(Tukey, 1949). Recent studies have utilized the Tukey HSD Post-hoc analysis alongside ANOVA to uncover significant differences and examine the associations between categorical variables (Kibirige et al., 2022; Ravichandran & Padmanaban, 2023).

By using Tukey's HSD, we can determine which specific pairs of regions have mean reputational losses that are significantly different from each other. This provided a more detailed understanding of the relationship between global regions and reputational loss, allowing for a nuanced interpretation of the results in the context of the research question.

Incorporating both ANOVA and Tukey's HSD post-hoc test into the data analysis methods ensured a comprehensive approach to addressing Research Question 4. While ANOVA provides an overarching view of the differences in mean reputational losses across global regions, Tukey's HSD offers a detailed breakdown of pairwise comparisons, highlighting specific regions where these differences are most pronounced.

III-7. Reliability and Validity

III-7.1. Reliability

Reliability, within the ambit of research, refers to the consistency, stability, and repeatability of findings. Ensuring reliability is imperative to establish that the results from the dataset can be consistently reproduced under similar conditions and with a similar methodology (Saunders et al., 2009). In the context of the study, where the random effects model is employed using the dataset, several elements ensure the reliability of the findings:

- **Dataset source and curation:** First, datasets for operational losses, financial metrics, and annual reports were primarily gathered from reputable databases and financial institutions. These datasets were widely used and cited in the industry, thus providing a level of assurance regarding their accuracy. Second, the data were carefully cleaned and preprocessed to remove any inconsistencies or errors that could affect the results. This involved cross verifying the data with multiple sources when available and applying robust techniques to handle missing or outlier data points (Hair et al., 2019).

- **Rich dataset:** The final dataset encompasses a broad spectrum of banks, cutting across various regions and bank sizes. This vast representation guarantees that the results are not overly influenced by outliers or specific data clusters, enhancing the universality of our findings.
- **Standardized methodology:** The methodologies chosen from the employment of the random effects model are based on solid statistical and empirical foundations (Eckert & Gatzert, 2017; Fiordelisi et al., 2013). This standardization minimizes potential biases or interpretative errors.
- **Replicability:** One key aspect of reliability is the ability of other researchers to replicate the study's findings. Therefore, a detailed description of the methodology was provided, and where possible, the scripts for data cleaning and analysis were made available for peer review (Hair et al., 2019).
- **R Statistical Environment:** Utilizing the R statistical package, a trusted and widely used tool in academic and professional research, augments the reliability of our analysis. The transparent nature of R, combined with its comprehensive documentation, ensures the reproducibility and verifiability of each step in our analysis by other researchers (R Core Team, 2020). Finally, to further affirm reliability, the study underwent multiple rounds of data analysis, each followed by a rigorous review process. This ensured that the findings were not only consistent but also held under different assumptions and conditions.

In conclusion, the reliability of the study is reinforced by the meticulous combination of an extensive dataset, rigorous methodology, and exhaustive validation processes. Such adherence to reliability principles ensures that the findings serve as a robust base for future research and policy decisions within the banking sector's operational loss and reputation risk spheres.

III-7.2. Validity

To ensure the validity of the study findings, the study implemented several measures across different facets of validity: content, construct, external validity, and statistical validity.

1. **Content validity:** The research design was carefully developed to ensure that all research questions were appropriately addressed. The variables chosen for the study were selected based on an extensive review of the literature and were corroborated by experts in the field to ensure their relevance and adequacy in capturing the phenomena under investigation (Eckert & Gatzert, 2017; Fiordelisi et al., 2013; Gillet et al., 2010).

2. **Construct validity**: The measurement instruments and methods were chosen because of their well-established validity in organizational and financial studies. A series of pilot tests were conducted to refine the measurement scales and operationalize the constructs effectively (R Core Team, 2020).

3. **External validity:** To enhance the generalizability of the findings, the sample size was chosen to be both sufficiently large and diverse, incorporating banks of varying sizes and operational frameworks. This diverse sample aimed to represent the broader banking sector, thus making the findings applicable to a wide range of organizations (Saunders et al., 2009).

4. **Statistical validity:** To safeguard against any threats to statistical validity, such as errors due to sampling or model specification, robustness checks were performed (Hair et al., 2019). These included sensitivity analyses and tests for multicollinearity, heteroscedasticity, and endogeneity.

Rigorous steps were taken at each phase of the research process to ensure the validity of the study. From the design stage to data collection and analysis, each aspect was carefully considered and vetted to meet the highest standards of academic rigor.

III-8. Ethical considerations

The research strictly complies with the ethical guidelines as outlined by the University of Cape Town's Commerce Ethics Handbook. This adherence is aimed at ensuring the overall integrity and reliability of the research process, safeguarding it from any ethical dilemmas that could compromise the study's validity.

One of the most frequent ethical challenges in research pertains to confidentiality. However, the nature of this study reduces such ethical complexities as it exclusively relies on secondary data that is already publicly available. This data encompasses documented events related to operational losses, and banks' financial metrics, all of which are obtained from publicly accessible sources. Consequently, issues related to participant consent or anonymity do not apply in this case.

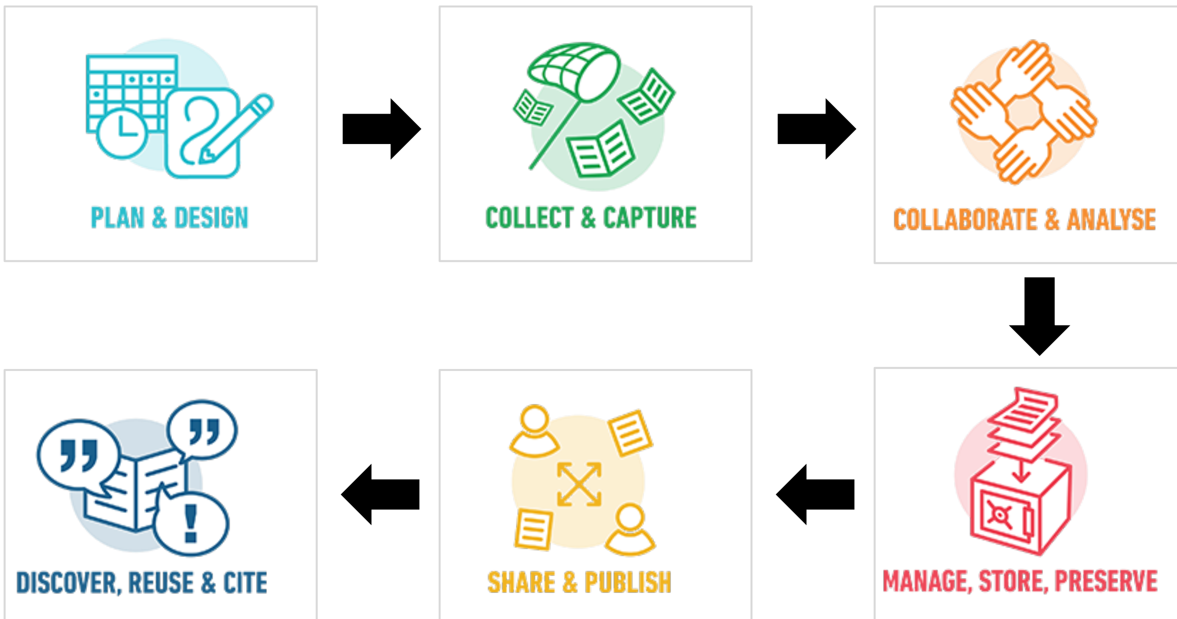
However, in line with institutional requirements, the research secured ethical clearance from the University of Cape Town Commerce Research Ethics Chair on March 29, 2021. The clearance, referenced as REC 2021/03/018, remains valid through December 31, 2023. This approval serves as an additional layer of ethical validation, confirming that the research design and data collection methods are in line with recognized ethical standards.

III-9. Data Management Plan

A Data Management Plan (DMP) is a methodical framework that traces the data's full life cycle in a research endeavor, ranging from its initial collection to its final archiving (Rice, 2011). For the purposes of this study, the University of Cape Town's Research Data Management (RDM) policy serves as the main guide for achieving data integrity, maintaining ethical protocols, and enhancing research transparency.

The Research Data Management (RDM) Policy at the University of Cape Town (UCT) aims to standardize research practices, particularly those concerning data management principles. Data serve as a crucial asset in research, and the importance of efficiently sharing this data to ensure its discoverability, accessibility, reusability, and interoperability cannot be overstated. The RDM lifecycle at the UCT is as follows:

Figure III-5: RDM lifecycle (UCT Digital Library Services, 2022)



- **Plan & Design:** The foundational phase of the present research project involves meticulous planning and design. This encompasses the anticipation of vital resources, like data storage solutions, and their associated costs. In this stage, strategies for data sharing are devised, all of which are anchored in a comprehensive Data Management Plan (DMP).
- **Collect & Capture:** The modern research landscape offers a plethora of software and hardware solutions, aiding in the efficient collection and capturing of data. this study leveraged state-of-the-art tools tailored to financial data acquisition.
- **Collaborate & Analyse:** In this age of collaborative research, myriad tools exist to facilitate data sharing and collaboration. Concurrently, R platforms and packages were used for data processing and in-depth analysis, ensuring the highest level of accuracy and insight.

- **Manage & Store:** Effective data management is pivotal for the longevity and accessibility of the research. The adopts best practices for data storage and preservation, ensuring that our dataset remains a valuable asset for future research endeavors. All the datasets are stored in Excel CSV on the UCT OneDrive cloud storage services.
- **Share & Publish:** Embracing the principles of open science, the study prioritized the open publication of the used data and research findings. Numerous platforms, both general and discipline-specific, stand ready to host and disseminate contributions to the academic community, including the UCT platforms.
- **Discover, Reuse & Cite:** With a wealth of data available, leveraging online tools and platforms is crucial for discovering existing datasets.

The UCT's RDM is designed to provide a formal framework for how research data will be managed throughout the life of a study project and beyond. The plan should delineate the administrative procedures for acquiring, validating, storing, safeguarding, and processing data. It offers a standardized methodology for handling various types of data, all while aligning with the overarching research aims and queries. Efficient data management is indispensable for assuring the research outcomes' reliability, validity, and applicability on a broader scale.

Additionally, the plan necessitates that analytical software and tools, including coding, algorithms, and visualization tools, be made available for generating and replicating the data.

The Research Data Management (RDM) policy adheres to the FAIR open data principles, which stand for 'Findable, Accessible, Interoperable, and Reusable.' These principles align with international best practices. The data management plan for this research study was crafted using the framework provided by the Digital Curation Centre (DCC), and it encompasses the six core themes as endorsed by the Digital Library Services Department at the University of Cape Town (Digital Library Services, 2020).

Regarding data types, formats, standards, and capture methods, the source data files for this study were saved in a comma-separated values (CSV) format to promote both interoperability and reusability.

To maintain data security and accessibility, all processed and archived data were stored in the same CSV format in encrypted databases with restricted access, only granted to the research team. Periodic backups are implemented to cloud-based University of Cape Town OneDrive (Microsoft) to safeguard against data loss. The study relied on secondary financial data sourced from reputable databases and financial institutions. It contains publicly disclosed operational losses from RISKBUSINESS (GOLD), and commercial banks' financial metrics from Bloomberg financial records. All datasets underwent a rigorous verification process to ensure they meet the quality criteria, such as accuracy and completeness.

Given that the data was sourced from a reputed source (Bloomberg, GOLD, and World Bank databases), it was assumed to be reliable, as all such institutions must adhere to international standards. The statistical software R was used for data processing and further qualitative checks were considered to minimize errors or duplications, thereby ensuring the highest data quality. Statistical analyses are conducted using validated and widely accepted software packages, R, known for their robust features in regression analysis and panel data analysis, respectively.

Prior to any analysis, the data is verified and cleaned, pre-processed, and cross-referenced with additional sources. Robust techniques are applied to handle missing or outlier data points to ensure the reliability and validity of the dataset.

Complete documentation of the data collection and analysis process is maintained to facilitate future replication or extension of this study. Analytical scripts and code are made publicly available.

This plan adheres to the ethical guidelines established by the University of Cape Town, ensuring that all data used is publicly available, thereby eliminating concerns related to confidentiality or data sensitivity. Ethical clearance for this study has been obtained from the relevant authorities.

IV. EMPIRICAL RESULTS AND DISCUSSIONS

"Change is inevitable. Change is constant."

Benjamin Disraeli

Chapter Four, titled "Empirical Results and Discussions," begins by exploring the dynamic nature of banking risks, emphasizing the ongoing need for enhanced risk management practices. This is succeeded by a section on Descriptive Statistics, which offers numerical insights into the research variables. Each research question is then methodically tackled in dedicated sections, encompassing empirical findings, interpretations, and discussions. The culmination of each of these sections is the Hypothesis testing, critically assessing the research's posited theories. The chapter wraps up with a summary and reflection on the principal outcomes from an international standpoint.

IV-1. The Ever-evolving landscape of banking risks

The banking industry, like many other sectors, exists in an environment of perpetual transformation. The shifting socio-economic dynamics, technological advancements, and regulatory changes are just a few factors that cause continuous evolution. Such a mutable context mandates an incessant exploration into risk management practices within banking, ensuring that every potential risk is meticulously analyzed and becomes pivotal for the robustness of risk management (Skoglund & Chen, 2015).

For instance, over the years, the Basel Accords have undergone several changes, echoing the industry's and regulators' acknowledgment of the dynamic nature of risks and the consequent need for an adaptive framework (Apostolik et al., 2009; Apostolik & Donohue, 2015). The transition from Basel I to Basel III is not merely a testament to the changing perceptions of risk but also an indication of the proactive measures taken to refine and strengthen risk management practices in banking. These accords have evolved in response to financial crises, technological developments, and changing market structures, emphasizing the need for financial institutions to be agile and responsive (Basel Committee on Banking Supervision, 2011, 2017).

Empirical research, historically, has been intrigued by the dynamics of change and the causality that underpins it. Delving into the causative factors, understanding the nuances of their interplay, and extrapolating their potential impacts have been subjects of intense investigation (Hall et al., 2016; Romanelli & Tushman, 1994). The challenge of discerning patterns within ever-changing variables and drawing meaningful insights from them is what makes empirical research both daunting and exhilarating (Hair et al., 2019).

In the realm of reputational research, the importance of studying changes in the landscape becomes even more pronounced. Reputation is a fragile asset, easily swayed by the shifting winds of public opinion, market dynamics, and internal organizational changes. By understanding these shifts and their implications, banks can preempt potential risks and navigate the turbulent waters of the financial industry more effectively (Fiordelisi et al., 2013; Ladipo & Adeosun, 2013; Walter et al., 2013).

IV-2. Descriptive insights: an overview of the study data

A thorough descriptive analysis served as the cornerstone of this study, meticulously quantifying the central tendencies, variability, and frequency of occurrences within the dataset. This statistical examination is essential, laying the groundwork for a comprehensive understanding of the variables under scrutiny (Dewberry, 2005). By establishing a baseline of the data's behavior, the research is positioned to delve deeper into the specific dynamics of reputational losses within the banking sector. Such a methodical approach to data interpretation is in line with the best practices in empirical research, ensuring that the findings are both robust and reliable (Hair et al., 2019, Eckert & Gatzert, 2017; Fiordelisi et al., 2013).

The descriptive statistical analysis (Appendix 1) in this study encompasses a range of variables to provide a detailed overview of the dataset. Central to this analysis is the RoA, which serves as a key indicator of the banks' financial performance (Akhigbe & McNulty, 2005). Additionally, the study examines Total Assets to assess the scale of the banks' operations. The magnitude of operational losses, alongside the specific categories of internal fraud incidents, are scrutinized to understand their impact on the banks. Furthermore, the geographical positioning of each bank is considered, providing insight into regional dynamics. Complementing these bank-specific metrics, macroeconomic indicators such as the GDP growth rate and the inflation rate for the respective countries of the banks are also analyzed. These variables collectively offer a comprehensive picture of the financial environment and the operational context within which the banks function.

IV-2.1. Central tendency analysis

The analysis of central tendency metrics offers insight into the general characteristics of key financial variables. By examining the mean, median, and mode of these metrics (Appendix 3), we can derive a foundational understanding of their distribution and their centrality patterns (Stockemer, 2019).

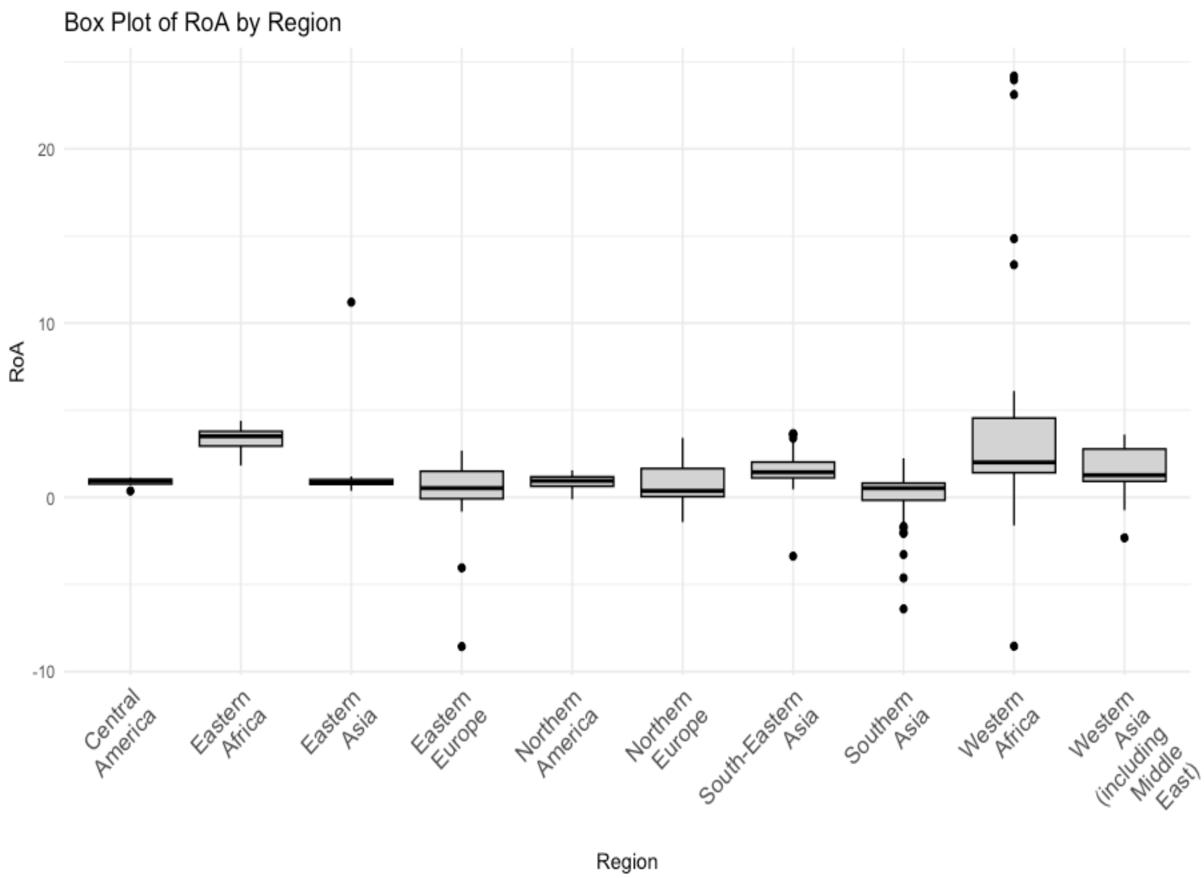
IV-2.1.a Return on Assets (RoA)

The mean RoA across the dataset is 1.23%. This suggests that, on average, banks yield a return of approximately 1.23% on their assets. The median RoA is slightly lower at 0.94%, indicating that half of the banks have a RoA below this value. The mode, being 0.00%, indicates that there are a considerable number of banks with RoA near 0.00%.

At the regional level, banks in Western Africa lead with the highest average RoA at 4.79%. Contrastingly, Eastern Europe banks report the lowest mean RoA of just 0.05%. The RoA mode in Northern Europe is 0.00%, suggesting many banks in this region break even.

Figure IV-1 visually represents the distribution of RoA across different regions, highlighting the central tendencies and variability within each region included in the study.

Figure IV-1: RoA distribution across geographical regions



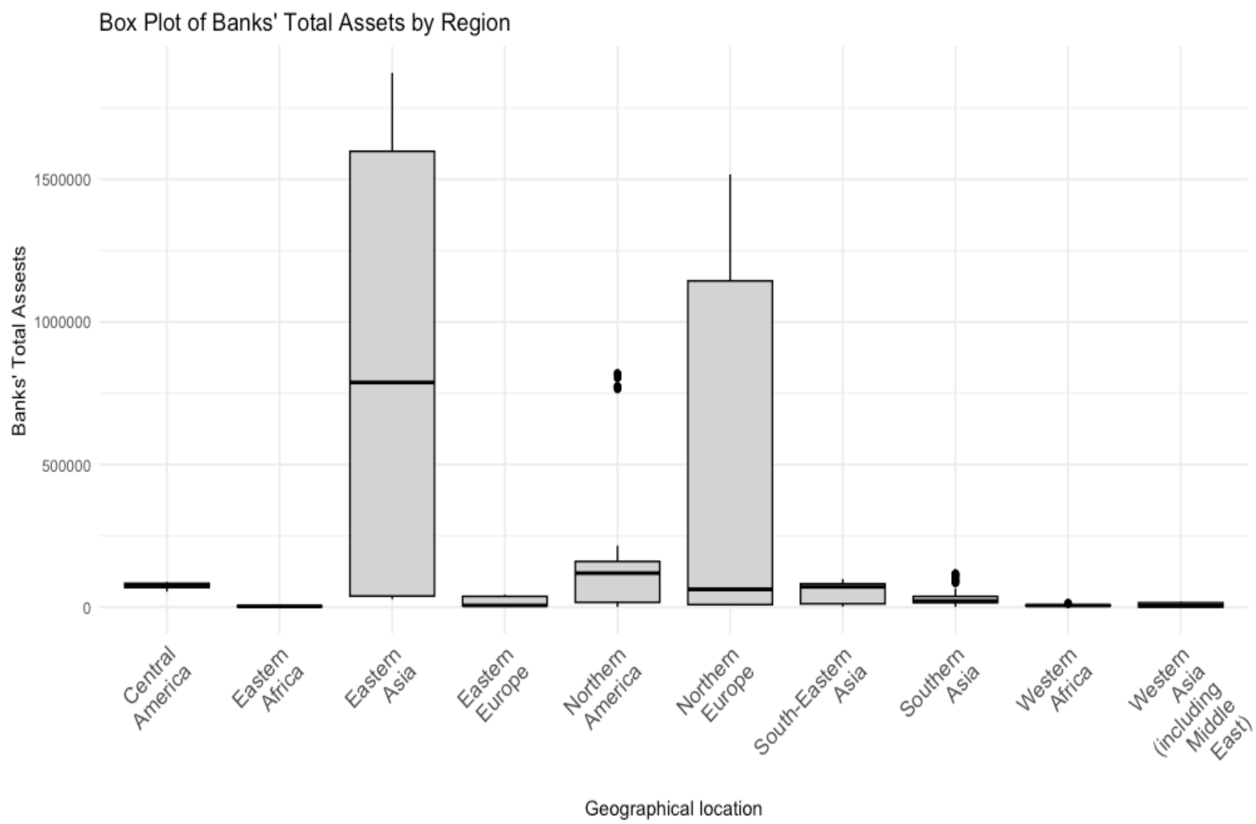
IV-2.1.b Total Assets

On average, banks have total assets worth $108,764.00 million. The median value is $20,820.49 million, which is significantly lower than the mean, hinting at a skewed distribution where a few banks hold significantly larger assets. The mode for total assets is $11.59 million, indicating a common value among many banks.

Eastern Asia banks exhibit the highest average assets, with a mean of $850,873 million. In contrast, Eastern African banks have the lowest mean assets, standing at $3,120 million.

The chart below depicts the distribution of the bank's Total Assets based on geographical location.

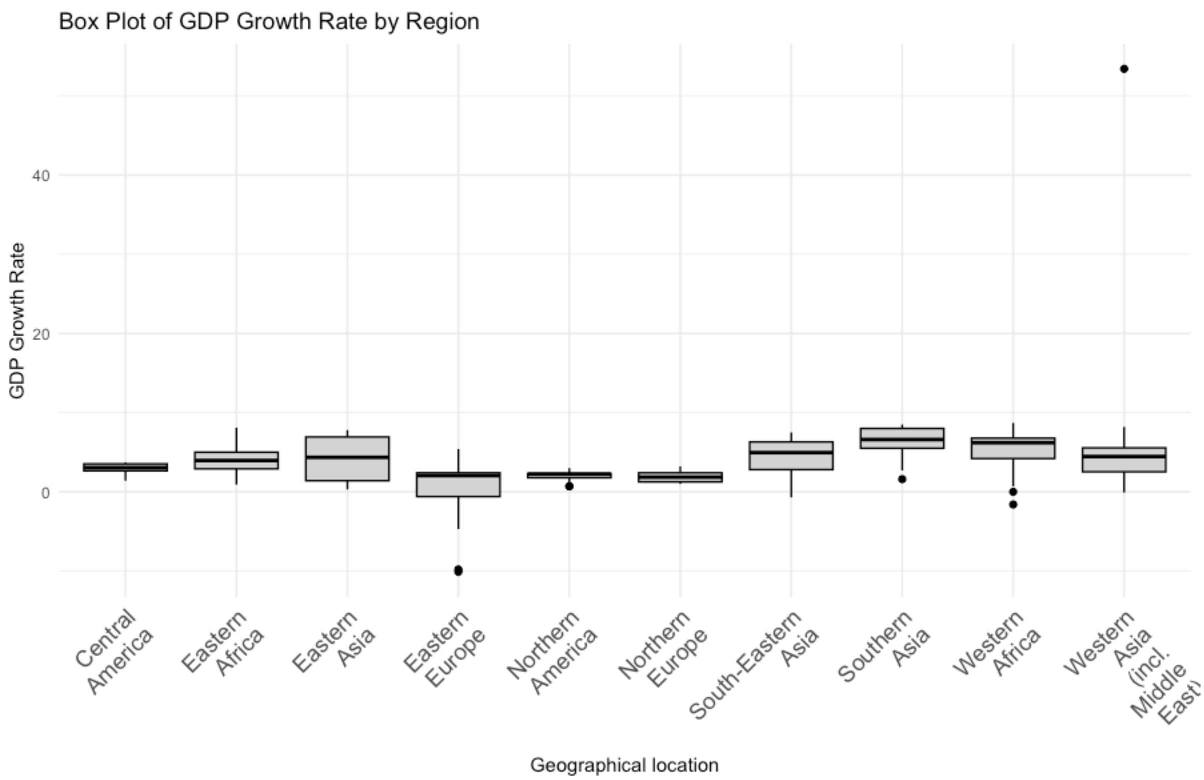
Figure IV-2: Total Assets distribution across geographical regions



IV-2.1.c GDP Growth Rate

This illustrative box plot, Figure IV-3, visually represents the distribution of GDP growth rates across various regions, as observed in the dataset. With a mean GDP growth rate of 4.47% and a slightly higher median of 4.70%, it indicates that a majority of the countries experience a growth rate above the average. The mode, at 2.30%, represents the most frequently occurring growth rate. Notably, Western Africa exhibits the highest mean GDP growth rate at 4.79%, while Southern Asia records a much lower average, with a growth rate of only 0.21%. This plot serves to highlight the regional disparities in economic growth within the dataset.

Figure IV-3: GDP Growth Rate distribution across geographical regions



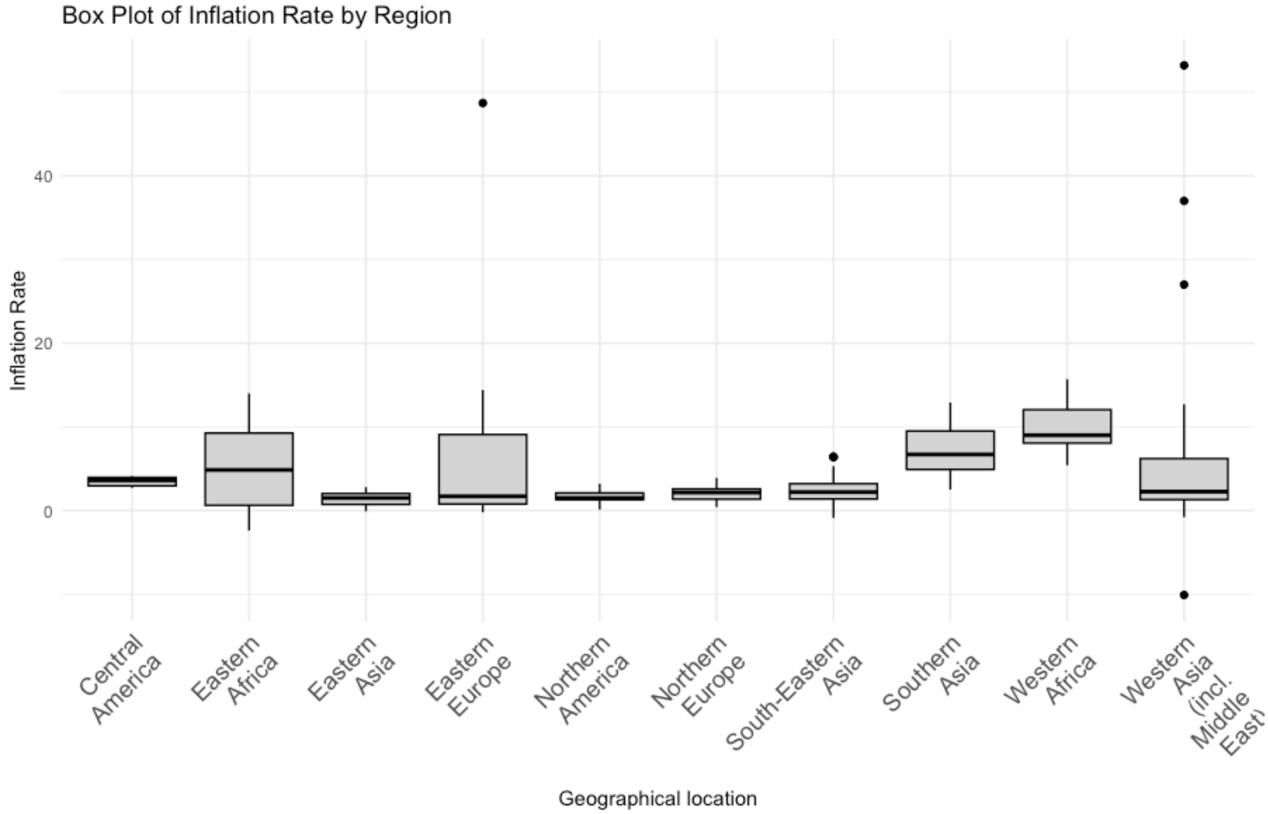
IV-2.1.d Inflation Rate:

The mean inflation rate is 5.09%. The median, at 3.35%, suggests that over half of the countries have inflation rates below this value. A mode of 4.90% indicates a common inflation rate value across the dataset.

Banks in Eastern Africa experience a notably high inflation rate, with the mean value being 3.29%. Conversely, Eastern Europe reports a lower mean inflation rate of 0.05%.

Figure IV-4 below offers a graphical representation.

Figure IV-4: Inflation Rate distribution across geographical regions



IV-2.1.e Intensity of operational loss

While the most common internal frauds loss in the sample is just under $1 million, there exist certain events with significantly higher losses, pushing the average to a whopping $60.04 million. The stark difference between the median and the mean underscores the presence of extreme values or outliers in the sample.

When examining the sample globally, “Embezzlement and Internal Fraud Schemes” emerges as one of the most commonly reported risk categories (22 banks out of 53). This frequent occurrence underscores the universal challenge banks face in mitigating internal threats and emphasizes the need for robust internal controls and monitoring systems across the banking sector worldwide.

The analysis of the size of operational losses across the different types of internal frauds reveals insightful trends and variances in the financial impact of various operational risks.

- Bribes Accepted by Employee: The mean and median size of operational loss in this internal fraud category are both \$3.23 million, with a mode of \$1.40 million. This suggests that while most reported cases of bribery involve losses of around \$1.40 million, the average is skewed upwards, indicating some instances with significantly higher losses.s

- Embezzlement and Internal Fraud Schemes: This category shows a significant discrepancy between the mean (\$22.50 million) and the median (\$2.41 million), with the mode at a striking \$122 million. This large difference suggests a few extreme cases of embezzlement and fraud that drastically increase the average loss, while most instances remain around \$2.41 million.

- Fraudulent Internal Credit Application for a Fictitious Customer: The losses here are comparatively lower, with a mean of \$1.56 million and a median slightly higher at \$1.69 million. The mode is at \$0.39 million, indicating that most losses in this category are on the lower end.

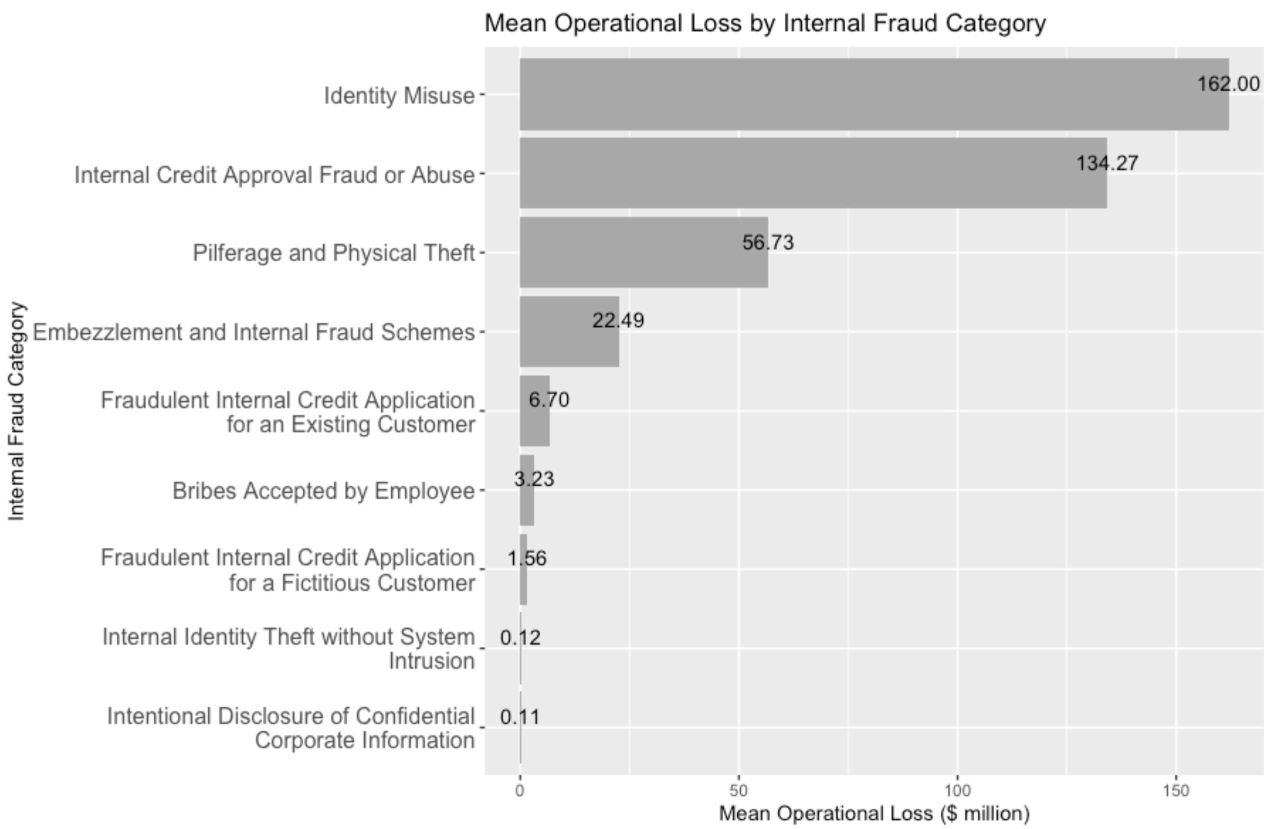
- Internal Credit Approval Fraud or Abuse: This category has a high mean loss of \$134 million, but a much lower median of \$15.2 million and a mode of \$0.99 million, suggesting a few extreme cases influencing the average significantly.

- Pilferage and Physical Theft: The mean loss here is \$56.7 million, considerably higher than the median of \$0.40 million and the mode of \$0.34 million. This disparity indicates that while most theft incidents involve small losses, there are exceptional cases with significantly larger impacts.

Overall, the analysis highlights the diversity in the size of operational losses across risk categories. Some internal fraud categories such as embezzlement and internal fraud schemes, exhibit a few high-impact incidents among generally lower losses.

Figure IV-5 provides a comprehensive visualization of the mean operational losses in various internal fraud risk categories, highlighting the financial impact of each category in a clear and concise manner.

Figure IV-5: Operational loss intensity by category of internal fraud

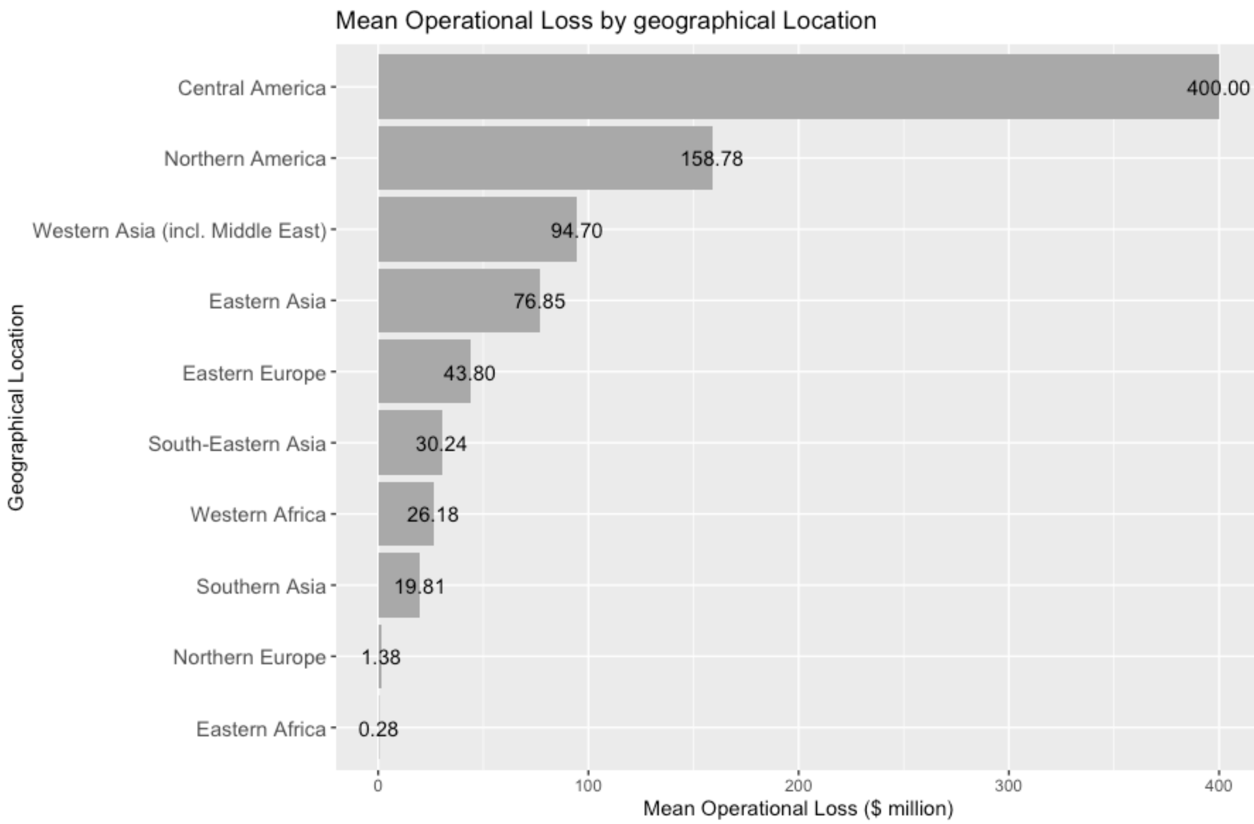


In terms of geographical analysis, various regions reported substantial operational losses, with Northern America emerging as the most prominent in terms of the magnitude of these losses. The region encountered events like “Internal Credit Approval Fraud or Abuse”, which, in certain instances, revealed substantial financial impacts reaching up to $391.29 million. This potentially indicates the severity of repercussions associated with such operational events in the Northern American banking sector.

Eastern Africa experienced relatively minor impacts from “Embezzlement and Internal Fraud Schemes” and “Internal Credit Approval Fraud or Abuse” with magnitudes around $0.20 and $0.35 million respectively. Meanwhile, Eastern Asia displayed a diverse range of "Embezzlement and Internal Fraud Schemes", averaging approximately $76.85 million.

Figure IV-6 showcases, on average, the distribution of these losses based on geographical location.

Figure IV-6: Operational loss intensity by geographical location



Regions like Eastern Europe and Northern America had multiple operational events. Eastern Europe witnessed "Embezzlement and Internal Fraud Schemes" with a $33.12 million impact, while "Internal Credit Approval Fraud or Abuse" averaged $49.13 million. In contrast, Northern America saw varied events such as "Embezzlement and Internal Fraud Schemes", which averaged $3.89 million, and others like "Internal Credit Approval Fraud or Abuse", revealing significant financial blows in certain instances. South-Eastern Asia had diverse events, with "Identity Misuse" standing out at $162 million.

Southern Asia's operational events like 'Embezzlement and Internal Fraud Schemes' averaged $14.43 million, while 'Internal Credit Approval Fraud or Abuse' presented a higher mean value of $27.03 million. Western Africa's 'Embezzlement and Internal Fraud Schemes' had a mean value of $32.65 million, indicating significant impacts. Lastly, Western Asia, including the Middle East, spotlighted events such as 'Pilferage and Physical Theft' with significant financial consequences.

Overall, the data underscores the varying financial impacts of operational risks across regions, emphasizing the importance of understanding and mitigating such risks.

IV-2.2. Dispersion analysis

In any data-driven analysis, understanding the dispersion or variability of data points around their central tendency provides essential insights into the spread and reliability of the dataset. Dispersion measures, including standard deviation, variance, and range, offer a quantitative grasp of the consistency or spread of the data (Stockemer, 2019). In the context of the study on commercial and retail banks, analyzing the dispersion of metrics like RoA and Total Assets illuminated the stability and variability of bank performances across different regions or risk categories (appendix 4). Through the dispersion analysis of the dataset, intricate details that held significant value for the research objectives were unearthed.

IV-2.2.a Comparative Dispersion

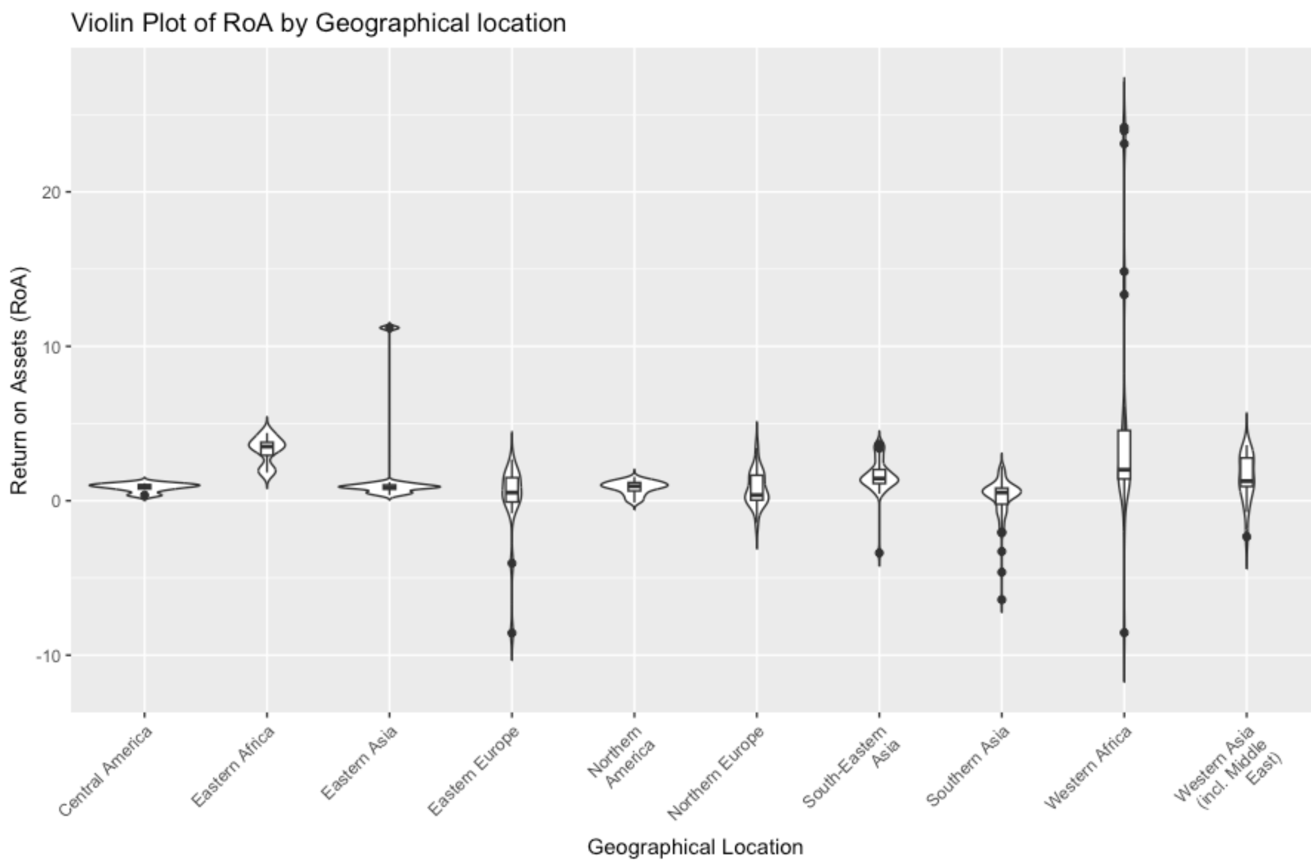
In the regional analysis of RoA, the average in Central America has a standard deviation of 0.28. This suggests that most banks' RoA in this region deviates from the average by about 28.3%. Additionally, the total assets in this region show considerable variability, with a standard deviation of approximately $12,572 million. Moving to Eastern Africa, banks in this region display a wider spread in RoA, with a standard deviation of 0.88 and a range of 2.57. Their total assets' variability stands at a standard deviation of $1,125 million.

Eastern Asia experiences substantial variability in its banking metrics. The region's RoA has a standard deviation of 3.00 and a total range of 10.8. Additionally, its total assets indicate a vast discrepancy in the size of banks within the region, with a standard deviation of approximately $854,201 million. Western Africa, on the other hand, showcases the highest RoA variability among all regions, with a standard deviation of 7.57 and a total range of 32.7. However, the region's total assets' deviation is more consistent, with a value of around $3,211 million. Lastly, banks in Western Asia, including the Middle East, show a moderate RoA variability with a standard deviation of 1.54, and their total assets deviate by about $7,173 million.

Diving into the internal fraud categories, banks with “Bribes Accepted by Employee” have a minor RoA variability, with a standard deviation of 0.05. However, their total assets' variability under this risk is significant, with a standard deviation of $21,994 million. The banks with the “Embezzlement and Internal Fraud Schemes” risk category stand out with the highest variability in RoA, showing a standard deviation of 5.08. Their total assets' variability is also pronounced, suggesting that banks of various sizes are susceptible to this risk. For those with “Fraudulent Internal Credit Application” categories, the RoA variability is non-existent. Likewise, their total assets' variability for these categories is also relatively low, indicating that these risks are consistent across banks of different sizes. The banks with the risk category “Pilferage and Physical Theft” have a RoA variability of 1.03, indicating a moderate variability in profitability. Their total assets' deviation is around $34,875 million.

The violin plot presented below, Figure IV-7, synthesizes the distribution of RoA across various regions, combining the precision of a box plot with the detailed density estimation of a kernel density plot, thereby offering a comprehensive view of both the central tendency and data dispersion by region.

Figure IV-7: Dispersion analysis of RoA by Region



Inside this violin shape, there's typically a box plot. The box plot provides a summarized view of the data: the median (a line inside the box), the interquartile range (the width of the box), and potential outliers (points outside the "whiskers" or ends of the box).

Looking at the violin plot for RoA across various regions, it presents the following:

- Density (Violin shape): The width of the shaded area at different levels indicates how many data points (or how dense the data) are at that level. If a region's violin plot is very wide at a certain RoA value, that means many banks in that region have that RoA. If it's narrow, fewer banks have that RoA. For example, Central America and Eastern Asia show wider shapes indicating that banks in these regions have similarities in RoA of this value.

- Central Tendency (Box inside the violin): The box inside each violin illustrates the middle 50% of the data for that region. The line in the middle of the box is the median RoA for the region. This gives a quick sense of the "typical" RoA for banks in that region.
- Variability: If the violin is very wide in some places and narrow in others, that indicates a lot of variability in the RoA for banks in that region. On the other hand, a uniformly wide or narrow violin suggests consistent RoA values across banks.

Each "violin" shows the range and commonality of RoA values for banks in a particular region. The wider the "violin" at a certain point, the more banks have that RoA. The box inside gives a quick snapshot of the "average" or "typical" RoA and its variability for banks in that region.

In summary, banks in geographical regions like Eastern Asia and Western Africa display significant variability in RoA, indicating diverse bank performances within these areas. “Embezzlement and Internal Fraud Schemes” emerge as a critical risk category, affecting banks of various sizes and profitability levels.

IV-2.2.b RoA’s time series analysis of dispersion

Over the span of 15 years, from 2004 to 2018, the dispersion in the RoA of banks underwent significant fluctuations. 2006 saw a relatively low standard deviation in RoA at 2.61. The observed dramatic amplification in dispersion around 2007 and 2008, where the standard deviation of RoA peaked at 14.6 and 14.3 respectively, might be potentially linked to the tumultuous financial environment during that period (Aebi et al., 2012).

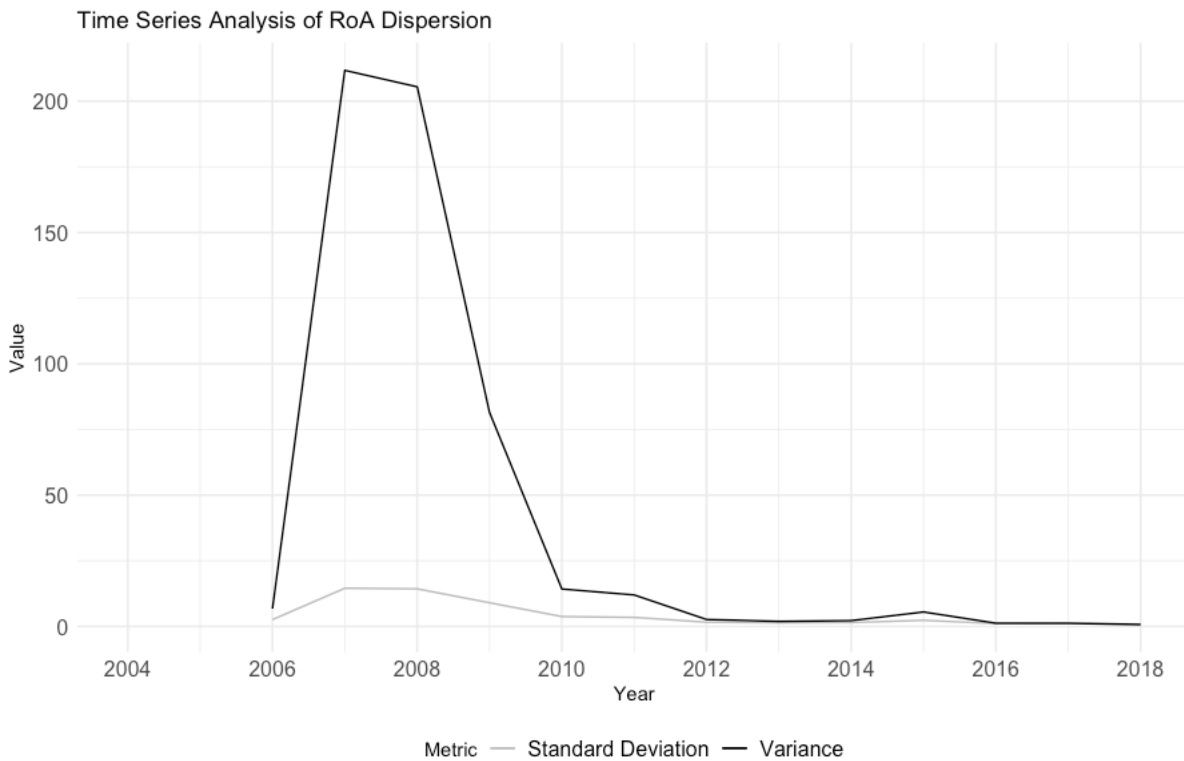
The 2008 Global Financial Crisis, precipitated by the collapse of large financial institutions due to exposure to subprime mortgages, coupled with the bailout of banks by national governments, led to sharp downturns in consumer wealth, severe disruptions in financial markets, and a downturn in economic activity. This crisis likely instigated the heightened variability among banks in their operational efficiency, as institutions grappled with the fallout, leading to erratic RoA performances (Aebi et al., 2012; Angelides & Thomas, 2011; Ozkan & Unsal, 2012).

The corroborating surge in the variance of RoA to 212 in 2007 and its slight reduction to 205 in 2008 further reinforces the hypothesis that banks were experiencing unprecedented fluctuations in their operational metrics during the crisis. This variability can be attributed to the differential impacts of the crisis on various banks, contingent on their exposure to toxic assets and their inherent operational strengths and weaknesses during that tumultuous period (Apostolik et al., 2009; Li, 2018; Petersen et al., 2012).

Following the tumultuous years of 2007 and 2008, the financial landscape started to show little signs of stabilization. There was a marked decrease in the dispersion of RoA after 2008. The standard deviation of RoA reduced to 9.03 by 2009, and this declining trend persisted until 2012 when it bottomed out at 1.63. Such a pattern might be indicative of a period of increasing stability, suggesting a return to more uniform operational efficiency among banks. From 2013 onward, the variability in RoA seemed to settle, as evinced by the minor shifts in both standard deviation and variance. By the close of 2018, the standard deviation reached a decade-low of 0.854, accompanied by a variance of 0.73. These figures highlight the most consistent and cohesive operational performances across banks during the entirety of the observation window.

Figure IV-8 presents a visual depiction of the dispersion in Return on Assets (RoA) over the observed years, effectively illustrating the time series trends.

Figure IV-8: Time series of RoA dispersion



IV-2.2.c Operational losses dispersion analysis

The analysis of the dispersion of the size of the operational losses across different risk categories provides valuable insights into the variability and spread.

The risk category "Embezzlement and Internal Fraud Schemes" shows the highest mean operational loss at $22.5 million. However, its median, which is only $2.41 million, indicates that the majority of the banks experienced losses much below the average. This discrepancy between the mean and median is further underpinned by a high standard deviation of $40.7 million and a range of $143 million, suggesting that a few extreme values (or outliers) heavily influenced the mean. This means that while most banks experienced moderate losses due to this risk, a few banks faced catastrophic losses.

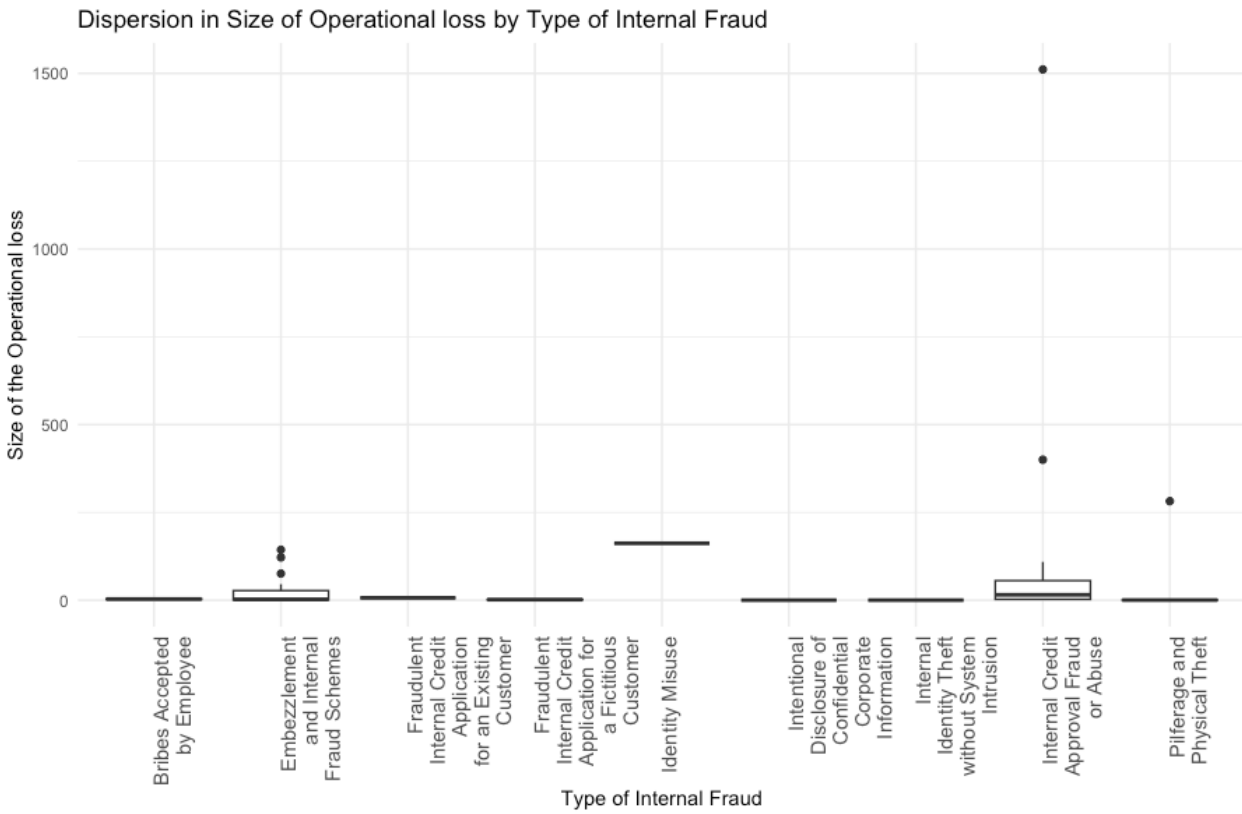
“Internal Credit Approval Fraud or Abuse” is another category with a significant disparity between the mean and median. With an average loss of $134 million but a median of just $15.2 million, it indicates that while most banks had relatively low losses, a few instances had extraordinarily high losses, as evidenced by a vast standard deviation of $367 million and a range of $1,510 million.

On the other end of the spectrum, categories like “Bribes Accepted by Employee” and 'Fraudulent Internal Credit Application for a Fictitious Customer' showed relatively modest average operational losses of $3.23 million and $1.56 million, respectively. The low standard deviation and range for these categories suggest more consistent losses across banks.

In conclusion, while some risk categories exhibited significant variability in operational losses across banks, others presented a more consistent picture. This variability underscores the importance of understanding the risk profile and preparing for potential outliers that can considerably impact the average operational losses.

The visual representation in Figure IV-9 clearly depicts these differences and anomalies. It allows for an immediate grasp of the range, median, and outliers within each category, making it easier to identify which types of fraud have the most variable and extreme loss sizes. This visual tool is instrumental in understanding the complexity and severity of risks associated with different types of internal fraud.

Figure IV-9: Dispersion in operational losses



IV-2.3. Frequency analysis

Frequency analysis provides a foundational understanding of the distribution and representation of categorical variables within a dataset. Assessment of the count and percentage of occurrences for each category allows for an evaluation of the prominence and significance of specific groups, regions, or classifications within the dataset (Stockemer, 2019).

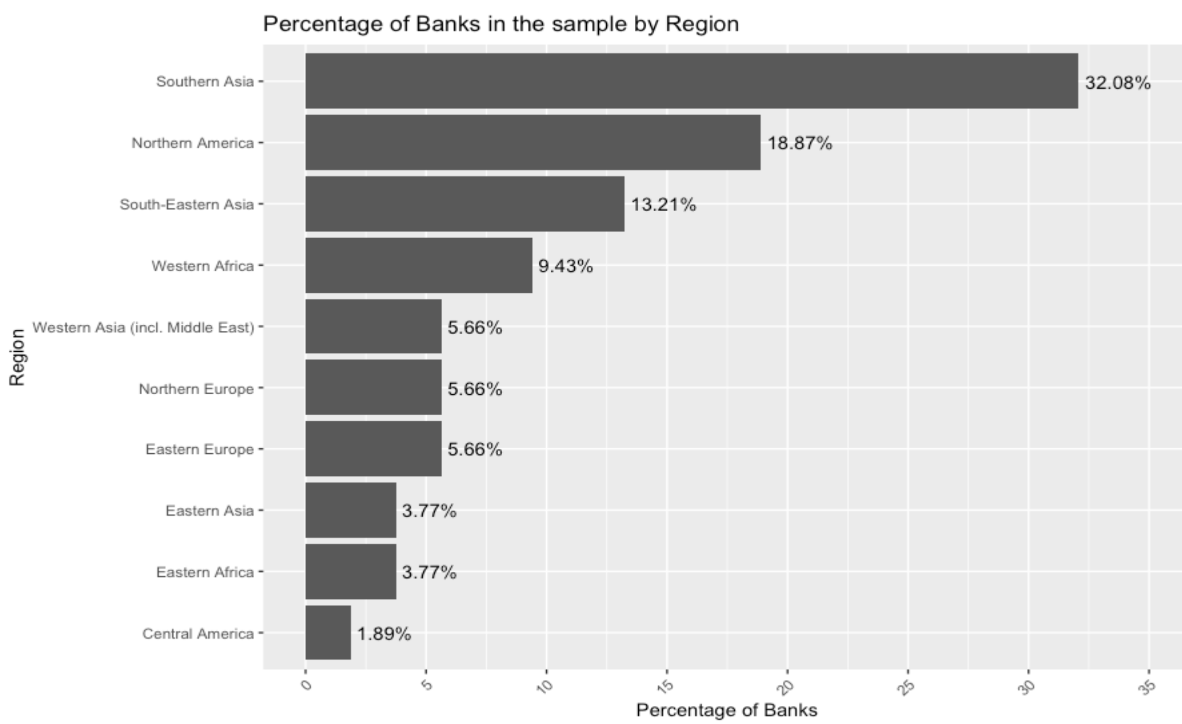
In the context of this study, such an analysis (Appemdix 5) is instrumental in revealing the geographical and categorical spread of the sampled banks, the size, and the risk categories. This not only ensures the diversity and inclusivity of the sample but also sets the stage for subsequent analyses, allowing for a more comprehensive interpretation of results in light of the sample's composition.

IV-2.3.a Distribution of banks by regions

In the sample under study, the distribution of the included 53 banks across various regions offers a snapshot of the global representation of the dataset. As illustrated in Figure IV-10, the most represented region is Southern Asia, accounting for 32.1% of the banks. This is followed by Northern America with a representation of 18.9%. South-Eastern Asia comes next, making up 13.2% of the sample. Western Africa contributes to 9.43% of the banks.

A closer look at other regions indicates a more evenly dispersed representation. Both Eastern Africa and Eastern Asia each make up 3.77% of the dataset, while Eastern Europe, Northern Europe, and Western Asia (including the Middle East) each account for 5.66%. Central America has the least representation, with just 1.89% of the banks.

Figure IV-10: Frequency of banks by region



From a broader perspective, this distribution highlights the global diversity of the sample, with a noticeable concentration in regions like Southern Asia and Northern America. The presence of banks from various parts of the world ensures a comprehensive and well-rounded understanding of the patterns and trends in the data, enhancing the generalizability and applicability of the study's findings on a global scale.

IV-2.3.b Distribution of banks by country

The dataset is notably weighted towards Indian banks, which constitute 14 entries, making up 26.4% of the total. This significant inclusion of Indian banks positions India as the most represented country within the sample. The United States is the second most represented, with 8 banks accounting for 15.1% of the sample. Collectively, these two countries contribute to over 40% of the dataset, highlighting a concentration of data from these regions.

Subsequently, Nigeria and Thailand each have 4 banks, comprising 7.55% of the dataset for each country. Their equal representation suggests that, while they are significant, they are not as dominant as India or the United States in this sample.

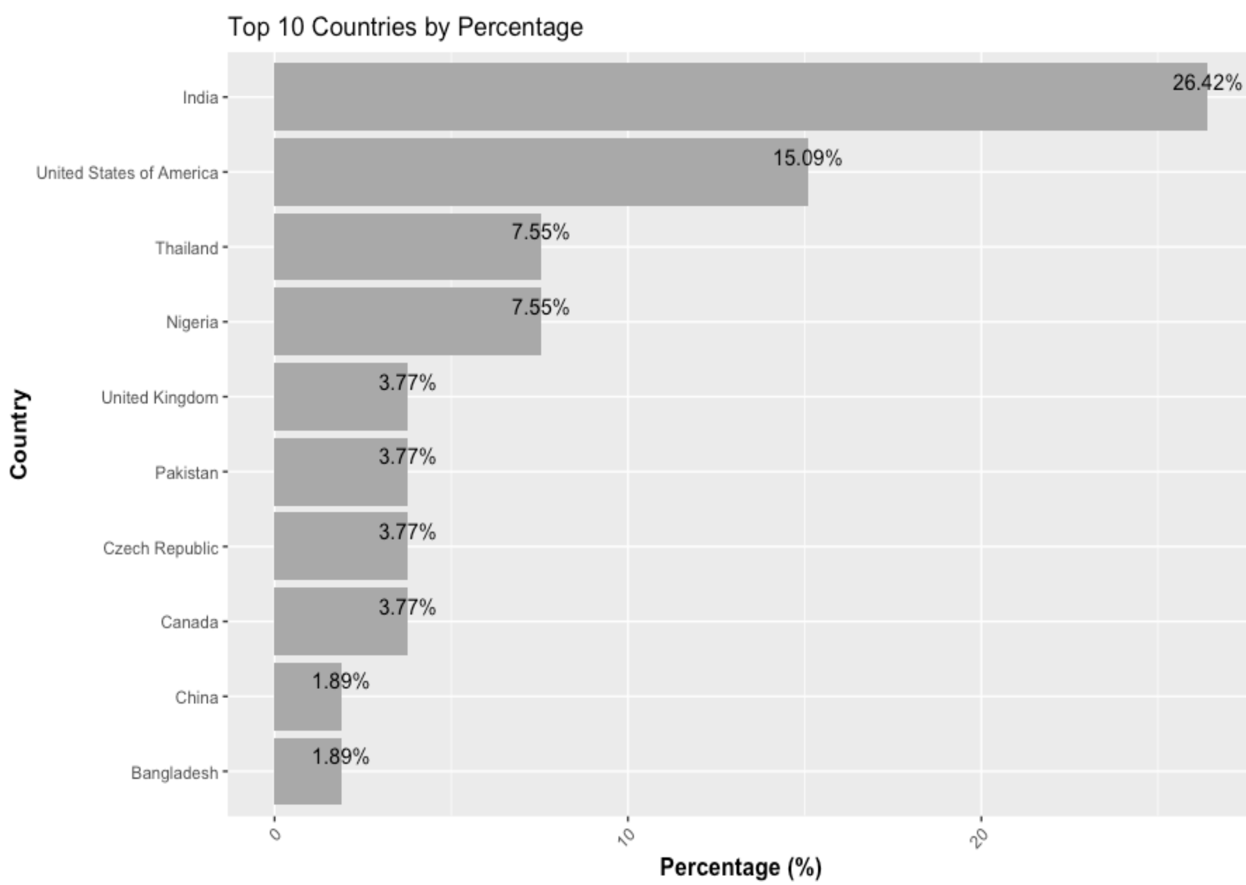
The distribution then diversifies further with Canada, the Czech Republic, Pakistan, and the United Kingdom each contributing 2 banks, which is 3.77% of the total for each country. Finally, countries like Bangladesh and China have the least representation with only 1 bank each, making up 1.89% of the sample.

The composition of the dataset is influenced by the selection criteria in the study sampling method, which prioritized banks with accessible financial data on the Bloomberg terminal and excluded those with recurrent operational losses over the years to focus on the impact of unique operational loss events. This methodology has inherently shaped the dataset's structure.

Furthermore, the data collection process revealed a disparity in the presence of banks on the Bloomberg terminal across different regions. Banks from the United States, Europe, India, and China are more frequently listed and have readily available financial metrics on the Bloomberg terminal. In contrast, African banks, despite their prevalence in operational loss databases, are often either not listed on the Bloomberg terminal or lack accessible financial metrics. This discrepancy has contributed to the regional representation seen in the dataset.

Figure IV-11 provides a visual depiction of the countries that feature most prominently in the sample used for this study.

Figure IV-11: Top 10 countries banks distribution in the sample



From a global standpoint, the distribution of countries across regions is not uniform, indicating a varied representation.

South-Eastern Asia leads the chart, representing 17.40% of the distinct countries in the dataset. This suggests a broader geographical coverage within this region, encompassing four different countries. Both Southern Asia and Western Asia (including the Middle East) follow closely, each housing 13.00% of the countries, which translates to three distinct countries for each region.

On the other hand, regions such as Central America, Eastern Africa, Eastern Asia, Eastern Europe, Northern America, Northern Europe, and Western Africa each contribute to 8.70% of the distinct countries in the sample. This uniformity indicates that each of these regions is represented by only two countries in the dataset.

In essence, while some regions like South-Eastern Asia have a broader representation with multiple countries, others have a more limited scope. This distribution offers insights into the geographical diversity of the sample and hints at the regions where data might be more or less granular.

IV-2.3.c Internal frauds categories by region

The various forms of internal frauds observed across distinctive global regions are highlighted in Table IV-1. This comprehensive breakdown showcases the percentage of each fraud type prevalent in different regions, offering a nuanced understanding of the landscape of internal frauds.

Notably, the most pervasive form of fraud across the regions appears to be "Embezzlement and Internal Fraud Schemes," which accounts for a significant 41.50% of the documented cases. Its prevalence is most marked in Eastern Asia, where every reported fraud case belonged to this category, and in Western Africa, where it constituted 80% of the frauds. In contrast, regions such as Northern Europe and Western Asia reported no instances of this specific fraud type.

Another form of fraud that draws attention is the "Internal Credit Approval Fraud or Abuse." This type of fraudulent activity is of particular concern in Central America, where it represents the entirety of reported fraud cases. Moreover, its presence is also substantial in Eastern Europe and Southern Asia, with 66.70% and 47.10% respectively of their fraud cases falling under this category. Overall, this type of fraud amounts to 32.1% of the total fraud instances.

Other fraud categories, although less prevalent, present unique regional patterns. For instance, "Pilferage and Physical Theft" is less common overall, contributing to 9.40% of total cases, but it sees heightened activity in Western Asia with a striking 66.70% of its fraud cases falling into this category. Similarly, "Bribes Accepted by Employee" is primarily observed in Northern Europe and Southern Asia, cumulatively contributing to 3.8% of the total fraud cases.

Furthermore, certain types of frauds, while not widespread, exhibit region-specific concentrations. Northern America, for example, reported 10% of its fraud cases as "Fraudulent Internal Credit Application," both for fictitious and existing customers. Types like "Identity Misuse" and "Intentional Disclosure of Confidential Corporate Information" are less frequent on a global scale but are especially prevalent in specific regions like South-Eastern Asia.

In synthesizing this data, it becomes evident that while some internal frauds are universally prevalent, others showcase regional specificity. The distribution and nature of these frauds, as captured in Figure IV-12 and Table IV-1, provide vital insights for understanding internal frauds distribution across regions. From this, global financial stakeholders can also glean insights, enabling them to customize their risk management approaches and policies effectively.

Figure IV-12: Internal frauds categories by regions

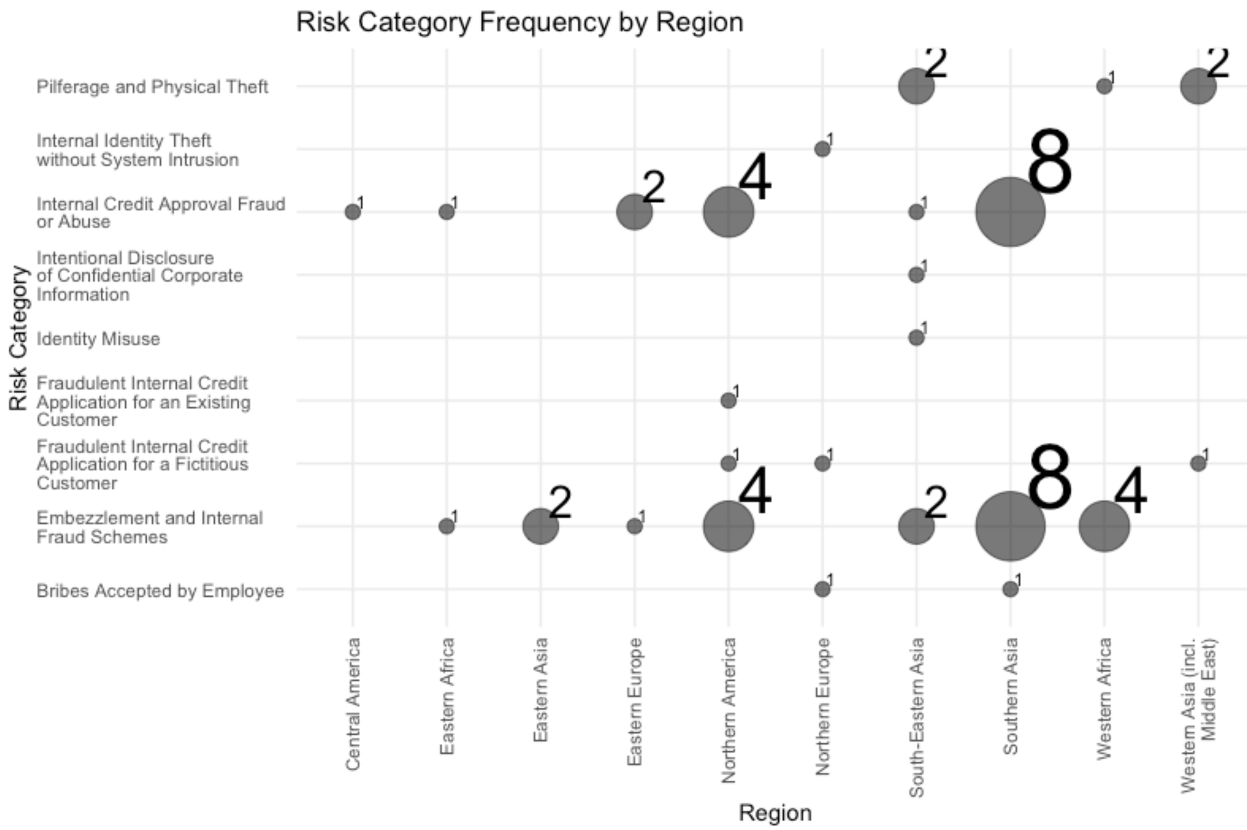


Table IV-1: Types of Internal frauds by region

Type of Internal frauds	Central America	Eastern Africa	Eastern Asia	Eastern Europe	Northern America	Northern Europe	South-Eastern Asia	Southern Asia	Western Africa	Western Asia	%
Bribes Accepted by Employee	0.00%	0.00%	0.00%	0.00%	0.00%	33.33%	0.00%	5.88%	0.00%	0.00%	3.77%
Embezzlement and Internal Fraud Schemes	0.00%	50.00%	100.00%	33.33%	40.00%	0.00%	28.57%	47.06%	80.00%	0.00%	41.51%
Fraudulent Internal Credit Application-Fictitious Customer	0.00%	0.00%	0.00%	0.00%	10.00%	33.33%	0.00%	0.00%	0.00%	33.33%	5.66%
Fraudulent Internal Credit Application-Existing Customer	0.00%	0.00%	0.00%	0.00%	10.00%	0.00%	0.00%	0.00%	0.00%	0.00%	1.89%
Identity Misuse	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	14.29%	0.00%	0.00%	0.00%	1.89%
Intentional Disclosure of Confidential Corporate Information	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	14.29%	0.00%	0.00%	0.00%	1.89%
Internal Credit Approval Fraud or Abuse	100.00%	50.00%	0.00%	66.67%	40.00%	0.00%	14.29%	47.06%	0.00%	0.00%	32.08%
Internal Identity Theft without System Intrusion	0.00%	0.00%	0.00%	0.00%	0.00%	33.33%	0.00%	0.00%	0.00%	0.00%	1.89%
Pilferage and Physical Theft	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	28.57%	0.00%	20.00%	66.67%	9.43%

IV-2.3.d RoA distribution skewness and kurtosis

The skewness and kurtosis values for RoA offer insightful details about its distribution:

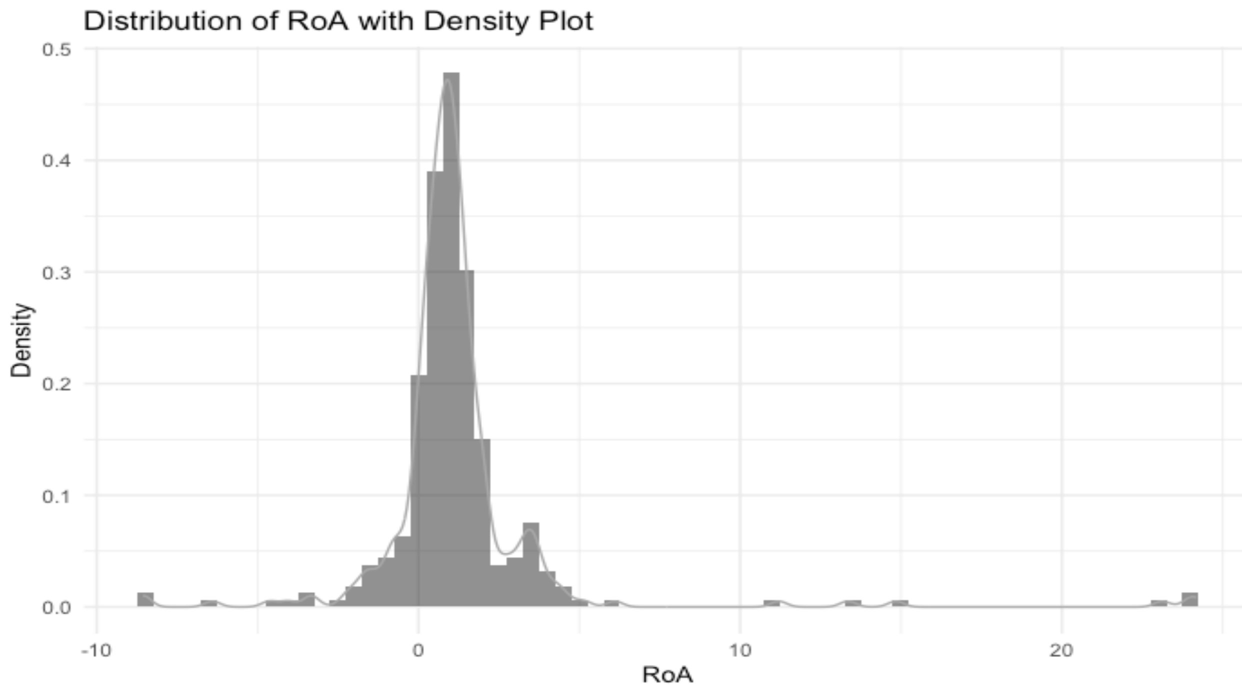
RoA's skewness (4.51): This positive value indicates that the distribution of RoA is right-skewed. In simpler terms, it means that the majority of the data values are clustered to the left, with a few larger values stretching out to the right. This suggests that while most banks have similar operational efficiency, a few banks have significantly higher RoA.

RoA's Kurtosis (32.98): This value is considerably larger than the kurtosis of a standard normal distribution, which is 3 (recognized as mesokurtic). A high kurtosis value like this indicates that the distribution has heavier tails and a sharper peak than a normal distribution. This signifies that there are more extreme values (or outliers) in the RoA distribution than what would be expected in a normal distribution.

In essence, the RoA across banks and years has a distribution where most values are clustered around the mean, but there are also a notable number of extreme values. This could imply that while the majority of banks maintain a standard operational efficiency, there are a few exceptional cases where banks either perform extraordinarily well or poorly.

From the histogram and density plot, Figure IV-13, the distribution of RoA can be clearly observed. A peak in the density plot indicates the most frequent values, while the spread of the histogram bars gives insights into the variability of the data. If there are any bars that are detached from the main cluster or appear isolated, they may represent outliers. Such outliers indicate banks that have exceptionally high RoA compared to the majority. Additionally, the shape of the density plot provides insights into the overall distribution, skewed to the right.

Figure IV-13: Distribution of RoA



IV-3. Effects of internal frauds disclosure on RoA

Understanding the ramifications of operational loss disclosures on the financial health of banks remains pivotal in the realm of banking and finance, both for scholars and practitioners (Fiordelisi et al., 2013; Gatzert, 2015; Gillet et al., 2010; Perry & de Fontnouvelle, 2005). This section addresses *Research Question 1: How does an internal fraud disclosure affect the RoA of commercial/retail banks as reputational loss in terms of quantifiable monetary value?* RoA, an essential metric, offers insights into a bank's operational efficiency and financial performance (Akhigbe & McNulty, 2005; Drake & Fabozzi, 2010; Terraza, 2015). As posited in III-2.1.a (hypothesis 1), there is a proposed connection between fraud disclosures and a bank's RoA, suggesting that such disclosures could result in quantifiable reputational losses.

Prominent studies, such as those by Eckert & Gatzert (2017) and Fiordelisi et al. (2013), have highlighted the potential adverse effects of operational losses, especially those stemming from internal frauds, on a bank's financial stature (Biell & Muller, 2013; Gillet et al., 2010; Perry & de Fontnouvelle, 2005). The unveiling of these improprieties might lead to diminished stakeholder trust, thereby possibly affecting key profitability indicators (Eberl & Schwaiger, 2005; Trotta & Cavallaro, 2012; Walter, 2016). In this section, the empirical nuances of this dynamic relationship are dissected, providing a comprehensive understanding of how internal fraud disclosures can shape the financial trajectory of banks.

IV-3.1. Quantifying the reputational loss

The cornerstone of the analysis, the event study methodology, has its roots deeply embedded in the financial research domain (Mackinlay, 1997). Initially devised to discern the impact of corporate announcements on stock prices, this methodology has been expansively employed across varied organizational contexts, ranging from mergers and acquisitions to shifts in corporate strategies or financial health (Cummins & Wei, 2006; Fiordelisi et al., 2013; Gillet et al., 2010; Sorescu et al., 2017). Central to this research, the event study framework facilitated the understanding of how RoA, a critical profitability metric, responds to the disclosure of internal frauds. By juxtaposing actual returns against anticipated ones in the aftermath of the event, we can fathom the depth of the reputational damage inflicted (Binder, 1998).

The Generalized Least Squared (GLS) Random Effects model (Appendix 2) is employed to enhance the precision of the analysis. Renowned for its adeptness in managing both observed and unobserved heterogeneities within data (Treiman, 2009), this model is particularly well-suited for longitudinal panel datasets, effectively capturing the complexities inherent in such structured datasets (Hair et al., 2019).

By differentiating between the immediate operational loss and the total financial deviation post-event, the model allowed to isolate the effects of reputational loss, providing a comprehensive view of the bank's financial health (Binder, 1998; Eckert & Gatzert, 2017; Heidinger & Gatzert, 2018). The mathematical rigor and adaptability of the Random Effects model, combined with the event study methodology (Kothari & Warner, 2007; Mackinlay, 1997; Wooldridge, 2002), formed the bedrock of the empirical investigation.

IV-3.2. Expected RoA

In quantifying the impact of internal fraud disclosures on a bank's RoA, a detailed methodological approach was implemented. Utilizing the multivariate regression analysis, the RoA data from the three years preceding the operational loss was examined. This historical data provides a foundational insight into the bank's performance trajectory before any potential disruptions. From this foundation, a projection for the subsequent three years was constructed, offering a comprehensive representation of the anticipated RoA trajectory in the absence of the operational loss. This constructed trajectory not only highlights the bank's expected financial path but also prepares the groundwork for understanding the deviations and potential reputational losses resulting from internal fraud disclosure. In essence, this approach provides a hypothetical, data-driven view into an alternate financial trajectory, facilitating a deeper understanding of the true ramifications of such operational setbacks on a bank's financial health.

IV-3.2.a Significance of Variables

Lag of RoA: The three lags of RoA (lag(RoA, 1:3)1, lag(RoA, 1:3)2, and lag(RoA, 1:3)3) are notably significant, with the first two lags having a positive relationship with the dependent variable and the third lag showing a negative association. This suggests that the recent historical performance of a bank, specifically the RoA from one and two years prior, positively influences its future RoA. However, the RoA from three years prior negatively affects the subsequent RoA.

Total Assets (A): The lag of total assets (lag(Total Assets, 1:3)3) is marginally significant at a 10% level, indicating that the assets from three years prior might have a small influence on the RoA.

Inflation Rate (I): The coefficient for Inflation Rate is statistically significant, suggesting that the inflation rate in a bank's operating country potentially plays a role in its RoA. A positive coefficient indicates that as inflation rises, the RoA also increases, potentially reflecting the bank's ability to manage inflationary pressures.

IV-3.2.b Regional Differences

The model also controlled for regional effects to account for heterogeneities across different global regions. However, none of the regional dummy variables showed significant results, indicating that after accounting for other factors, the region in which a bank operates does not have a substantial standalone effect on its RoA.

IV-3.2.c Model Fit

The R-squared value is 0.87184, suggesting that the model explains approximately 87.18% of the variation in the dependent variable (RoA). The adjusted R-squared, which accounts for the number of predictors in the model, is 0.85639, indicating that the model explains a substantial proportion of the variance in RoA after adjusting for the number of variables included. The F-statistic, 959.220 ($p < 0.001$), is highly significant, confirming that the model as a whole is a good fit. This implies that the model is quite effective in capturing the determinants of RoA (Treiman, 2009).

The empirical findings derived from the application of the Random Effects model suggest a pronounced influence of a bank's historical performance and prevailing macroeconomic indicators, such as inflation, on its RoA. Conversely, when considering other determinants, regional variations appear to have a less definitive standalone effect on the RoA. Table IV-2 presents the detailed outcomes of this analysis.

Table IV-2: Random Effects Model Coefficients for RoA (p-values & z-values)

	Dependent variable: RoA coefficient
lag(RoA,1:3)1	0.460*** (0.06)
lag(RoA,1:3)2	0.360*** (0.06)
lag(RoA,1:3)3	-0.145*** (0.04)
lag(TotalAssets,1:3)1	0 0.00
lag(TotalAssets,1:3)2	0.00001 (0.00)
lag(TotalAssets,1:3)3	-0.00001 (0.00)
Inflation Rate	0.067* (0.03)
GDP Growth Rate	-0.01 (0.05)
factor(g2_Region) Eastern Africa	0.115 (0.72)
factor(g2_Region) Eastern Asia	-0.902 (0.81)
factor(g2_Region) Eastern Europe	0.69 (0.68)
factor(g2_Region) Northern America	-0.024 (0.62)
factor(g2_Region) Northern Europe	0.336 (0.70)
factor(g2_Region) South-Eastern Asia	0.325 (0.63)
factor(g2_Region) Southern Asia	-0.771 (0.64)
factor(g2_Region) Western Africa	-0.058 (0.69)
factor(g2_Region) Western Asia(incl. Middle East)	-0.25 (0.68)
Constant	0.297 (0.61)
Observations	159
R-squared	0.872
Adjusted R-squared	0.856
F Statistic	959.220***

Random Effects Model note (R): * p < 0.05; ** p < 0.01; *** p <0.001

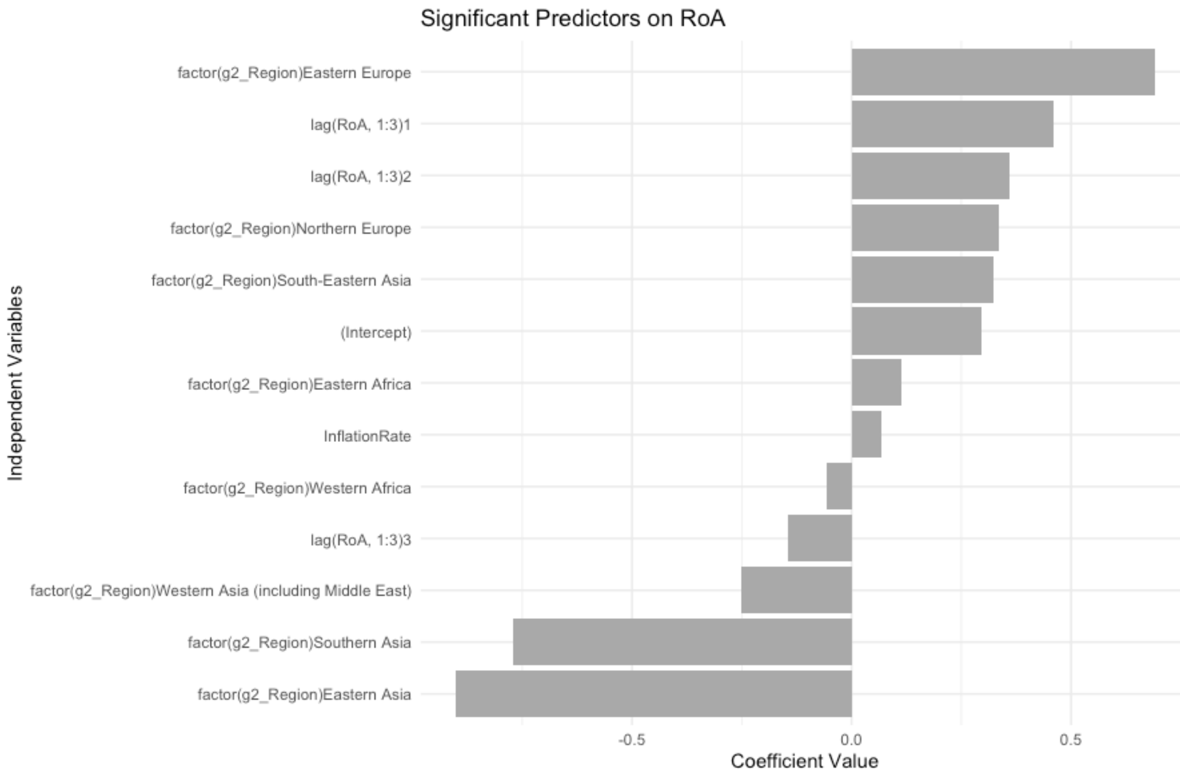
	Independent variables	Estimate	Std. Error	z-value	Pr(>|z|)
1	(Intercept)	0.296855771	0.606544006	0.489421655	0.624543208
2	lag(RoA, 1:3)1	0.459849456	0.055550675	8.278017389	1.25243E-16
3	lag(RoA, 1:3)2	0.359505955	0.057786566	6.22127213	4.9314E-10
4	lag(RoA, 1:3)3	-0.145296943	0.041849637	-3.47188062	0.000516826
5	lag(Total Assets, 1:3)1	-2.32172E-06	4.95049E-06	-0.468987339	0.639078686
6	lag(Total Assets, 1:3)2	1.22581E-05	8.90157E-06	1.37707191	0.168490016
7	lag(Total Assets, 1:3)3	-1.04985E-05	5.829E-06	-1.801077337	0.071690691
8	Inflation Rate	0.066987285	0.031932138	2.097801422	0.035922691
9	GDP Growth Rate	-0.01022717	0.051029461	-0.200416968	0.84115449
10	factor(g2_Region) Eastern Africa	0.115011822	0.722206153	0.159250681	0.873471376
11	factor(g2_Region) Eastern Asia	-0.90178344	0.81205888	-1.110490215	0.266787842
12	factor(g2_Region) Eastern Europe	0.689585317	0.679194862	1.015298195	0.309963704
13	factor(g2_Region) Northern America	-0.024174154	0.615863234	-0.039252471	0.9686891
14	factor(g2_Region) Northern Europe	0.335973667	0.696606099	0.482300783	0.629592291
15	factor(g2_Region) South-Eastern Asia	0.324562306	0.631971815	0.513570855	0.60755206
16	factor(g2_Region) Southern Asia	-0.77114287	0.639942027	-1.205019888	0.228195624
17	factor(g2_Region) Western Africa	-0.057875569	0.688039018	-0.084116696	0.93296365
18	factor(g2_Region) Western Asia	-0.249858189	0.676182661	-0.36951286	0.711745489

As evidenced by the p-values, the statistically significant variables in the model are lag(RoA, 1:3)1, 2, and 3 (highly significant, $p < 0.001$), with the first two lags demonstrating a significant positive impact and the third lag exhibiting a negative impact. Additionally, the inflation rate (0.067, $p < 0.05$) is found to be significant and exhibits a positive effect on RoA, indicating that inflation may prove advantageous for firms in terms of profitability. The GDP growth rate and regional variables were found to exert no significant influence on RoA, indicating that these factors are of lesser importance in this model. The total assets variables are not statistically significant, indicating that changes in assets do not have a notable impact on RoA within the lags under consideration.

The z-scores, which quantify the number of standard deviations a data point is from the mean, also demonstrate that historical values of RoA are the most reliable and significant predictors of future performance. The lag(RoA, 1:3)1 and 2 coefficients are positive (respectively 0.4598 and 0.3595) with a high z-value (respectively 8.28 and 6.22), indicating that these lagged values of RoA have a positive and statistically significant impact on current RoA. However, the lag(RoA, 1:3)3 coefficient is negative, with a significant z-value of -3.47, indicating a significant negative relationship with the current RoA. This suggests that the impact of RoA from three periods ago is adverse, which might imply a decline in returns or a correction after a few periods.

In the ensuing analysis, attention is shifted toward understanding the relative importance of significant predictors on the expected RoA (eRoA). Figure IV-14 visually encapsulates the magnitude of influence each predictor exerts. By delineating the effect sizes, the chart provides a clear hierarchy of predictors in terms of their impact. Notably, while all predictors featured have shown statistical significance in their relationship with RoA, their practical importance can be considerably varied. This discrepancy between statistical significance and practical relevance underscores the importance of considering effect sizes when interpreting results (Saunders et al., 2009). The chart, therefore, serves as a pivotal tool in swiftly discerning which predictors have the most profound influence on expected RoA, aiding in the prioritization of factors when considering strategic interventions or policy changes.

Figure IV-14: Effect size of significant predictors on Expected RoA



In summary, the z-values indicated that the lagged RoA variables show strong statistical significance, implying that past values of RoA have a significant impact on the model. The Inflation Rate also shows potential significance. In contrast, lagged Total Assets and regional factors do not exhibit statistical significance in the model.

IV-3.3. Abnormal return (AR) analysis

In financial research, "abnormal return analysis" is a key method used to understand market responses to specific events. In an event study, the abnormal return (AR) measures the gap between a security's actual return during an event and its expected return without that event. This difference sheds light on the market's interpretation and response to various events, such as corporate announcements or unexpected financial news (Kothari & Warner, 2007; Mackinlay, 1997).

In the context of this study, the AR takes on a nuanced role. While it retains its foundational concept of representing the deviation from an expected trajectory, it is molded to capture the lingering impact of internal fraud disclosures on the RoA of banks. Thus, instead of merely reflecting immediate market reactions, the AR in this model encapsulates the sustained reputational damages and the subsequent changes in profitability indicators, offering a comprehensive view of the long-term implications of such disclosures on end-of-year metrics.

IV-3.3.a AR descriptive analysis

The overall mean AR is -0.0552, suggesting that, on average, banks underperformed relative to their eRoA. This is further accentuated by the observation that in the immediate end-of-year metrics following the event, while the AR was slightly positive, it veered into negative territory in the subsequent years, remaining consistently negative in Years 2 and 3. In the subsequent years, both the mean and median AR values drifted into the negative spectrum, underlining a sustained underperformance relative to market expectations. This pattern can be attributed to the lag effect of the operational loss and subsequent reputational damage, where the full brunt of the repercussions becomes more evident as time progresses.

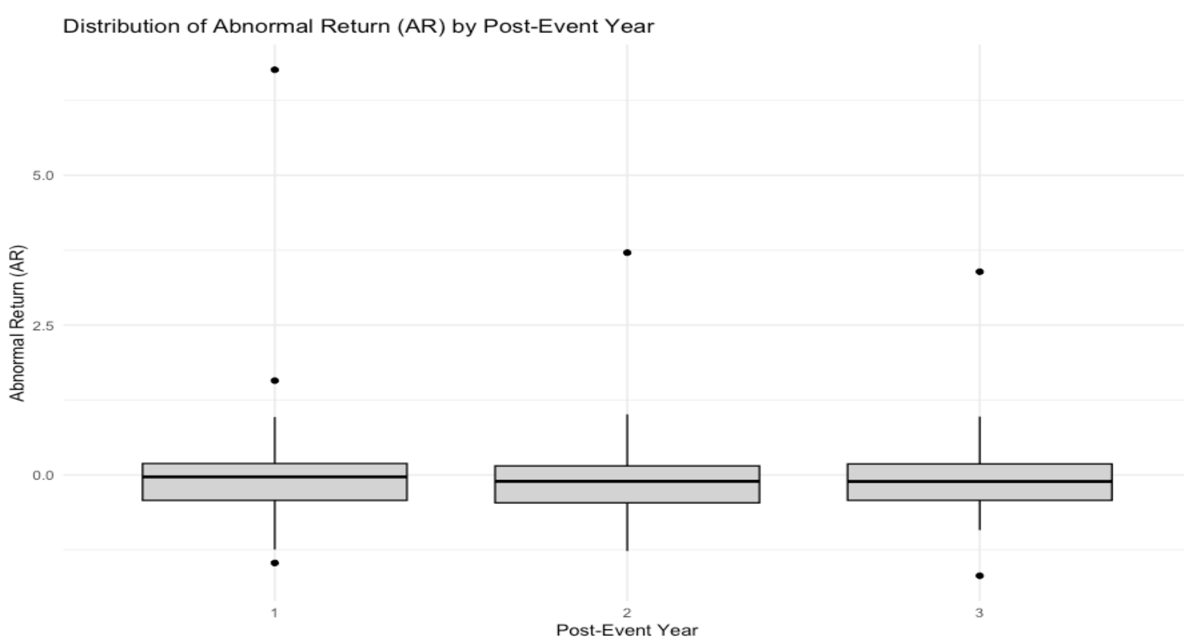
Table IV-3: Abnormal Return summary statistics

			Post Event Years		
	Metric	*Overall*	*Year 1*	*Year 2*	*Year 3*
1	Count	159	53	53	53
2	Mean	(0.05520)	0.02221	(0.09150)	(0.09710)
3	Standard Deviation	0.84783	1.09289	0.71404	0.68248
4	Min	(1.68130)	(1.46835)	(1.26885)	(1.68130)
5	25th Percentile	(0.43034)	(0.42409)	(0.46503)	(0.42363)
6	Median (50th Percentile)	(0.06536)	(0.03238)	(0.10651)	(0.10844)
7	75th Percentile	0.17681	0.19076	0.15121	0.18387
8	Max	6.75922	6.75922	3.70816	3.39052

The variability in AR (as measured by the standard deviation of RoA) is highest in Year 1 and decreases in subsequent years.

Figure IV-15 presents a graphical representation of the distribution of AR values, offering enhanced insights into their dispersion and central characteristics.

Figure IV-15: Distribution of AR by Post-Event Year

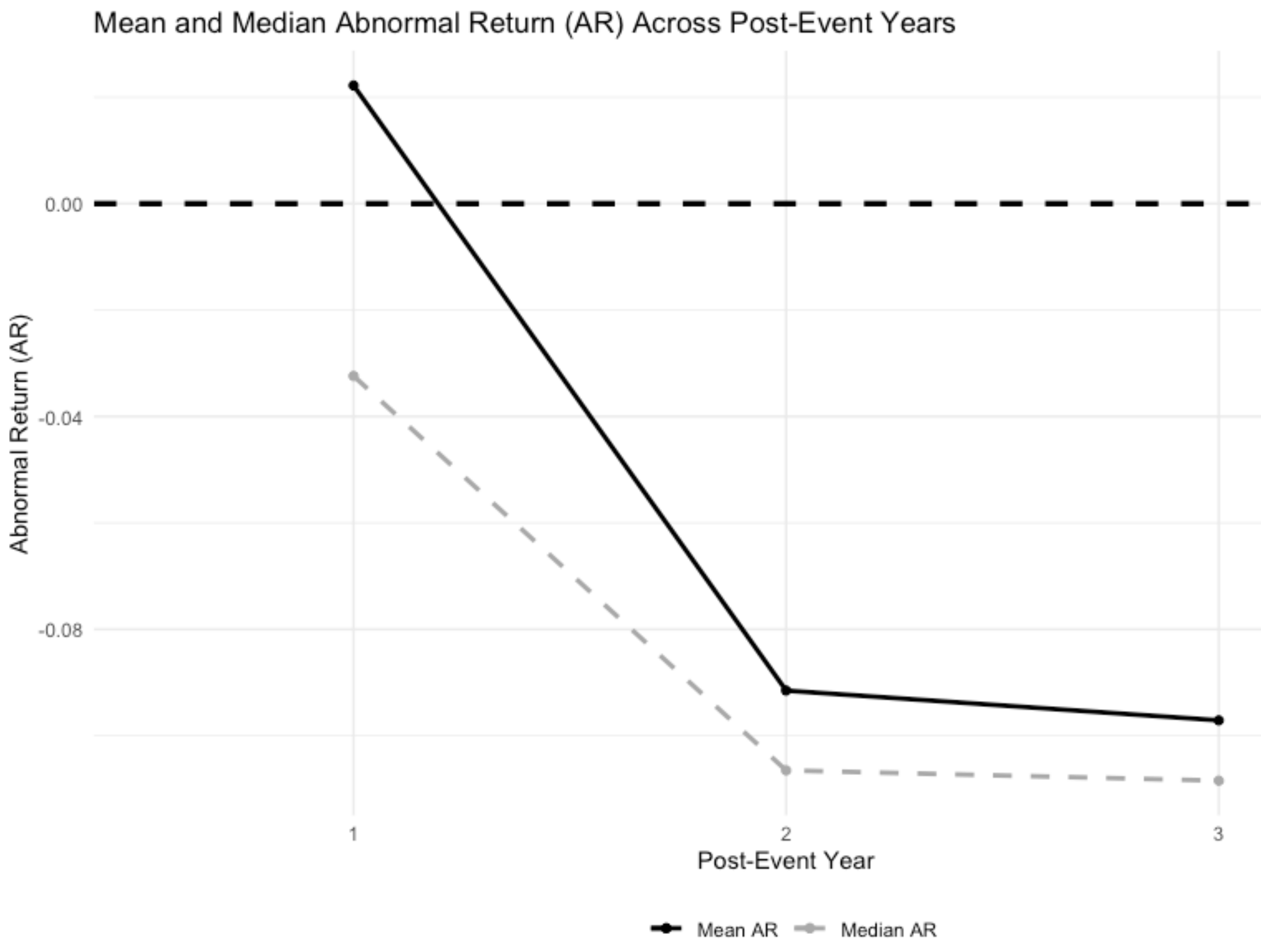


IV-3.3.b Negative AR: A closer look

In the analysis of the AR values, special emphasis is placed on the negative figures due to their significant implications. An examination of the data reveals that during the first year post-event, there were 28 instances where banks reported negative AR values. This frequency slightly increased in the second year with 32 instances and marginally decreased to 31 instances in the third year. When observing the magnitude of these negative returns, the first-year post-event registered the most pronounced average negative AR at -0.4807. Subsequent years displayed a trend of moderation, with average negative ARs of -0.4541 and -0.4540 for the second and third years, respectively. However, the marginal difference in magnitude across the three years underscores a consistent theme. These observations suggest that operational loss events and ensuing reputational loss, exert a sustained impact on banks' financial performance, as manifested by the persistent negative ARs in subsequent years. To further deepen this empirical exploration, a comparative study of the mean and median AR values over the three post-event years was instrumental in identifying overarching trends or patterns.

The chart below, Figure IV-16, illustrates the progression of both mean and median AR values across three post-event end-of-year metrics, highlighting the divergence and trends in banks' performance relative to market expectations.

Figure IV-16: Post-Event years Mean and Median AR



IV-3.3.c Intensity of Reputation Loss (Rl)

The dataset comprises 159 observations, evenly distributed across the three post-event years, with each year accounting for 53 banks. This uniform distribution ensures that the year-to-year comparisons are grounded in equal sample sizes, providing a consistent basis for analysis. It is noted banks in the sample, on average, recorded a positive value of approximately $442 million, which could signify either a gain or a diminished loss. However, this average is influenced by extreme values. A notably high standard deviation of about $2,363 million indicates a significant dispersion of values. This level of variability points to a wide range of outcomes, from substantial losses to considerable gains. The minimum value, -$690 million, highlights instances of significant negative outcomes within the dataset. Conversely, the maximum value reaches an impressive $17,979 million, indicating the presence of extremely positive outliers, banks with considerable reputational gain.

The median of -$2.11 million, marginally negative, signifies that more than half of the observations are clustered around a small negative value, possibly indicating frequent modest losses or negative impacts. The 25th percentile (-$52.7 million) and the 75th percentile ($96.7 million) further underscore the skewed nature of the dataset, with a quarter of the data experiencing notable losses and only a quarter surpassing the $96.7 million mark.

Table IV-4 presented below offers a comprehensive overview of the statistics related to Reputational losses:

Table IV-4: Reputational Loss (Rl) summary statistics

			Post Event Years		
	Metric	***Overall***	***Year 1***	***Year 2***	***Year 3***
1	Count	159.00	53.00	53.00	53.00
2	Mean	441.58	485.71	460.35	377.47
3	Standard Deviation	2,363.12	2,353.80	2,579.00	2,180.30
4	Min	(689.63)	(689.63)	(503.95)	(589.77)
5	25th Percentile	(52.72)	(45.96)	(63.77)	(65.64)
6	Median (50th Percentile)	(2.11)	16.23	(7.15)	(8.01)
7	75th Percentile	96.65	130.08	70.05	63.13
8	Max	17,979.40	16,039.55	17,979.40	15,294.65

Year-wise examination yields the following:

- In the first year, the mean value of 'Rl' is slightly higher than the overall average at $486 million. However, the standard deviation remains high at $2,354 million, mirroring the overall dataset's variability. The year's data ranges from a minimum of -$690 million to a maximum of $16,040 million.

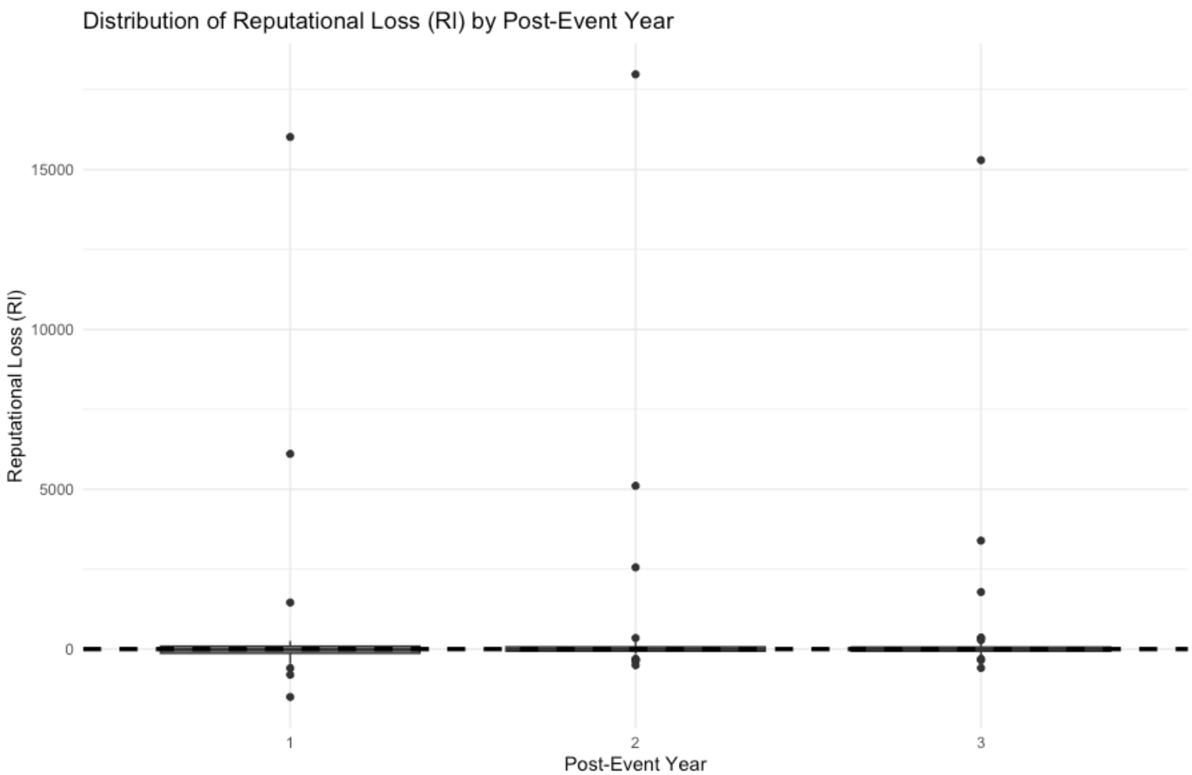
- The second year shows a slight decrease in the mean value to $460 million. The standard deviation increases to $2579 million, suggesting even greater variability. Notably, this year records the dataset's highest maximum value of $17,979 million, highlighting an extremely positive outlier.
- The third year sees a further decline in the mean value to $377 million, continuing the downward trend observed over the years. The standard deviation slightly decreases to $2,180 million, suggesting a reduction in variability. The maximum value this year is $15,295 million, still indicating the presence of significant positive outliers.

The trend over the years indicates a decrease in the average 'Rl' values, although the presence of high positive outliers each year significantly impacts these averages. The high standard deviations and the spread of the percentiles suggest that the Rl are not clustered around the mean but rather spread across a wide range of values.

The most significant reputational loss recorded was -$690 million, most pronounced in the first year. The subsequent years also saw significant losses but not as severe as the first year.

Figure IV-17 provides a visual representation of how reputational losses varied and distributed across the three years following the operational event, highlighting the presence of important outliers.

Figure IV-17: Distribution of Reputational Loss (Rl) by Post-Event Year



In the boxplot, the interquartile range (IQR), typically represented by the 'box,' is reduced to a line here, indicating a concentration of data points. This line demonstrates the middle 50% of the data values. The negative median values result in the box (or line) positioning below or near the zero line, reflecting a central tendency towards lower or minimal reputational loss. However, the presence of very high maximum values and substantial standard deviations is evident in the appearance of outliers. These outliers, depicted as individual points significantly distant from the main 'whiskers' of the boxplot, are particularly telling. They signify occurrences of exceptionally high reputational loss, markedly skewing the average upwards. These extreme values are vital for understanding the full spectrum of reputational loss impacts, especially how rare, high-magnitude events can disproportionately influence the overall average.

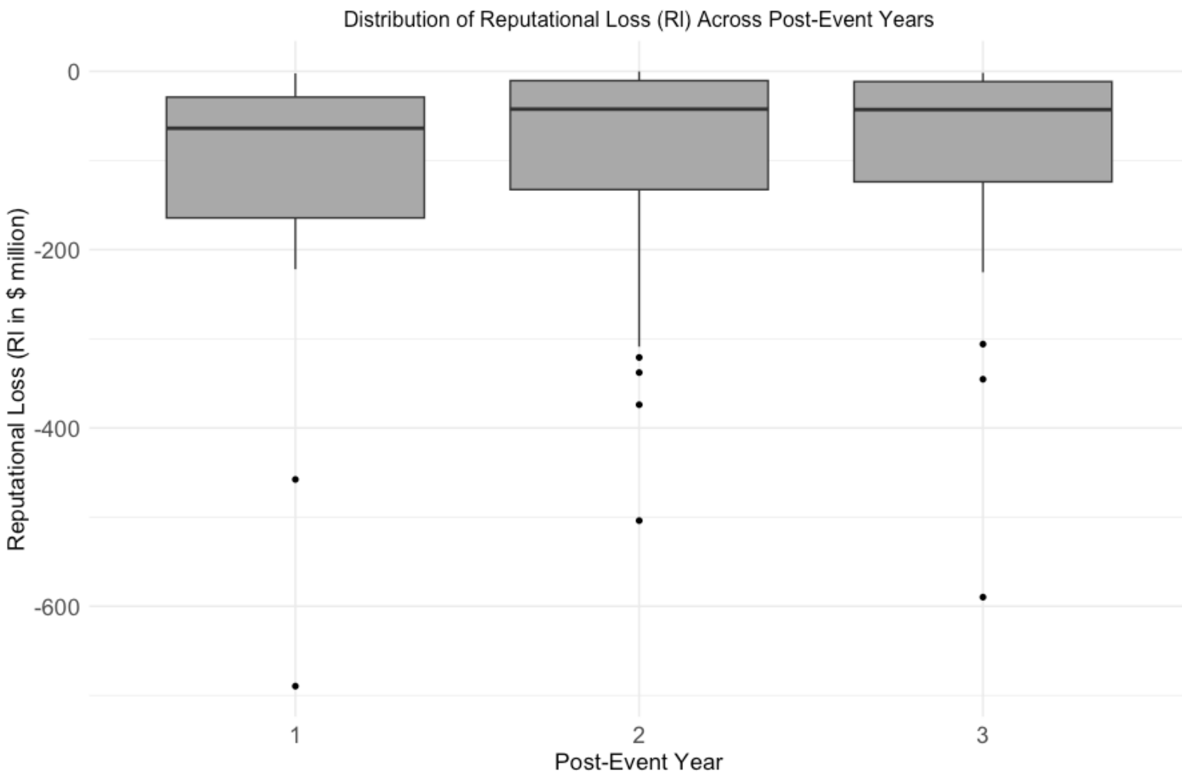
Comparing across the three years, although the mean and SD values are somewhat similar, any changes in the spread of the IQR or the positioning and number of outliers will be informative. An increase in the range or number of outliers in later years might suggest escalating impacts of reputational loss over time.

Out of the 53 banks in the study's sample, 66.04% experienced a Reputational Loss (Rl) in at least one of the three post-event years (negative values indicating a loss), illustrating the pervasive impact of operational events on the reputation of a majority of banks.

Following an operational event, the data reveals a sequential evolution in the number of banks experiencing Reputational Loss (Rl). In the initial post-event year, approximately 37.7% of banks in the dataset registered a negative Rl. This suggests that the immediate repercussions of the operational incident impacted just over a third of the institutions. However, by the second post-event year, this proportion surged to 60.4%, indicating a magnified influence of the initial event, depending on which month the operational loss was disclosed in year one. An internal fraud disclosure in January for example will potentially have a more severe impact on the end-of-year financial metrics, compared to an event disclosed in November. Interestingly, by the third post-event year, while there was a marginal decrease to 58.5%, the percentage remained high, highlighting a sustained adverse effect on a majority of banks. Such persistent high proportions in the subsequent years after the event underline the enduring nature of reputational impacts resulting from operational events and emphasize the imperative of effective strategies to address and recover from such setbacks.

Figure IV-18 below offers a visual representation of the distribution of negative Reputational Loss (Rl) across the three post-event years, highlighting the extent and persistence of reputational damage experienced by 66% of the banks in the sample.

Figure IV-18: Reputational Loss (Rl) negative figures distribution



Among the banks that recorded at least one negative Rl post-event:

- An average reputational loss of approximately $54 million was observed. Although these banks encountered a negative Rl in at least one instance, the mean might incorporate positive outcomes from other years.
- A median reputational loss of $20 million, lower than the mean, suggests potential skewness in the distribution due to extreme values.
- The substantial standard deviation of $213 million indicates the broad range and variability of reputational impacts.
- The most severe reputational loss was $690 million, emphasizing the profound negative consequences that certain operational events can impose.

In the context of reputational impact, the observation of a maximum abnormal gain amounting to $1,527 million is indicative of an important dynamic within the banking sector. Despite experiencing negative reputational impacts (Rl) in a given year, banks have exhibited the capacity to achieve notable reputational recoveries in the following years. Instances where limited reputational loss is recorded in the aftermath of fraud possibly highlight the robustness of the banks' mechanisms to recover from such adversities. These mechanisms, which may include transparent communication, prompt corrective measures, and strategic public relations efforts, contribute to a bank's ability to not only regain its standing but potentially improve its reputation following an incident. As an illustrative case, in 2016, Wells Fargo experienced a significant decline in stock price subsequent to the announcement of an operational loss. However, just two months later, the company's share price not only recovered but also surged past its pre-event value (Egan, 2016b; Wells Fargo, 2017b). This inherent resilience within banks plays a pivotal role in shielding them against the enduring adverse effects typically associated with reputational harm post-internal fraud events.

On the other hand, the remaining banks in the sample, which did not register a negative Rl in any post-event year, demonstrated the following:

- An impressive average abnormal gain of $1,480 million, suggests these banks either had effective damage control mechanisms, enjoyed positive market perception, or benefited from other advantageous factors.
- The median gain, at $116 million, is substantially lower than the mean, indicating that the mean might be influenced by a few exceptionally high Rl values.
- A standard deviation of $3,977 million showcases the vast range of Rl values within this group.
- The minimum Rl value was a modest gain of $7.12 million.
- The maximum gain reached an astounding $17,979 million, highlighting the potential for considerable reputational benefits even amidst the wider industry context of operational events.

From the analysis, it's evident that the Reputational loss (Rl) carries significant weight in the context of this study. Negative values of Rl suggest losses over and above the operational losses and are indicative of reputational damage which translates to monetary repercussions. The frequency and magnitude of Rl (negative abnormal return) values across the three post-event years underscore the lingering effects of operational loss events on the reputation of banks. The persistence of these negative values, especially their prevalence in all three post-event years, signifies the enduring impact of such events on the financial standing of banks, even beyond the immediate operational loss.

IV-3.3.d Statistical significance of mean AR

Following Fiordelisi et al. (2013), the Boehmer et al. (1991) Z test statistic was employed to test the statistical significance of the AR mean. This test is designed to measure the fluctuations in return consistency that are prompted by specific events. Initially, the study considered the entire sample of banks. The Z statistic derived from this comprehensive dataset stood at −0.73. Although this negative value indicates a deviation from the expected returns, it's essential to interpret this value within the context of the study dataset's characteristics and the broader financial landscape. Indeed, a Z value of −0.73 suggests that the event, on average, led to a decline in returns across all banks, albeit not very pronounced.

Acknowledging the significant influence of outliers and the diverse performance of individual banks within the dataset, coupled with the observation that over two-thirds of the banks experienced some form of reputational loss in the three years following the event, a more nuanced analysis was undertaken. This refined approach aimed to delve deeper into the intricacies of the data, particularly focusing on how these variations and extreme values affect the overall trend and interpretation of reputational loss across the sample. This time, the focus was shifted to banks that had at least one negative abnormal return post-event (66.04%). Intuitively, these banks would arguably be the ones most affected by the adverse events in question. The Z statistic test for this subset of banks was markedly more negative, standing at −4.05. This value, being more pronounced than the earlier statistic, underscores the pronounced negative abnormal returns for these particular banks. The divergence in the Z values between the two datasets emphasizes the heterogeneity in the banks' reactions to internal fraud events. While the overall market might show a mild reaction, the banks directly and more severely impacted by such events exhibit a significant deviation in their returns.

IV-3.4. Model validity and robustness checks

In empirical research, ensuring the validity and robustness of a model is paramount (Hair et al., 2019; Keith, 2019). This not only bolsters the reliability of the findings but also enhances the credibility of the conclusions drawn from the analysis. In this section, the focus shifts to a comprehensive examination of the underlying assumptions and characteristics of the multivariate regression model employed in this study. Through a series of diagnostic tests, including checks for multicollinearity, heteroskedasticity, and autocorrelation, the robustness of the model is ascertained. Such rigorous validation procedures ensure that the interpretations and policy implications derived from the model stand on a solid empirical foundation, making them both meaningful and actionable in real-world scenarios (Treiman, 2009).

IV-3.4.a Multicollinearity Test

In the context of multiple regression analysis, multicollinearity arises when two or more independent variables exhibit strong correlations, thereby reducing the distinctiveness of the information they provide. Such correlations can lead to unstable estimates of regression coefficients, making interpretations challenging (Stockemer, 2019). The Variance Inflation Factor (VIF) serves as a diagnostic tool to detect the severity of multicollinearity. As per general guidelines, a VIF value exceeding 5 (with a corresponding tolerance value of less than 0.2) is considered indicative of multicollinearity, while a VIF greater than 10 generally suggests a pronounced degree of multicollinearity (O'Brien, 2007). However, O'Brien (2007) contends that high VIF values, even more than 10, 20, 30, or 40 on their own don't necessarily invalidate regression results or necessitate variable elimination or the application of specialized regression techniques.

For the lagged RoA from the previous three years, a VIF value slightly above 2 was observed, suggesting a moderate level of multicollinearity. This indicates that these lagged RoA values, while having some correlation with other predictors, retain a degree of uniqueness in the information they contribute to the model. The lagged Total Assets from the previous three years presented a VIF just above 3, suggesting that these values, though moderately correlated with other predictors, do not compromise the model's integrity.

The Inflation Rate's VIF slightly exceeded 2, falling within the moderate range. This infers that the Inflation Rate, while intertwined with other predictors, maintains a satisfactory level of distinctiveness. The GDP Growth Rate, with a VIF below 3, also displayed very moderate multicollinearity, indicating that its relationship with other predictors remains within acceptable bounds.

In sum, the analysis underscores a lack of significant multicollinearity among the predictors in the regression model, with most variables displaying very moderate VIF values. Even with the elevated VIF of the regional categorization, its lack of statistical significance in the model indicates that its potential multicollinearity does not detrimentally impact the model's overarching conclusions (Stockemer, 2019). This suggests that, after accounting for other influential factors, the specific region in which a bank operates does not exert a considerable independent effect on its RoA. The model's design, which controlled for regional effects, was aimed at addressing potential heterogeneities across different global regions. Yet, the results emphasize that regional distinctions, in this context, do not have a marked standalone impact on banking performance metrics like RoA.

IV-3.4.b Heteroskedasticity Test and robust standard errors

Heteroskedasticity in regression models can lead to inefficient and inconsistent parameter estimates, particularly affecting the reliability of standard errors, which, in turn, can render hypothesis tests and confidence intervals invalid (Wooldridge, 2002). In the context of financial data, heteroskedasticity is often a major concern given the dynamic and volatile nature of financial markets (Alexander, 2008). Given these potential implications, it was paramount to test for and, if necessary, address heteroskedasticity in the regression model.

In this research, to address the potential heteroskedasticity in the random-effects GLS model, robust standard errors were employed. The use of heteroskedasticity-robust standard errors, sometimes termed "White standard errors" after White (1980), is a prevalent approach in econometrics to ensure that hypothesis tests remain valid even in the presence of heteroskedasticity. Essentially, these robust standard errors provide corrections to the conventional standard errors, making them more reliable for inference.

Upon application of the robust standard errors, the results reveal that the first “lag” of RoA remains statistically significant, suggesting a degree of momentum in banks' performance from one year to the next. However, other potential predictors, like regional dummies and certain economic indicators, do not display statistical significance. It's pivotal to note here that while the statistical significance provides evidence about the relationships in the model, it doesn't necessarily convey their economic or practical importance (Coyle, 2017).

The application of the White test for heteroskedasticity through robust standard errors (HC3) reveals that the concerns regarding the uneven variance of the error terms within the model are mitigated. The robust standard errors presented in the output (…) account for heteroskedasticity, ensuring that the estimated coefficients remain reliable despite the potential presence of heteroskedasticity. The analysis indicated that the lagged Return on Assets (RoA) for the first and second periods (lag(RoA, 1:3)1 and lag(RoA, 1:3)2) are statistically significant at conventional levels, with p-values less than 0.05. This signifies their importance as predictors of current RoA, exhibiting a clear influence on the dependent variable.

Table IV-5: White test coefficients

	Variables	Estimate	Std. Error	z-value	Pr(>|z|)
1	(Intercept)	0.29685577	0.31933207	0.92961465	0.35415943
2	lag(RoA, 1:3)1	0.45984946	0.12322753	3.73171052	0.00027499
3	lag(RoA, 1:3)2	0.35950595	0.21317288	1.6864526	0.09392006
4	lag(RoA, 1:3)3	-0.1452969	0.24574539	-0.5912499	0.55529964
5	lag(TotalAssets, 1:3)1	-2.322E-06	4.3487E-06	-0.5338924	0.59425669
6	lag(TotalAssets, 1:3)2	1.2258E-05	2.4393E-05	0.50253539	0.61607493
7	lag(TotalAssets, 1:3)3	-1.05E-05	2.4892E-05	-0.421753	0.67384765
8	Inflation Rate	0.06698729	0.07471	0.89663083	0.37144425
9	GDP Growth Rate	-0.0102272	0.09304432	-0.1099172	0.91263135
10	factor(g2_Region) Eastern Africa	0.11501182	0.32695835	0.35176291	0.72554122
11	factor(g2_Region) Eastern Asia	-0.9017834	1.57891035	-0.5711429	0.568812
12	factor(g2_Region) Eastern Europe	0.68958532	0.72102062	0.95640166	0.34050628
13	factor(g2_Region) Northern America	-0.0241742	0.18349057	-0.131746	0.89537298
14	factor(g2_Region) Northern Europe	0.33597367	0.63796533	0.52663311	0.59927588
15	factor(g2_Region) South-Eastern Asia	0.32456231	0.36578677	0.88729919	0.37642883
16	factor(g2_Region) Southern Asia	-0.7711429	0.49480344	-1.5584833	0.12136046
17	factor(g2_Region) Western Africa	-0.0578756	0.50147364	-0.115411	0.90828357
18	factor(g2_Region) Western Asia	-0.2498582	0.60327356	-0.4141706	0.67937851

The robust standard errors ensure that these findings are credible, even if heteroskedasticity exists. In essence, the analysis stands on solid ground with the robust approach, negating the effects of heteroskedasticity on the standard errors, and by extension, on the statistical inference derived from the model. The validity of the coefficient tests is thus maintained, affirming the reliability of the empirical findings.

IV-3.4.c Autocorrelation Test

Autocorrelation, also referred to as serial correlation, pertains to the correlation of a variable with itself across different time periods. In the context of regression analysis, especially panel data, the presence of autocorrelation can compromise the efficiency of coefficient estimates, which can result in unreliable statistical inferences. The Wooldridge test is a widely used diagnostic tool to identify the presence of autocorrelation in panel data models (Stockemer, 2019).

The null hypothesis of the Wooldridge test is that there's no first-order autocorrelation in the idiosyncratic errors. If the p-value associated with the test is below a pre-defined significance level (e.g., 0.05), one would reject the null hypothesis, suggesting the presence of autocorrelation (Born & Breitung, 2016; Romano & Tirlea, 2022).

For the given regression model, the Wooldridge test returns a chi-squared statistic of 0.04172 with 3 degrees of freedom. The associated p-value is 0.9978, which is significantly higher than conventional significance thresholds. Given this p-value, there's no statistical basis to reject the null hypothesis.

In conclusion, based on the Wooldridge test results, there's no evidence of first-order autocorrelation in the idiosyncratic errors of the panel data regression model. This suggests that the model's coefficient estimates are not biased due to autocorrelation, and standard statistical inferences derived from the model are likely to be reliable.

IV-3.5. Reputational loss: Overall discussion

Internal frauds, defined as deliberate misconduct to defraud financial institutions, often perpetrated by an institution's own personnel, pose a severe threat to the banking sector's integrity and stability (Office of the Comptroller of the Currency, 2019). While the immediate financial implications of such frauds are evident, there is an equally significant aftermath that banks face in the form of reputational damage (Eckert & Gatzert, 2017a; Fiordelisi et al., 2014a; Gillet et al., 2010a).

The analysis of the data suggests that reputational losses ($Rl_{i,t}$), quantified as the monetary abnormal return minus the amount of operational loss, have a discernible impact on a bank's RoA. RoA, being a key metric to assess a bank's profitability relative to its total assets (Akhigbe & McNulty, 2005; Terraza, 2015), can be influenced by various external and internal factors. The presence of internal frauds and the subsequent reputational damage seem to be potent factors affecting this metric (Deephouse, 2000; Gillet et al., 2010).

Across the post-event years analyzed, a considerable proportion of banks exhibited reputational losses (negative abnormal return), a clear indication of the adverse impact of internal frauds on the banks' public perception and trust. This reputational damage, when translated into financial metrics, manifests as a decline in RoA, reflecting reduced profitability (Fiordelisi et al., 2013; Gatzert, 2015). The persistence of these negative values across subsequent years underscores the lasting impact of such events, suggesting that the recovery from reputational damage is neither immediate nor straightforward.

Moreover, while the average values might indicate some recovery or even abnormal gains in reputational metrics, a deeper dive into the data reveals that a significant portion of banks continue to experience negative reputational losses even years after the fraud event. This emphasizes the profound and lasting nature of the reputational damage that internal frauds can inflict upon financial institutions (Gatzert, 2015).

Furthermore, it's crucial to understand the wider implications of these findings. A decline in RoA due to reputational losses can deter investors, affect the bank's stock prices, and even influence customer trust, leading to a potential decline in deposits or business (Basel Committee on Banking Supervision, 2009). In an industry where trust and credibility are paramount, the effects of reputational damage can ripple through various facets of a bank's operations and can even impact its long-term sustainability (Gunawardena et al., 2019; Singh et al., 2020; Trotta et al., 2016).

In conclusion, while internal frauds pose immediate financial challenges to banks, the subsequent reputational losses they trigger have a prolonged and significant impact on banks' profitability, as evident from the decline in RoA. Addressing and mitigating the effects of such reputational damage should be a priority for banks, not just from a profitability standpoint but also to uphold the trust and confidence placed in them by their stakeholders.

IV-3.6. Hypothesis 1 testing: Impact of Internal frauds disclosure on RoA

Research Question 1 probes the relationship between internal fraud disclosures and the RoA of commercial/retail banks, with a focus on reputational loss translated into quantifiable monetary terms. Unlike the majority of empirical studies that concentrate on immediate market reactions (Cummins et al., 2006; Fiordelisi et al., 2013; Gillet et al., 2010; Perry & de Fontnouvelle, 2005), this inquiry extends to the examination of year-end financial metrics to determine the enduring impact on financial performance.

The influence of corporate reputation on financial outcomes has been substantiated by Eberl & Schwaiger (2005), who demonstrated a significant correlation between corporate reputation and financial performance, specifically net income after tax. Deephouse (2000) corroborated this by showing that a bank's media reputation positively affects its performance, as reflected in its RoA. Conversely, McGuire et al. (1990) posited that it is the prior financial performance, particularly RoA, that influences a bank's reputation. Rose & Thomsen (2004) supported this view, suggesting that financial performance is a determinant of reputation.

Given the critical role of operational losses and internal frauds in shaping financial performance, this study formulates the following hypotheses to delve into the dynamics between reputational risk and financial performance. The investigation particularly aimed to understand the potential reputational damages following internal frauds and their subsequent effects on the banks' RoA:

Null Hypothesis (H_{01}): An internal fraud disclosure has no impact on the RoA of commercial/retail banks.

Alternative Hypothesis (H_1): An internal fraud disclosure has a significant negative impact on the RoA of commercial/retail banks.

Empirical evidence drawn from the present analysis revealed salient insights about the repercussions of internal frauds on a bank's financial performance. Notably, the average net abnormal return (excluding the operational loss) across banks was found to be approximately $442 million, with a significant portion of banks exhibiting negative reputational losses in the years following the event. Such pronounced negative values, depicting losses, add weight to the hypothesis, indicating the substantial adverse repercussions of internal frauds on banks' profitability.

In the realm of hypothesis testing, the Z value of −4.05 for the AR mean is statistically significant at conventional levels. Consequently, for banks with at least one negative AR post-event (66.04%), ***the null hypothesis(H_{01}) can be soundly rejected in favor of the alternative***. This confirms that these banks, potentially more vulnerable or impacted by the event, experienced significant deviations in their returns compared to anticipated performance.

While the broader market exhibits a varied reaction to internal fraud events, a deeper dive reveals that banks more directly affected by such events suffer pronounced negative abnormal returns. Furthermore, it aligns with the extant literature, reinforcing the adverse financial ramifications of internal frauds on affected banks (Eckert & Gatzert, 2017; Gillet et al., 2010; Perry & de Fontnouvelle, 2005).

When viewed through the lens of statistical robustness, the model employed in this analysis proved to be valid and reliable. The statistical validity of the model further underscores the confidence in the results and their alignment with the alternative hypothesis (H_1).

In sum, the empirical evidence, both from the present analysis and extant literature, affirms the primary hypothesis. Internal fraud disclosures, aside from their immediate financial implications, have broader ramifications on banks, manifesting as reduced profitability and a decline in RoA. Such findings reinforce the criticality of transparency, ethical practices, and stringent internal controls in banking institutions, ensuring their financial and reputational resilience in an environment underscored by trust and credibility (Gunawardena et al., 2019).

IV-4. Correlation between operational loss and reputational loss

A natural expectation might be that the larger the size of an operational loss, especially stemming from internal frauds, the more pronounced the reputational damage would be, manifesting in larger reputational losses (Cummins et al., 2006; Perry & de Fontnouvelle, 2005). This perspective is anchored in the assumption that stakeholders, encompassing both customers and investors, would exhibit heightened reactions to substantial operational losses.

This consideration arises from the direct involvement of the bank when internal fraud takes place. Such fraud may be perpetrated by a director, current or former employee, or other parties directly involved in the bank's operations, either acting alone or in collusion, or by facilitating or contributing to fraudulent activities in any way (Office of the Comptroller of the Currency, 2019). Such significant losses could be perceived as indicators of underlying systemic issues within the banking institution, potentially jeopardizing its financial stability and long-term viability (Eckert & Gatzert, 2017). Contrary to this expectation, Fiordelisi et al., (2014) observed that the reputational repercussions stemming from both minor and major operational losses tend to be comparable in magnitude. This counterintuitive finding underscores the complexity of the relationship between operational and reputational losses, prompting a deeper exploration into the interplay between the intensity of operational setbacks and the scale of reputational consequences.

IV-4.1. Losses correlation analysis

To empirically assess this relationship, a Pearson correlation analysis was conducted between the size of the operational loss (Ol) and the cumulative reputational loss over the three post-event years for each bank. The Pearson correlation coefficient provides a measure of the linear association between two variables, with values ranging from -1 to 1, where -1 indicates a perfect negative linear relationship, 1 indicates a perfect positive linear relationship, and 0 indicates no linear relationship.

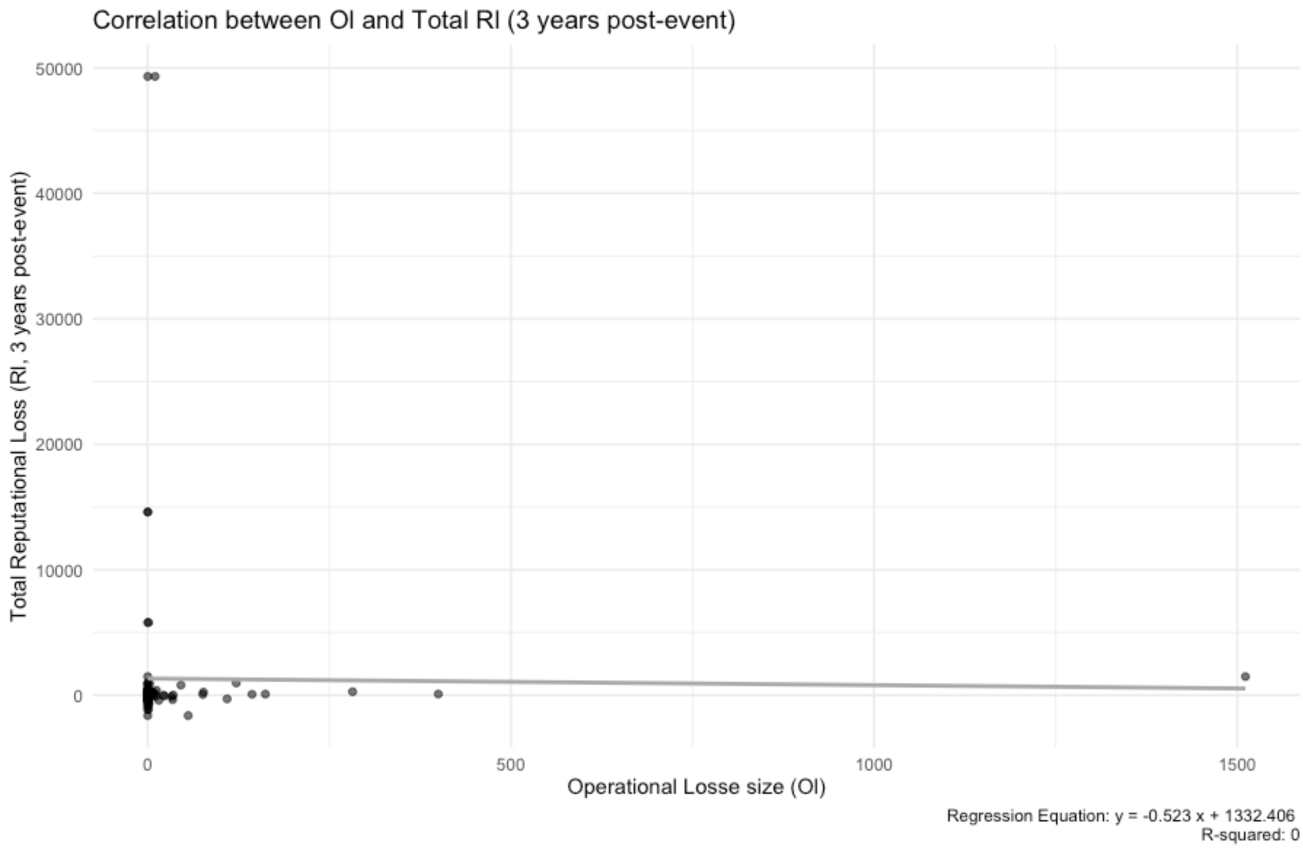
The Pearson correlation coefficient of -0.0115, observed in the dataset, points to a nearly negligible linear relationship between the size of operational losses and the subsequent magnitude of reputational loss experienced by banks over a three-year period. This finding, indicating an almost non-existent correlation, is particularly surprising and counter-intuitive, especially when considering the established global expectations set by prior literature in the field.

In general, one might expect a more pronounced correlation, suggesting that larger operational losses would lead to greater reputational damage, or conversely, that substantial losses might drive more effective damage control measures, mitigating reputational impact. However, the coefficient being so close to zero suggests that the size of operational losses is not a reliable predictor of reputational damage magnitude.

Interestingly, this result aligns with observations made by Fiordelisi et al. (2014). This suggests that the relationship between operational losses and reputational damage is not as straightforward as previously thought. The magnitude of an operational loss, by itself, might not be a clear predictor of the reputational damage a bank might face. It underscores the complexity of factors influencing a bank's reputation post-incident, which may include the nature of the loss, media coverage, market conditions, the bank’s response strategies, and public perception, among others (Wanjohi et al., 2017).

Figure IV-19 provides a visual representation of the correlation analysis, illustrating the subtle relationship between the size of operational losses and the magnitude of reputational loss experienced by banks.

Figure IV-19: Operational and Reputational losses correlation



Considering the statistical insignificance of the correlation coefficient, and in light of the economic or financial theory and the practical context, it can be confidently inferred that there isn't a significant correlation between the size of an operational loss and the magnitude of the reputational loss (Stockemer, 2019). Hence, while operational loss events are undoubtedly detrimental, their size alone does not dictate the scale of reputational repercussions.

IV-4.2. Hypothesis 2 testing: operational and reputational losses nexus

Research Question 2 posed an inquiry into whether there exists a discernible correlation between the magnitude of an operational loss due to internal fraud and the subsequent quantified monetary value of the reputational loss. This line of inquiry is crucial as the financial implications of operational events, particularly those caused by internal frauds, have been a focal point of academic and industry discussions (Cummins et al., 2006; Eckert, 2017; Gillet et al., 2010; Perry & de Fontnouvelle, 2005).

The underlying rationale for this research question is rooted in the understanding that larger operational losses from internal frauds might attract greater media coverage and public scrutiny, amplifying reputational damage and its ensuing monetary implications. This view finds backing in several empirical studies. Gillet et al. (2010) for instance, observed that when instances of internal fraud are unveiled, the market value's decline often overshadows the declared operational loss, hinting at significant reputational fallout in comparison to other types of operational risk events. This detrimental effect is especially pronounced when the loss forms a substantial chunk of the firm's net earnings.

Perry & de Fontnouvelle (2005) conducted an in-depth analysis into this realm and unearthed some noteworthy findings. They observed that internal fraud events inflict considerable damage on a bank's financial standing, with market values plummeting to nearly twice the size of the operational loss percentage. This indicates pronounced reputational damage, primarily when the operational event stems from internal frauds. In stark contrast, operational losses triggered by external factors did not manifest any significant reputational ramifications.

Delving deeper, Perry & de Fontnouvelle (2005) emphasized that in companies where stakeholder rights are robustly upheld, the decline in market value was even more profound, registering a dip of over six times the internal fraud loss amount. Similarly, Eckert & Gatzert (2017) accentuated that reputational losses often eclipse the original operational loss. Disregarding the potential repercussions of reputational damages might lead to a severe underestimation of certain operational risks, more so in the context of fraud events.

Cummins et al. (2006) further buttressed this viewpoint through their empirical research, highlighting that operational losses invariably trigger significant negative stock market reactions. These adverse reactions, interestingly, surpass the announced loss size, suggesting underlying reputational damage that gets factored into the stock prices.

Given this backdrop, the study formulated the following hypotheses:

Null Hypothesis (H_{02}): There is no correlation between the magnitude of operational loss and reputational loss.

Alternative Hypothesis (H_2): There is a significant positive correlation between the magnitude of operational loss and reputational loss.

The empirical analysis of the present study revealed a Pearson correlation coefficient of −0.0115 between the magnitude of operational losses and the cumulative reputational loss over the three post-event years for each bank. This coefficient, being close to zero, indicates a negligible linear relationship between these two variables (Stockemer, 2019).

Despite the insights from Perry & de Fontnouvelle (2005) and Cummins et al. (2006), the findings from this study suggest that the size of an operational loss may not be a potent predictor of the magnitude of reputational damage a bank might sustain. ***The Null Hypothesis (H_{02}) therefore cannot be rejected.*** This empirical result aligns with the observations made by Fiordelisi et al., (2014), which demonstrate that operational losses, whether minor or significant, lead to comparable reputational repercussions. While the magnitude of operational losses is undeniably a crucial metric, the study finds that it doesn't singularly dictate the reputational implications. This divergence underscores the multidimensional nature of reputational risks and operational losses, hinting that several other determinants might influence the depth and breadth of reputational fallout.

IV-5. Intensity of reputational loss and bank size

Bank size, often seen as a reflection of its market presence, operational scale, and financial robustness (Schildbach, 2017), can play a pivotal role in how a bank navigates through reputational crises. Intuitively, one might posit that larger banks, with their vast resources and established market positions, would be better equipped to manage and mitigate the effects of reputational damage. Conversely, smaller banks, with limited resources, might find themselves more vulnerable to the adverse impacts of such crises (Fiordelisi et al., 2013).

Grounded in the RBT, it's posited that a bank's tangible and intangible assets play a pivotal role in its competitive advantage. A comparative analysis of operational losses between smaller and larger banks suggests that a bank's size can act as a buffer against reputational losses. The juxtaposition of Chase Bank Kenya with Wells Fargo Bank presented earlier (in chapter one, "Introduction") serves as an exemplary case of how a bank's size can act as a buffer against damage to its reputation (Egan, 2016; Olingo, 2017). The correlation between bank size and the intensity of reputational loss offers insights into this dynamic, shedding light on whether size indeed acts as a buffer against reputational challenges or if it presents its own set of vulnerabilities.

IV-5.1. Variation of loss intensity by bank's size

The dataset under examination encompasses 53 distinct banking institutions, each observed over a span of three years after an internal fraud event. As outlined in the research methodology (in study variables), the banks within this sample have been systematically classified based on their size. This classification, grounded in empirical standards (Akhigbe & McNulty, 2005; Terraza, 2015), utilizes the metric of "Total Assets" to categorize banks into three distinct tiers: Small, Medium, and Large.

To ensure a rigorous and nuanced understanding of the relationship between bank size and the intensity of reputational loss, the correlation between these variables has been computed at multiple granularities:

IV-5.1.a Reputational loss and bank size correlation: global analysis

This level of analysis considers the entire sample, providing a holistic view of the correlation between "Total Assets" (A) and reputational loss intensity (Rl) across all 53 banks over the three-year post-event period. This global perspective offers insights into overarching trends and patterns that might be prevalent across the banking sector.

In the analysis, the global correlation coefficient derived between Total Assets (A) and Reputational loss (Rl) stands at 0.9136276. This value signifies a pronounced positive association between the two variables. Interpreting this in the broader context, it can be inferred that as a bank's total assets — which serve as a representative measure for its size — augment, there is a concurrent escalation in the intensity of its reputational loss. This observation underscores the potential vulnerabilities even larger banks might face in terms of reputational risks, despite their substantial asset base.

IV-5.1.b Reputational loss and bank size correlation: Individual bank analysis

At this granularity, each bank is analyzed over the three-year post-event timeframe. This approach allows for the identification of bank-specific dynamics and variations, offering a more detailed perspective on how individual banks, with their unique operational and strategic nuances, relate their size to reputational loss intensity.

The empirical results present a mixed picture. While the global correlation suggests a strong positive relationship between bank size and reputational loss intensity, individual bank analysis reveals a more nuanced scenario.

- **Positive Correlation:** Out of the banks listed, 26 banks exhibit a positive correlation between their size and reputational loss intensity. This means that for these banks, as their size increases, the intensity of reputational loss also increases. Notably, banks such as BBVA USA, Czech Export Bank, and Guaranty Trust Bank (GTBank) have correlations close to 1, indicating a very strong positive relationship.
- **Negative Correlation:** Conversely, 24 banks show a negative correlation, suggesting that as their size increases, the intensity of reputational loss decreases. Banks such as Bank of Maharashtra, China CITIC Bank International, and Punjab

& Sind Bank have correlations close to -1, indicating a very strong negative relationship.

- **Neutral or Weak Correlation:** A few banks, such as Access Bank Plc and General Motors Acceptance Corporation (GMAC), have correlations close to 0, suggesting a weak or no relationship between bank size and reputational loss intensity.

IV-5.1.c Reputational loss and bank size correlation: Categorical analysis

This level of analysis delves into the correlation within each size category: Small, Medium, and Large. By segmenting the banks based on their size and analyzing the correlation within these segments, this approach aims to uncover whether bank size, as a categorical variable, plays a consistent role in influencing the intensity of reputational loss.

The analysis, when segmented by categories, offers a deeper and more detailed insight into the interplay between reputational loss and the bank's size.

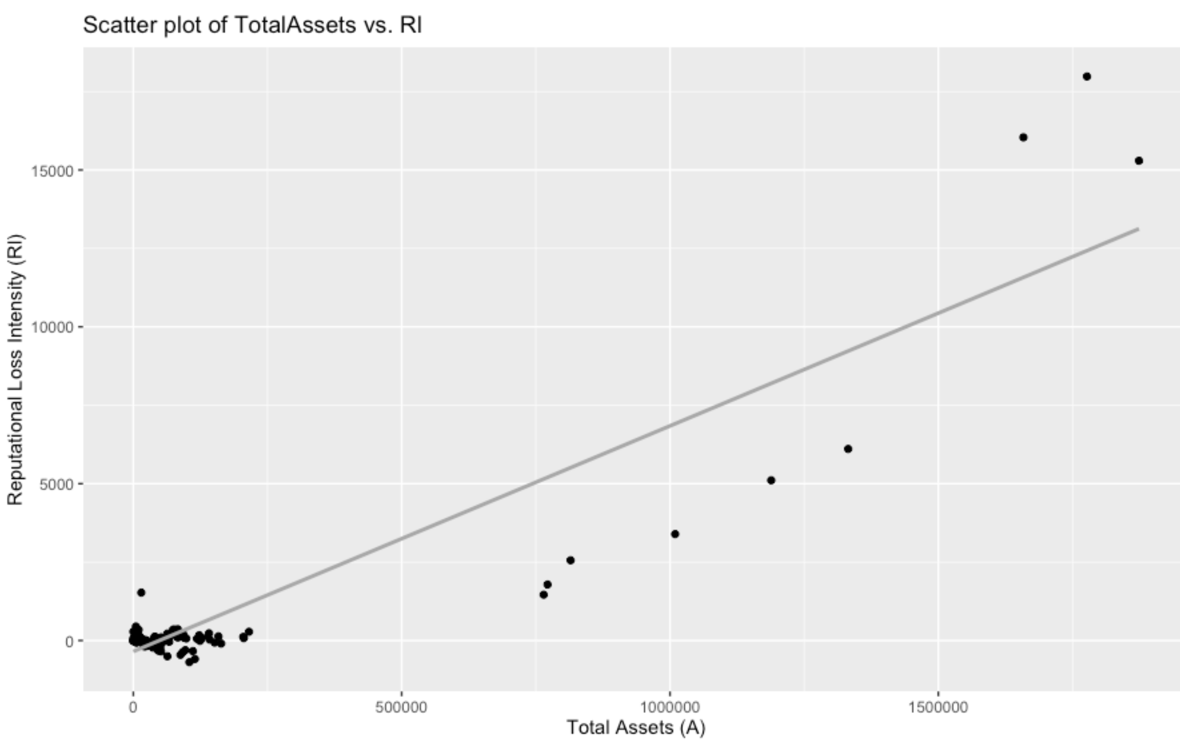
- **Small Banks:** The correlation is -0.403, indicating a moderate negative relationship between bank size and reputational loss intensity. This suggests that smaller banks tend to experience more significant reputational damage as their assets decrease.
- **Medium Banks:** The correlation is 0.229, suggesting a weak positive relationship. This indicates that medium-sized banks might experience a slight increase in reputational loss intensity as their assets increase, but the relationship is not as strong.
- **Large Banks:** The correlation is 0.919, indicating a strong positive relationship. This suggests that larger banks, despite their size, also experience an increase in reputational loss intensity as their assets increase. However, the magnitude of this loss might be cushioned by their larger asset base and other protective factors.

IV-5.1.d Summary of the correlation analysis and discussion

At the global scale, the correlation coefficient provided a holistic view of the relationship between Total Assets (A) and the incurred Reputational loss (Rl) across the entire dataset. The strong positive value (0.9136276) indicated that, generally, as banks increase in size (as measured by total assets), there's a tendency for the intensity of reputational loss to also rise. This suggests that larger banks, despite their vast resources, might not be entirely insulated from reputational challenges.

Figure IV-20 provides a visual representation of the relationship between a bank's total assets and the intensity of its reputational loss, with a regression line illustrating the overall trend observed in the data.

Figure IV-20: Reputational loss and Bank size correlation



Delving into individual banks over the three-year post-event timeframe, the correlations revealed a more varied picture. Each bank, with its unique operational nuances and strategic approaches, exhibited different degrees of correlation between size and reputational loss intensity. While 26 banks exhibit a positive correlation, 24 banks show a negative correlation and some banks recorded positive correlation, a few banks have correlations close to 0. This level of granularity highlighted the importance of considering individual bank dynamics and external factors when assessing the relationship.

Segmenting the banks based on size (Small, Medium, Large) and analyzing the correlation within these categories offered a more segmented perspective. The results from this analysis underscored that smaller banks tend to experience a more severe intensity of reputational damage compared to medium and large banks. The negative correlation for small banks, for instance, suggested a potential vulnerability to reputational damage as their assets decrease, while the positive correlations for medium and large banks indicated varying degrees of reputational risk as their assets increase.

In summary, while the global correlation provided an overarching trend, the individual bank and categorical analyses offered more detailed and nuanced insights, emphasizing the multidimensional nature of the relationship between bank size and reputational loss intensity. There is a limited number of empirical studies examining the relationship between a bank's size and the extent of reputational harm (Fiordelisi et al., 2013, 2014). Small banks, as indicated by the negative correlation (-0.403), seem to be more vulnerable to reputational damage compared to their larger counterparts.

In conclusion, while the global correlation and individual bank analyses provide a general trend, the grouping by bank size offers a more nuanced understanding. The results empirically support the notion that smaller banks are at a heightened risk of reputational damage compared to medium and large banks.

IV-5.2. Hypothesis 3 testing: bank size influence on reputational loss

Research Question 3 delved into the association between the intensity of Reputational loss and the size of the bank in question, with the latter being quantified by its Total Assets. This exploration finds its theoretical foundation in the Resource-Based Theory, which suggests that both tangible and intangible assets of a bank play a crucial role in shaping its competitive edge (Barney, 1991; Fombrun, 2012). Stemming from this theoretical stance, it could be postulated that the size of a bank, as reflected by its total assets, might serve as a buffer against reputational challenges. Fiordelisi et al. (2013) further contribute to this discourse by presenting empirical findings that indicate a potential escalation in reputational risks as a bank's profits and size expand. In light of these considerations, the study articulated the subsequent null and alternative hypotheses:

Null Hypothesis (H_{03}): Bank size has no correlation with the intensity of reputational loss.

Alternative Hypothesis (H_3): Smaller banks experience a significantly greater intensity of reputational loss compared to larger banks.

The global correlation coefficient between Total Assets (A) and Reputational loss (Rl) was found to be 0.9136276. This strong positive correlation suggests that as banks grow in size, the intensity of reputational loss also tends to escalate. This observation challenges the intuitive notion that larger banks, with their vast resources, are insulated from reputational challenges.

The empirical results from individual banks over the three-year post-event period revealed a mixed scenario. While 26 banks exhibited a positive correlation, suggesting an increase in reputational loss intensity with size, 24 banks showed a negative correlation. A few banks had correlations close to 0, indicating a weak or no relationship.

The segmented analysis based on bank size (Small, Medium, Large) provided deeper insights:

- Small Banks: The negative correlation of -0.403 suggests that smaller banks experience more significant reputational damage as their assets decrease.
- Medium Banks: A weak positive correlation of 0.229 indicates that medium-sized banks might experience a slight increase in reputational loss intensity as their assets grow.

- Large Banks: A strong positive correlation of 0.919 suggests that larger banks, despite their size, also experience an increase in reputational loss intensity as their assets grow.

The empirical results provide compelling evidence in support of the alternative hypothesis (H_3). The findings suggest that smaller banks are more vulnerable to reputational damage compared to their larger counterparts. This vulnerability could be attributed to factors such as limited resources, higher visibility and scrutiny, and operational capacities.

On the other hand, larger banks, despite their vast resources, are not entirely immune to reputational challenges. There is a probability of an increase in reputational loss as the bank's size increases (Fiordelisi et al., 2013). The results underscore the multifaceted nature of the relationship between bank size and reputational loss intensity, emphasizing the need for banks of all sizes to prioritize and invest in reputational risk management strategies.

IV-6. Regional variations in reputational loss impact

In the context of global banking, regional dynamics significantly influence the outcomes of financial institutions. Given the importance of understanding these regional variations in reputational loss, it becomes crucial to expand our analysis beyond the predominantly studied regions of the US and Europe (Cummins et al., 2006; Eckert, 2017; Fiordelisi et al., 2013). Current empirical evidence suggests that reputational losses are notably higher in Europe compared to the US. However, such findings warrant a more extensive analysis to provide a holistic view of how various global regions navigate and are impacted by reputational challenges, especially those arising from internal fraud disclosures. Through this study, the objective was to elucidate patterns, discrepancies, and valuable insights that highlight the relationship between regional contexts and the severity of reputational loss.

IV-6.1. Regional losses variation

The analysis of variance (ANOVA) was employed to discern the potential variations in the intensity of reputational loss (Rl) across different global regions. The results from the ANOVA are indicative of a statistically significant difference in the means of Rl across these regions (Stockemer, 2019).

A closer examination of the results reveals the following:

- **Degree of Freedom (Df):** The degrees of freedom for the "Geographical location" variable (g2_Region) is 9, suggesting that the dataset encompasses 10 distinct regions. The residuals, which represent the error term, have a degree of freedom of 43.
- **F value:** Standing at 4.094, this test statistic for the ANOVA implies that the means of Rl across the regions are significantly different than what might be expected by mere chance.
- **P-value (Pr(>F)):** A pivotal metric in hypothesis testing, the p-value here is 0.00075, substantially below the conventional threshold of 0.05. This low p-value, further emphasized by the '***' notation (indicating significance at the 0.001 level), allows us to reject the null hypothesis. This suggests that the observed differences in reputational loss across regions are statistically significant and not just a product of random variation (Cummins et al., 2006; Eckert, 2017).

The findings showed that the intensity of reputational loss is not uniform across different global regions. The significant p-value underscores that these variations are statistically meaningful, emphasizing the importance of regional contexts in influencing the magnitude of reputational loss stemming from internal fraud disclosures (Fiordelisi et al., 2013). Future research might delve deeper into the specific regional factors and dynamics that contribute to these observed differences.

To delve deeper into these differences and identify which specific regions exhibited significant disparities in their means, a Tukey's Honest Significant Difference (HSD) post-hoc test was employed. Recent research has employed the Tukey HSD post-hoc test in conjunction with ANOVA to identify relationships and discern significant distinctions among categorical variables (Kibirige et al., 2022; Ravichandran & Padmanaban, 2023).

Table IV-6 displays in detail the outcomes of the Tukey HSD Post Hoc analysis. The "Difference" column in the Tukey HSD results represents the disparity in means between the regions under comparison. A positive value suggests that the first region in the pair has a higher mean than the second, and vice versa for a negative value (Tukey, 1949). The lower and upper columns provide the 95% confidence interval for this difference. A confidence interval that does not encompass zero indicates a significant difference between the two regions. The adjusted p-value, typically set at a threshold of 0.05, further confirms the statistical significance of these differences.

For instance, a comparison between Eastern Asia and Central America reveals a significant difference in the mean reputational loss, with Eastern Asia having a higher mean of approximately 7,876 million. This difference is statistically significant with a p-value of 0.0440415. Similar significant differences are observed between Eastern Asia and several other regions such as Eastern Africa, Eastern Europe, Northern America, and Northern Europe, among others. Notably, for many region pairs, the p-values exceed the 0.05 threshold, suggesting no significant difference in their reputational loss means.

Table IV-6: Tukey HSD Post Hoc results: Top 10 significant comparisons

No	Regions Comparison	difference	Lower	Upper	p adj
1	Southern Asia-Eastern Asia	(8,214.90)	(12,950.13)	(3,479.67)	3.09E-05
2	Northern America-Eastern Asia	(7,739.88)	(12,646.46)	(2,833.29)	0.00017159
3	South-Eastern Asia-Eastern Asia	(7,923.75)	(13,002.55)	(2,844.96)	0.00020666
4	Western Africa-Eastern Asia	(7,973.03)	(13,272.75)	(2,673.32)	0.000375
5	Eastern Europe-Eastern Asia	(8,055.10)	(13,837.57)	(2,272.64)	0.00120719
6	Western Asia (incl. Middle East)-Eastern Asia	(7,996.01)	(13,778.47)	(2,213.54)	0.00134152
7	Eastern Asia-Eastern Africa	8,064.46	1,730.09	14,398.83	0.00406896
8	Northern Europe-Eastern Asia	(5,990.35)	(11,772.81)	(207.88)	0.0369216
9	Eastern Asia-Central America	7,875.80	117.81	15,633.79	0.04404147
10	Southern Asia-Northern Europe	(2,224.56)	(6,191.29)	1,742.18	0.68805389

The regional comparisons, particularly the top 10 with the lowest p-values, suggest significant regional differences in the dataset analyzed. In essence, while the overarching ANOVA results indicated regional variations in reputational loss, the Tukey HSD post-hoc test offers a granular perspective, pinpointing specific regions with significant disparities.

The analysis of reputational risk across different geographical regions, as indicated by the Tukey test results, reveals a nuanced landscape of regional variations. While the data suggests that reputational risk does indeed vary across regions, this variation is not uniformly significant across all regional comparisons.

The table highlights that certain regions exhibit marked differences in reputational risk, with a few pairings showing statistically significant variations. These specific instances point to the influence of regional factors on reputational risk, which could be attributed to diverse economic, cultural, regulatory, or operational practices prevailing in different geographies.

However, it's important to recognize that not all regional comparisons in the study demonstrate significant differences. Numerous pairings exhibit no statistically significant variation, emphasizing that while geographical factors can have an influence on reputational risk, they are not consistently decisive in determining its extent. This observation aligns with the findings of the random effects model used in the study, which did not identify the geographical location of the bank as a significant predictor of reputational risk. This suggests a multifaceted interplay of factors at play, indicating that relying solely on regional characteristics may not be adequate to fully comprehend or anticipate the nuances of reputational risk. Therefore, a more holistic approach, considering a broader spectrum of variables, is essential for a deeper understanding of reputational risk dynamics (Fiordelisi et al., 2013; Heidinger & Gatzert, 2018).

IV-6.2. Hypothesis 4 testing: Regional variation in impact of Reputational Losses

Research Question 4 seeks to understand how the impact of reputational losses stemming from internal fraud disclosures differs across banks situated in various global regions. The global banking landscape is characterized by diverse regional dynamics, each influenced by a unique blend of regulatory frameworks, cultural nuances, media landscapes, and stakeholder perceptions. These regional factors can significantly shape the magnitude and implications of reputational losses, especially those arising from internal fraud disclosures (Fiordelisi et al., 2013).

Given the interconnected nature of the global financial system, understanding these regional variations becomes paramount for banks operating in multiple jurisdictions. Previous empirical studies have predominantly focused on the U.S. and European banking sectors, revealing distinct patterns in how banks from these regions experience reputational losses. For instance, European banks have been observed to incur more pronounced reputational damages compared to their U.S. counterparts (Fiordelisi et al., 2013; Heidinger & Gatzert, 2018). However, a comprehensive global perspective remains elusive, creating a knowledge gap that this study aimed to address by formulating the following null and alternative hypotheses:

Null Hypothesis (H_{04}): There is no regional variation in the impact of reputational losses stemming from internal fraud disclosures.

Alternative Hypothesis (H_4): The impact of reputational losses stemming from internal fraud disclosures varies significantly across global regions.

The empirical analysis of reputational losses across global banking regions was conducted using ANOVA and the Tukey HSD post-hoc test. The ANOVA results revealed a statistically significant difference in the means of reputational loss (Rl) across the regions, with an F value of 4.094 and a p-value of 0.00075, indicating a highly significant result at the 0.001 level.

While the ANOVA offered a global picture, the Tukey HSD test allowed to observe variations between regions. It was observed that Eastern Asia's mean reputational loss was higher than Central America's by approximately $7,876 million (p-value: 0.0440415) and Eastern Africa's by about $8,065 million (p-value: 0.0040690). Conversely, Eastern Europe's mean was lower than Eastern Asia's by around $8,055 million (p-value: 0.0012072). These findings underscore that the impact of reputational losses, especially those stemming from internal fraud disclosures, varies significantly across global regions. However, a few region pairs did not showcase significant differences, suggesting that while some regions have distinct patterns, others might share similar reputational loss dynamics. This variation highlights the importance of considering regional nuances when addressing reputational risks in the banking sector.

In light of the evidence provided by the ANOVA and Tukey HSD test results, ***the null hypothesis (H_{04}) can be rejected in favor of the alternative hypothesis (H_4)***. This confirms that the impact of reputational losses stemming from internal fraud disclosures does indeed vary significantly across global regions. This verification underscores the importance of a region-centric approach in understanding and managing reputational risks in the banking sector.

IV-7. Overall findings discussion

The study's exploration into the dynamics of reputational risk in the banking sector, through four research questions, has yielded insightful findings. The first question delved into the impact of internal fraud disclosures on banks' RoA. The findings revealed that internal fraud disclosures have a profound impact on banks' financial performance (Cummins et al., 2006; Gatzert, 2015; Gillet et al., 2010), notably the RoA, not just in the immediate aftermath but also in the long term. More importantly, the study highlighted that over 66% of the banks incurred actual reputational losses, a fact that underscores the severity and widespread nature of the impact. The rejection of the null hypothesis in this regard is particularly telling, as it establishes a critical connection between a bank's reputation and its financial performance. These findings emphasize the importance of maintaining robust internal controls and ethical practices, not only as a compliance measure but also as a crucial component of financial health and sustainability in the banking sector. This shift in understanding points to a need for a more comprehensive approach to managing and mitigating reputational risks in the wake of internal fraud incidents.

The second research question examined the correlation between operational losses from internal fraud and the monetary value of reputational loss, uncovering a negligible correlation (Pearson coefficient of −0.0115). This finding contradicts the expected outcome where larger operational losses would amplify reputational damage (Gillet et al., 2010; Perry & de Fontnouvelle, 2005), suggesting instead that the size of the loss is not a primary determinant of reputational impact (Fiordelisi et al., 2014). This potentially points to the role of other factors like the nature of the fraud, the bank's response strategies, and public perception in shaping reputational harm.

The third question investigated the relationship between a bank's size and the intensity of reputational loss, revealing a strong positive correlation. Contrary to Resource-Based Theory, which posits that larger banks are less susceptible to reputational damage (Barney, 1991; Fombrun, 2012), the study suggests that as banks grow, their vulnerability to reputational losses increases (Fiordelisi et al., 2013). This indicates the need for effective reputational risk management strategies across banks of varying sizes.

Finally, the fourth question addressed the impact of reputational losses across different global regions, finding significant regional variations. For example, Eastern Asia experienced more pronounced effects compared to regions like Central America and Eastern Africa. This variation highlights the influence of regional factors such as regulatory environments, cultural contexts, and stakeholder expectations on reputational losses, underscoring the need for region-specific approaches in managing these risks.

In summary, the findings from this study present a complex and multifaceted view of reputational risk in the banking sector. They highlight the importance of considering a range of factors, both internal and external to the bank, in understanding and managing reputational risk. This comprehensive approach is crucial for banks aiming to navigate the intricacies of reputational challenges effectively.

V. CONCLUSIONS

"It takes twenty years to build a reputation and five minutes to ruin it. If you think about that, you'll do things differently."

Warren Buffett

"Conclusions," the concluding chapter of this research, offers a thorough synthesis of key findings and their wider implications. The chapter opens with a detailed justification of the research outcomes, contextualized within the existing literature and real-world applications. It then delves into an in-depth discussion of the theoretical and practical significance of these findings, offering a balanced perspective on their relevance and utility. A critical examination of the study's strengths and limitations is also presented, providing a clear foundation for future research directions. This final chapter does more than just summarize the research journey; it underscores the contributions made to the field, culminating in a reflective summary that underscores the study's overarching importance and potential impact.

V-1. Research outcome justification

The essence of empirical research lies in its ability to provide reasoned explanations and justifications for its outcomes, particularly in the light of existing literature (Creswell & Creswell, 2018). The necessity for reasoned explanations takes on greater importance in the study of reputational risk in banking, a field characterized by its emerging nature and the lack of broad consensus despite significant academic advancements (Eckert, 2017; Fiordelisi et al., 2013; Gatzert, 2015; Gillet et al., 2010; Heidinger & Gatzert, 2018). This focus is essential because it ensures that new research in this emerging area is rigorously grounded and contextualized within the broader academic discourse. Given the evolving nature of reputational risk and its implications for the banking sector, empirical studies need to not only contribute new data but also critically interpret these findings, ensuring they are relevant and add substantive value to the existing body of knowledge. This approach helps in building a more cohesive understanding of reputational risk, guiding future research and practical applications in a field where established guidelines and theories are still being developed and refined.

V-1.1. Impact of reputational risk on banks' financial performance

The first and foremost question this study addressed is the empirical impact of reputational risk, particularly arising from internal frauds, on the financial performance of commercial and retail banks. The posed research question was: *How does an internal fraud disclosure affect the Return on Assets (RoA) of commercial/retail banks in terms of quantifiable monetary value?* The corresponding hypotheses were framed as follows: The Null Hypothesis (H_{01}) posits that an internal fraud disclosure has no impact on the RoA of commercial/retail banks, whereas the Alternative Hypothesis (H_1) suggests that such a disclosure has a significant negative impact.

The motivation behind this inquiry stems from a consensus in the literature that operational losses, especially those resulting from internal frauds, can adversely affect a bank's financial health. Numerous studies (Fiordelisi et al., 2013; Gillet et al., 2010; Perry & de Fontnouvelle, 2005) have highlighted how these frauds, when disclosed, can tarnish a bank's reputation, potentially eroding stakeholder trust and, consequently, significantly impacting market value. These empirical studies that investigate reputational loss after operational events, commonly utilize the event study method (Eckert & Gatzert, 2017; Fiordelisi et al., 2013; Gatzert, 2015; Gillet et al., 2010; Perry & de Fontnouvelle, 2005). This approach defines reputational loss as the total abnormal returns (ARs) - the difference between actual returns and expected returns based on a market model - occurring within a designated period around the event (event window), essentially capturing the decline in stock market value beyond the immediate loss caused by the event. This calculation provides a direct measurement of the market's immediate reaction to the reputational event, thereby offering an insight into the financial implications of reputational damage. It typically represents investors' altered expectations about the company's future cash flows, reflecting the market's reassessment of the firm's value in light of the operational incident (Cummins et al., 2006; Gatzert, 2015).

While the “market reaction” approach provides valuable insights into the immediate market reaction, it has certain limitations, particularly in capturing the long-term financial impact of reputational loss. To address this gap, our study introduces a novel approach by estimating the reputational loss as a deviation in RoA post-event.

RoA, a key indicator of a bank's profitability (Akhigbe & McNulty, 2005; Wanjohi et al., 2017), measures how effectively a company is using its assets to generate earnings. Although some research, like those of Deephouse (2000) and Heidinger & Gatzert (2018) has explored the influence of reputational factors on RoA, they have not employed the event study methodology. This study, therefore, offers a new perspective by integrating RoA to analyze the long-term financial impact of reputational loss on banks.

By assessing the deviation in RoA following an internal fraud event, we gain a more comprehensive understanding of the financial repercussions of reputational damage over a longer period. This deviation, akin to the market reaction model approach, is computed not with stock prices but using the bank’s RoA. It involves comparing the expected RoA, presuming the absence of a reputational event, with the actual RoA observed in the years following the event. This comparison offers a distinct and clear view of the bank's financial performance, both prior to and subsequent to experiencing reputational loss.

This approach enhances the understanding of the financial impact of reputational loss in several ways:

- Long-term financial impact: Unlike market reactions that provide immediate but short-lived insights, RoA deviation reveals how reputational damage affects a bank's profitability over an extended period.

- Comprehensive financial measurement: RoA offers a broader measure of financial performance, encompassing not just market perceptions but also operational efficiency and asset utilization.
- Quantifying reputational loss: By translating reputational damage into a quantifiable change in RoA, we better understand the monetary value of reputational loss, thereby translating an intangible concept into a tangible financial metric.
- Comparative analysis: The deviation in RoA allows for a comparative analysis of financial performance before and after the event, providing a clearer picture of the reputational event's impact.

Upon analyzing the study's data, it became evident that reputational losses, calculated as the difference between the monetary abnormal return and the operational loss amount, significantly influence a bank's RoA. This finding is critical in translating the often intangible concept of reputational damage into a tangible financial metric, indicating a decline in profitability (Fiordelisi et al., 2013; Gatzert, 2015; Roberts & Dowling, 2002). This correlation is pivotal as it underscores the direct financial repercussions of reputational impacts on banks, thus supporting the theory that reputational factors, though seemingly abstract, can have concrete effects on a bank's financial health profitability (Fiordelisi et al., 2013; Gatzert, 2015; Roberts & Dowling, 2002).

In the analyzed sample, over 66% of the banks recorded at least one instance of reputational loss, marked as a negative abnormal return. The average reputational loss among these banks was about $54 million, influenced by varying outcomes across different years. A lower median loss of $20 million suggests a skewed distribution due to extreme cases. The wide variability in reputational impact is further highlighted by a substantial standard deviation of $213 million. The maximum recorded loss reached $690 million, underlining the severe consequences that certain events can have on a bank's reputation. The persistence of these negative values across subsequent years underscores the lasting impact of such events, suggesting that the recovery from reputational damage is neither immediate nor straightforward. This substantial figure, above the immediate market reaction, revealed a more profound and enduring impact on financial performance (Fiordelisi et al., 2013; Gatzert, 2015).

To further elaborate, the empirical evidence from this study reveals a significant Z value of -4.05 for the AR mean, which is statistically significant at conventional levels. For banks experiencing at least one negative AR post-event, the null hypothesis (H_{01}) can be confidently rejected in favor of the alternative. This outcome confirms that banks, particularly those more vulnerable or impacted by the event, experienced significant deviations in their returns compared to expected performance. This deviation is indicative of the substantial impact that reputational damage, specifically from internal frauds, has on the financial performance of banks.

This result is aligned with the broader literature on reputational risk in the banking sector. Studies have consistently shown that events leading to reputational damage, such as internal fraud, result in severe negative financial outcomes (Biell & Muller, 2013; Perry & de Fontnouvelle, 2005). However, the study advances this understanding by quantifying the impact in terms of RoA, a key measure of profitability (Wanjohi et al., 2017). The decline in RoA post-fraud disclosure highlights the extent to which reputational damage can permeate a bank's financial performance.

Furthermore, the rejection of the null hypothesis in this context is particularly telling. It not only corroborates the theoretical linkage between a bank’s reputation and its financial performance, as evidenced in prior studies (Eberl & Schwaiger, 2005; Gatzert, 2015; Roberts & Dowling, 2002) but also extends this understanding by providing empirical evidence of the magnitude of impact. This insight is crucial for banks, as it underscores the need for robust internal controls and ethical practices to safeguard against reputational risks.

The observed decrease in RoA in our study is more than just a numerical result; it signifies profound implications for the banking industry. This finding highlights that the financial repercussions of reputational damage are substantial and capable of significantly altering a bank's expected financial trajectory. It brings to light the critical need to reconsider the framework of risk management in banking, which traditionally focuses on operational losses without adequately accounting for the additional layer of reputational risk (Fiordelisi et al., 2013; Heidinger & Gatzert, 2018).

Empirically, as evidenced in the literature and reinforced by our study's findings, it is evident that banks often experience a negative abnormal return that extends beyond the disclosed operational loss (Gillet et al., 2010). This suggests that the financial impact of reputational damage is an additional burden, which, if ignored, can lead to discrepancies in understanding and managing banking risks effectively. Acknowledging the presence and potential impact of reputational damage in the wake of operational losses is crucial for a more accurate and comprehensive approach to risk management in banks.

This realization necessitates a shift in how banks manage their risks, especially in the wake of operational mishaps. A prudent step would be to empirically investigate how banking risk management frameworks can incorporate reputational risk following operational incidents. One potential avenue could be the introduction of a capital charge, or a specific provision aimed at covering potential reputational damages (Eccles et al., 2007). This would not only provide a financial cushion to absorb the impact of such risks but also encourage banks to develop more robust strategies to prevent reputational harm.

In essence, the significant decrease in RoA as a result of reputational damage underscores the urgency for banks to broaden their risk management perspectives. It highlights the need for an integrated approach that considers both operational and reputational risks, ensuring that banks are better prepared and equipped to handle the complexities of modern financial risk management. This approach would contribute to the resilience and sustainability of financial institutions, safeguarding them against the multifaceted nature of risks in the banking sector.

V-1.2. The nexus of operational and reputational losses

The second research question addressed in this study investigates whether there is a discernible correlation between the size of operational losses, specifically those caused by internal fraud, and the subsequent monetary value of reputational loss that follows. This inquiry is crucial for understanding the financial implications of operational events within the banking sector. The hypotheses formulated for this investigation are as follows: The Null Hypothesis (H_{02}) posits that there is no correlation between the magnitude of an operational loss and the subsequent reputational loss. In contrast, the Alternative Hypothesis (H_2) suggests a significant positive correlation between these two variables, indicating that larger operational losses might lead to more substantial reputational damage, measurable in monetary terms.

This investigation is pivotal, as it addresses a critical aspect of risk management: understanding the financial implications of operational events, particularly those related to internal frauds, a subject that has been extensively discussed in both academic and industry circles (Cummins et al., 2006; Eckert & Gatzert, 2017; Gillet et al., 2010; Perry & de Fontnouvelle, 2005). The premise of this research query assumes that larger operational losses resulting from internal fraud might garner significant media attention and public scrutiny, potentially amplifying the reputational damage and its financial consequences. This hypothesis finds support in empirical research, such as the study by Gillet et al. (2010), which noted that the market value decline often exceeds the operational loss value in cases of internal fraud, pointing to a significant reputational impact. This effect is particularly noticeable when the loss constitutes a considerable portion of the firm's net earnings. Furthering this line of thought, Perry & de Fontnouvelle (2005) observed that internal fraud events led to a substantial decline in market values, nearly twice the operational loss percentage. This finding is indicative of significant reputational damage, especially when compared to operational losses caused by external factors, which seemed to have negligible reputational effects. Their analysis also revealed that in firms with strong stakeholder rights, the market value decline was even more pronounced, exceeding six times the amount of the fraud loss.

Eckert & Gatzert (2017) reinforced this notion, emphasizing that reputational losses often overshadow the original operational loss. This phenomenon suggests that not considering the potential reputational repercussions in the event of operational losses, particularly fraud, might lead to a severe underestimation of the risk involved. Cummins et al. (2006) supported this perspective, showing that operational losses typically trigger negative stock market reactions that exceed the announced loss size, implying underlying reputational damage factored into stock prices.

Against this backdrop, the study's empirical analysis yielded a Pearson correlation coefficient of −0.0115 between operational loss magnitude and cumulative reputational loss over three years post-event. This negligible coefficient suggests a nearly non-existent linear relationship between these variables, leading to the inability to reject the Null Hypothesis (H_{02}). This outcome, in line with Fiordelisi et al. (2014), suggests that the reputational repercussions of operational losses are similar regardless of their magnitude, challenging the prevailing belief that the size of an operational loss is a significant predictor of the extent of reputational damage. It potentially suggests that other factors may play a more crucial role in determining the severity of reputational fallout. The study's results imply a complex interplay between various determinants of reputational risk and operational losses, indicating that the financial impact of reputational damage cannot be solely attributed to the size of the operational loss.

Among the various factors that merit deeper exploration, the role of trust in the banking sector stands out as particularly significant. Empirical studies have consistently underscored the critical importance of trust in shaping a bank's reputation and its overall operational success (Gaultier-Gaillard et al., 2009; Gunawardena et al., 2019; Singh et al., 2020). This aspect of banking, with its profound implications for customer relationships and institutional integrity, warrants further investigation to fully understand its impact on both operational and reputational risk management. Trust is a foundational element in financial institutions, particularly sensitive to internal dynamics, such as fraud events, regardless of their size. In the context of internal frauds, the breach of trust is intrinsic and immediate upon revelation, as it directly undermines the integrity of the institution. This breach can significantly impact stakeholders' perceptions and confidence in the bank (Fiordelisi et al., 2013). As soon as a fraud is disclosed, regardless of its financial magnitude, it can rapidly erode the trust that stakeholders have in the institution.

The lack of correlation found in our study between the magnitude of operational loss due to fraud and the extent of reputational damage presents a contrasting view to existing literature. This could be attributed to the unique nature of internal frauds within banking operations. Internal fraud, unlike other operational incidents, is often perceived as a direct betrayal by the institution itself (Office of the Comptroller of the Currency, 2019). Such acts may have a profound impact on diminishing trust, a key component in the banking sector. This dynamic may lead to reputational damage that does not necessarily correspond linearly with the financial magnitude of the loss.

Understanding this unique characteristic of internal fraud is crucial for banks. It highlights the importance of maintaining stringent internal controls and ethical standards to prevent such breaches. This insight is particularly vital for banking institutions, as it suggests that the consequences of fraud events extend far beyond their financial dimension and can severely impact the bank’s reputation, irrespective of the fraud's scale. Thus, vigilance in managing and preventing internal frauds is imperative, not just to safeguard financial assets but to protect the indispensable trust and reputation of the banking institution.

In essence, these results matter significantly in the discourse on reputational risk, as they broaden our understanding of the multifaceted nature of reputational damage in the banking sector. They highlight the need for a more nuanced approach to risk assessment and management, one that considers a broader range of factors beyond the mere size of operational losses. This insight is essential for banks and financial institutions in refining their strategies for managing reputational risks, ensuring that they are better prepared for the complexities and subtleties of these challenges.

V-1.3. Correlation in bank's size and reputational damage

A key aspect of this study involved investigating the relationship between a bank's size, as indicated by its total assets, and the intensity of reputational loss it experiences. This inquiry, encapsulated in Research Question 3, delved into whether the size of a bank influences the severity of the reputational damage it incurs. The Null Hypothesis (H_{03}) posited that there is no significant correlation between the size of a bank and the intensity of the reputational loss it suffers. In contrast, the Alternative Hypothesis (H_3) proposed that smaller banks, in comparison to their larger counterparts, are likely to experience more intense reputational losses. This investigation aimed to shed light on the dynamics between a bank's scale of operations, as represented by its total assets, and the impact of reputational challenges it faces.

This line of inquiry is grounded in the Resource-Based Theory, which posits that a bank's tangible and intangible assets significantly influence its competitive advantage (Barney & Clark, 2007; Fombrun, 2012; Wernerfelt, 1984). From this theoretical perspective, one might hypothesize that larger banks, given their substantial assets, could be better equipped to mitigate reputational challenges. Supporting this notion, Fiordelisi et al. (2013) present empirical evidence suggesting an increase in reputational risks as a bank's profits and size grow.

The study's empirical analysis revealed a global correlation coefficient of 0.9136276 between Total Assets (A) and Reputational Loss (Rl). This strong positive correlation challenges the intuitive assumption that larger banks are less susceptible to reputational damage. Interestingly, the data from individual banks over a three-year post-event period painted a more complex picture. While 26 banks showed a positive correlation, implying an increased intensity of reputational loss with growing size, 24 banks exhibited a negative correlation, and a few showed negligible or no relationship.

The study's segmented analysis, categorizing banks by size, revealed distinct patterns in the correlation between bank size and reputational loss intensity. For smaller banks, a negative correlation of -0.403 was observed, indicating that these banks tend to suffer more substantial reputational damage as their assets decrease. In the case of medium-sized banks, a weak positive correlation of 0.229 was found, suggesting a slight escalation in the intensity of reputational loss as their assets grow. Notably, larger banks exhibited a strong positive correlation of 0.919, implying that as their total assets increase, they also experience a greater intensity of reputational loss. These findings offer nuanced insights into how the size of a bank influences its vulnerability to reputational harm.

Smaller banks' negative correlation with reputational loss can be linked to their inherent operational characteristics and the crucial role of trust in banking (Choudhry, 2018; Walter, 2016). Smaller banks typically operate with limited resources and are more visible and integral within their local communities and customer bases. The significance of trust in these institutions is paramount, often more critical than financial resources, as their success and customer loyalty may heavily depend on their reputational standing.

In contrast, medium-sized banks exhibit a weak positive correlation, indicating a slight increase in reputational loss intensity with asset growth. This could be due to their transitional phase of growth, where they begin to face complexities similar to larger banks but without the full suite of resources and infrastructures to manage them effectively. As they expand, they might attract more scrutiny, both from regulators and the public. However, their growth also provides them with more resources to manage and recover from reputational setbacks compared to smaller banks.

For larger banks, the strong positive correlation with reputational loss can be explained by their significant public profile and the broader impact of their operations. Larger banks, as discussed by Fiordelisi et al. (2013), often deal with a more extensive customer base, higher regulatory scrutiny, and greater media attention. This heightened visibility means that any operational misstep, particularly those involving internal fraud, can trigger substantial reputational damage, echoing across their wider network of stakeholders and markets. Despite their vast resources, these banks face the challenge of maintaining a positive reputation at a scale where any negative event can quickly become magnified, as supported by the research of Gillet et al. (2010).

These findings support the alternative hypothesis (H_3) and highlight the varying vulnerabilities to reputational damage based on bank size. Smaller banks, perhaps due to limited resources, higher visibility, and constrained operational capacities, appear more susceptible to reputational harm. Conversely, larger banks, despite their extensive resources, are not immune to reputational risks. This increase in reputational loss with bank size is contrary to the protective buffer hypothesis suggested by Resource-Based Theory.

V-1.4. Reputational loss regional variations

The final aspect of this study focused on exploring regional differences in the impact of reputational losses, specifically those resulting from internal fraud disclosures. This exploration, encapsulated in Research Question 4, sought to understand the variability in the repercussions of reputational damage across banks located in different global regions. The Null Hypothesis (H_{04}) proposed that there is no significant variation in the impact of reputational losses resulting from internal fraud disclosures across different global regions. In contrast, the Alternative Hypothesis (H_4) posited that the impact of these reputational losses varies substantially from one region to another. This investigation aimed to shed light on whether the regional context plays a decisive role in the extent and nature of reputational damage experienced by banks following internal fraud incidents.

The global banking landscape is notably diverse, with regional dynamics influenced by distinct regulatory frameworks, cultural nuances, media landscapes, and stakeholder perceptions (Apostolik et al., 2009), all of which can significantly shape the magnitude and implications of reputational losses. This regional specificity in the context of reputational damage, especially following internal fraud incidents, seems important for understanding how different banking environments respond to such crises. Previous studies have primarily focused on the U.S. and European banking sectors, revealing distinct patterns in the way banks in these regions experience reputational losses.

Notably, European banks have been shown to incur more severe reputational damages compared to their U.S. counterparts (Fiordelisi et al., 2013; Heidinger & Gatzert, 2018).

Employing ANOVA and the Tukey HSD post-hoc test, the study conducted an empirical analysis of reputational losses across different banking regions. The ANOVA results showed a statistically significant difference in reputational loss means across regions (F value of 4.094, p-value of 0.00075), indicating significant regional disparities. The Tukey HSD test provided a more detailed view, revealing, for instance, that Eastern Asia experienced significantly higher mean reputational losses than Central America and Eastern Africa. Conversely, Eastern Europe's mean reputational loss was notably lower than Eastern Asia's.

These results highlight that the impact of reputational losses, especially those from internal fraud, varies substantially across different regions. However, it's also notable that some regions did not exhibit significant differences, suggesting that while some regions have distinct patterns of reputational loss, others might share similar dynamics. This finding emphasizes the importance of considering regional factors when managing reputational risks in the banking sector.

The rejection of the null hypothesis (H_{04}) in favor of the alternative (H_4), based on the empirical evidence, confirms the significant variation in the impact of reputational losses due to internal fraud disclosures across different global regions. This finding underscores the necessity of a region-centric approach to understanding and managing reputational risks in the banking sector. Understanding these regional nuances is crucial for banks, particularly those with a global presence, as it highlights the need for a more tailored approach to reputational risk management. Strategies effective in one region may not be as impactful in another, acknowledging that a one-size-fits-all approach may not be effective in addressing the nuanced and varied nature of reputational risks across the global banking landscape. This necessitates a more personalized and localized risk management framework. This regional perspective is vital for developing robust and effective policies that can mitigate the adverse effects of reputational damage more efficiently.

V-2. Research contributions

The global research aim was to dissect the complex interplay between reputational risk and financial performance in the banking sector, encompassing a diverse range of commercial and retail banks across various geographies. The study focuses on the long-term impacts of reputational risks on banks' RoA, within the broad and varied context of the global banking landscape. By examining how reputational issues translate into enduring financial outcomes, the research seeks to provide a deeper understanding of these dynamics.

The findings from the study make a substantial contribution to both theoretical understanding and practical application in the area of reputational risk in banking. By bridging gaps in existing literature and introducing new methodologies, it enriches the theoretical framework surrounding reputational risk. Simultaneously, it provides practical insights that are crucial for banking professionals and regulators, offering guidance for more effective risk management practices. These contributions reflect a balanced blend of academic rigor and real-world applicability, setting a new benchmark for future studies in the field.

V-2.1. Research theoretical contributions

The theoretical framework of the study is anchored in the integration of the Resource-Based Theory (RBT) and the Unified Theory of Reaction in Assets Market. RBT offers insights into how banks can leverage internal resources and capabilities to build and protect their reputational capital, which is crucial for risk mitigation and recovery(Barney, 1991a; Wernerfelt, 1984b). It emphasizes the importance of a bank's internal resources in strengthening against reputational damage (Fombrun, 2012a). In contrast, the Unified Theory focuses on the external dimensions, particularly market perceptions, and reactions to reputational events, highlighting how these perceptions can influence financial outcomes.

This dual-theoretical approach provides a comprehensive perspective, encompassing both the internal mechanisms within banks for managing reputational risks and the external market reactions to such events (Adeabah et al., 2022; Barney, 1991; Barney & Clark, 2007; Fiordelisi et al., 2013; Fombrun, 2012; Gillet et al., 2010; Perry & de Fontnouvelle, 2005)which finally will reflect on the bank's end-of-year metrics (Akhigbe & McNulty, 2005; Terraza, 2015). This blend of theories facilitates a holistic understanding of reputational risk, considering both the micro-level strategies within banks and the macro-level market dynamics. The integration of these theoretical viewpoints has been instrumental in developing a nuanced understanding of how reputational risks impact financial performance, offering significant contributions to the fields of financial risk management and banking. This study, by bridging internal resource-based strategies and external market perceptions, aimed to enhance the current understanding of reputational risk in the global banking sector.

The major theoretical contributions of this research are multifaceted, each enriching our understanding of reputational risk in the banking sector from different angles.

V-2.1.a Approach to quantify the reputational loss (Rl)

In advancing our understanding of reputational risk within the banking sector, the study introduces a novel approach to quantifying reputational loss (Rl) that significantly diverges from traditional methodologies. Instead of focusing on short-term market reactions typically analyzing deviation in stock price and market value, this research adopts a more holistic perspective by examining deviations in RoA. This approach shifts the focus from immediate market responses to a longer-term view, assessing the sustained impact on a bank's profitability and operational efficiency. By focusing on RoA, the study provides a clearer understanding of how reputational issues impact a bank's profitability and overall financial health over an extended period, rather than just the immediate aftermath of an event.

Traditionally, event studies have been instrumental in capturing the immediate market perceptions following an event, but they may fall short of adequately reflecting the prolonged financial implications of reputational damage. By concentrating on RoA, the study moves beyond the limitations of these traditional methods, offering a deeper insight into how reputational risks affect the fundamental financial workings of banks. This methodology aligns more closely with the operational performance of a bank (Wanjohi et al., 2017), providing a comprehensive view of the financial consequences of reputational damage that extends beyond mere market valuation.

The methodological shift aligns with the Unified Theory of Reaction in Assets Market (Adeabah et al., 2022; Fiordelisi et al., 2013), which is further explored through the examination of RoA deviation in an event study for this research. The event study methodology employed in this research allows for a detailed analysis of how specific events, such as internal frauds, affect a bank's market value and asset returns over time. This approach not only reinforces the Unified Theory but also extends its application, providing empirical evidence of the sustained impact of reputational events on financial performance.

This innovative approach is particularly necessary because it considers the broader implications of reputational damage on a bank's financial health. Unlike market-based assessments, which can be swayed by a range of external factors, analyzing RoA offers a more intrinsic understanding of a bank’s financial condition post-reputational damage. This method effectively captures how reputational harm, stemming from incidents like internal frauds, can infiltrate and alter a bank's fundamental financial stability.

Furthermore, the research provides empirical evidence, with statistical significance, about the impact of internal frauds on a bank's RoA. This correlation between reputational risk and financial outcomes has been extensively documented, suggesting that reputational factors are critical determinants of a bank's financial health (Biell & Muller, 2013; Eberl &

Schwaiger, 2005; Fiordelisi et al., 2013; Gatzert, 2015; Walter, 2016). Studies have consistently shown that events leading to reputational damage, such as internal fraud, can have far-reaching financial implications, potentially resulting in decreased profitability and RoA (Gillet et al., 2010; Heidinger & Gatzert, 2018). This is corroborated by the observed average and median losses in our study, which reflect a notable decline in financial performance post-reputational damage. The high standard deviation and extreme cases of reputational loss further emphasize the profound impact such events can have. This alignment with established research not only validates the findings of this study but also reinforces the understanding that reputational risk is a significant and tangible factor in the financial stability and performance of banks. It underscores the need for robust management strategies to mitigate reputational risks and safeguard financial performance.

The primary theoretical contribution of this study then lies in its novel approach to quantifying reputational loss using end-of-year financial metrics, specifically the RoA, rather than the more commonly used immediate market reactions. By empirically demonstrating this relationship, the study enriches the theoretical discussion around reputational risk management. It underscores the importance of considering not just the immediate financial losses but also the broader, more enduring financial effects of reputational damage.

V-2.1.b Reassessing the Resource-Based Theory: Bank Size and Reputational Risk

One of the pivotal revelations of this research is the nuanced relationship between a bank's size, as measured by its total assets, and its susceptibility to reputational damage. Traditionally, the RBT posits that a bank's growth in size, encompassing both tangible and intangible assets, should theoretically enhance its capacity to manage reputational risks. This assumption is based on the idea that larger banks, with their expanded customer base, more sophisticated operations, and perceived trustworthiness, would be less vulnerable to reputational harm (Barney, 1991; Fombrun, 2012). The underlying rationale is that banking, fundamentally reliant on trust, would naturally shield larger, more reputable banks from reputational damage (Gaultier-Gaillard et al., 2009; Gunawardena et al., 2019; Heidinger & Gatzert, 2018).

Contrary to this conventional wisdom, the findings of this study present a compelling counter-narrative. They reveal that despite their size and the presumed trust of the public, larger banks may not only be susceptible to reputational damage but might experience it more intensely, particularly in cases of internal fraud. This finding is at odds with the RBT's suggestion that a bank's scale and resources act as a protective barrier against reputational damage. It echoes the concerns raised by Fiordelisi et al. (2013) and brings to light the need for a more critical examination of RBT in the context of reputational risk. The study raises pertinent questions about the conditions and types of operational losses under which a bank's assets – both tangible and intangible – can effectively serve as a buffer against reputational harm.

This research, therefore, not only challenges the traditional applications of RBT in reputational risk management but also suggests that the theory may require refinement or expansion in the context of banking risk management. It highlights the need for a more complex understanding of how a bank’s size and resources interplay with the dynamics of reputational risk, especially in the wake of internal frauds. This nuanced understanding seems important for developing more effective risk management strategies that are attuned to the realities of larger banking institutions. In doing so, the study contributes significantly to the theoretical discourse, calling for a reevaluation and possible extension of RBT to encompass the multifaceted nature of reputational risks in the banking sector.

V-2.1.c Region variation of reputational loss

The study's exploration of regional variations in reputational loss within the banking sector marks a substantial theoretical advancement in the field of reputational risk management. This research addresses a significant gap in the existing literature, which has predominantly focused on reputational risk within the US and European banking sectors, often overlooking how these dynamics play out across different global regions. To the researcher's knowledge, no prior study has systematically investigated reputational risk from a global perspective, often neglecting the unique dynamics and implications across various international contexts. This broader approach offers a more comprehensive view of reputational risk management on a global scale. By empirically demonstrating and confirming the existence of regional variations in reputational loss (as indicated by the rejection of the Null Hypothesis H_{04} in favor of the Alternative Hypothesis H_4), the study adds a critical new dimension to our understanding of reputational risk in the global banking context.

The adoption of a global perspective in assessing the intensity of reputational loss is a noteworthy theoretical contribution. This approach extends beyond the conventional scope of research that typically centers on specific markets, such as the US and Europe. By encompassing a broader, more diverse global banking landscape, the study illuminates the nuanced ways in which reputational risk is manifested and experienced in different regions around the world. This global lens reveals that the repercussions of reputational damage are not homogenous but are shaped by an array of regional-specific factors, including cultural norms, regulatory environments, economic conditions, and stakeholder expectations.

This aspect of the research is particularly important as it aligns with and contributes to the emerging narrative in reputational risk literature (Fiordelisi et al., 2013; Heidinger & Gatzert, 2018). It underscores that the impact of reputational damage varies significantly across regions, necessitating banking institutions to adopt more localized and contextually informed approaches to managing these risks. The study highlights the importance of considering these regional dynamics when assessing the overall impact of reputational risks.

By revealing the differing impacts of reputational damage across various global regions, the research advocates for banking strategies and policies that are finely attuned to the distinct challenges and characteristics inherent to different geographical banking markets. This global perspective is not only crucial for banks operating internationally but also for researchers seeking to understand the complexities of reputational risk in a more holistic manner. The insights gained from this study are instrumental in guiding the development of contextually relevant and effective reputational risk management practices, tailored to meet the specific needs of the banking sector worldwide.

In summary, the study bridges gaps in the existing literature by extending the understanding of the relationship between internal fraud disclosures, operational losses, bank size, and regional dynamics in the context of reputational losses. It challenges and refines existing theories, such as the Resource-Based Theory, by providing empirical evidence on how larger banks are not necessarily insulated from reputational damage.

V-2.2. Research practical contributions

The findings of this research provide pivotal insights into the application of reputational risk management in real-world settings, particularly within the banking sector. The methodological innovation not only enhances the theoretical framework surrounding reputational risk but also provides practical insights for banking professionals in formulating more effective risk management policies. The study yielded multiple practical contributions, and insights that are crucial for banking executives, risk management professionals, and policymakers in shaping more effective and resilient banking practices.

Implications for key stakeholders are presented in Table V-1 below:

Table V-1: Findings implications for stakeholders

Stakeholder	Implications
Policymakers	Improve policies promoting transparency and ethical practices in banking.
	Introduce a capital charge for reputational risks to enhance resilience against reputational damage.
	Foster the integration of reputational risk management within broader regulatory frameworks to ensure banks are prepared for complex reputational challenges.
Financial Institutions / Regulatory boards	Banks must integrate reputational risk into their existing risk management frameworks, emphasizing both proactive and reactive strategies.
	Regulators can establish benchmarks for ethical conduct and transparency, ensuring that financial institutions disclose reputational risks and their mitigation strategies.
	Encourage financial institutions to allocate resources for reputational risk management, including internal controls, PR strategies, and crisis management protocols.
Large Banks	Larger banks, facing higher exposure to reputational risks, should strengthen monitoring and management systems for reputational risks.
	They can enhance their crisis management plans with region-specific strategies tailored to local regulatory and cultural contexts.
	Focus on strengthening corporate culture to align with ethical practices, ensuring a robust reputation management framework.

Stakeholder	Implications
Small Banks	Smaller banks should prioritize building resilience and trust with the public, with emphasis on ethical conduct and transparent communication.
	Develop simpler but effective crisis management and reputational risk monitoring strategies to prevent significant damage.
	Invest in cost-effective reputational risk management systems that cater to their specific size and exposure.
Investors	Transparent communication regarding reputational risk management will boost investor confidence.
	Investors should be aware of the reputational risk strategies employed by banks, which can safeguard long-term financial stability and public trust.
	Foster stronger relationships with banks through trust-building initiatives, increasing confidence in the bank's management of reputational risks and overall corporate sustainability.

V-2.2.a Enhancing risk management frameworks

A vital practical contribution of this study is the emphasis on incorporating reputational risk into the overarching risk management strategies of banking institutions. The research underlines the importance of both proactive and reactive measures in mitigating reputational risks, which are crucial for maintaining the integrity and financial stability of banks.

Proactive strategies entail a focus on regular and thorough audits of both financial and operational activities. These audits are essential in identifying potential vulnerabilities that could lead to reputational damage. Additionally, banks should establish transparent communication policies that ensure clear, honest, and timely information sharing with all stakeholders. This transparency is key to building and maintaining trust, a foundational element in the banking sector's reputation.

Maintaining strong ethical standards across all levels of operation is another critical aspect. Ethical conduct not only prevents the occurrence of events that could harm the bank's reputation but also positions the bank as a trustworthy and reliable institution. This ethical commitment should be ingrained in the corporate culture and reflected in all business practices and decisions.

On the reactive side, banks need to have well-defined crisis management plans specifically tailored to handle reputational risks. These plans should include steps for immediate response to incidents, strategies for damage control, and measures for rebuilding trust post-crisis.

The research suggests that risk management strategies should be customized according to the size of the bank. Larger banks, facing greater exposure to reputational risks, might require more robust systems for monitoring and managing these risks. In contrast, smaller banks should concentrate on building resilience and public trust, considering their vulnerability to significant reputational damage. The global perspective on reputational loss intensity underscores the importance of developing region-specific risk management strategies for multinational banks. This implies adapting to the cultural, regulatory, and economic contexts of each region to manage reputational risks effectively. The findings can also facilitate better cross-border collaboration and regulatory alignment, as they provide a clearer picture of how reputational risks manifest differently across global regions.

The study's findings, particularly the nuanced understanding of the relationship between bank size, regional variations, and the impact of reputational losses, provide valuable insights for tailoring these risk management strategies. Banks of different sizes and in various regions can use this information to develop more effective, context-specific approaches to reputational risk management.

In conclusion, this research provides a robust framework for integrating reputational risk into bank risk management strategies. It offers practical guidance for banks to not only prevent reputational damage but also to effectively respond and recover from such incidents, thereby enhancing their resilience and sustainability in an increasingly complex and interconnected financial landscape.

V-2.2.b Guiding policy formulation and enhancing regulatory compliance

The insights gained from this research can significantly inform policymakers and regulatory bodies in the banking sector. By leveraging these findings, they can develop and implement policies that emphasize and promote transparency and ethical banking practices. Such policies are crucial for maintaining the integrity of the banking system and for fostering trust among stakeholders, which is essential for the long-term sustainability of financial institutions.

One of the key practical implications of this study is the potential introduction of a capital charge specifically for reputational risk within the existing bank risk management framework. This concept represents a forward-thinking approach to banking regulation, addressing the need for banks to have dedicated financial reserves specifically for mitigating reputational risks. The introduction of such a capital charge could serve as a financial buffer, enhancing the resilience of banks against the adverse effects of reputational damage.

This idea aligns with the broader goal of regulatory compliance, ensuring that banks are not only protected against traditional financial risks but are also prepared to handle the complexities of reputational challenges. The proposal for a reputational risk capital charge could encourage banks to invest more in risk management practices that specifically address reputational issues, such as improved internal controls, enhanced public relations strategies, and stronger crisis management protocols.

Moreover, these findings can guide regulatory bodies in setting standards and benchmarks for ethical conduct and transparency in banking operations. Regulators can use these insights to enforce regulations that require banks to disclose potential risks to their reputation and to demonstrate how they manage these risks effectively.

In essence, this research contributes to the practical realm by providing a foundation for policy formulation and regulatory initiatives aimed at strengthening the banking sector's defenses against reputational risks. It suggests a more holistic approach to risk management, incorporating reputational considerations into regulatory frameworks and policies. This approach not only safeguards the financial health of banks but also ensures their adherence to high ethical standards and transparency, ultimately contributing to a more robust and trustworthy banking system.

V-2.2.c Fostering ethical culture and transparent Communication in Banks

Another significant practical contribution of this research is the emphasis on the importance of internal training and development within banks. Banks are encouraged to invest in comprehensive training programs that focus on instilling ethical practices, enhancing crisis management skills, and honing effective communication strategies. Such programs are instrumental in cultivating an organizational culture where every employee understands the potential impacts of their actions on the bank’s reputation and its financial implications.

Training programs should be designed to raise awareness among employees about the critical nature of reputational risks. Employees at all levels need to be educated on how their behavior and decisions can influence the bank’s reputation, both positively and negatively. It's essential that they are equipped with the knowledge and skills to navigate complex situations while upholding the highest standards of ethical conduct. This commitment to ethical behavior should permeate every aspect of the bank's operations, from customer interactions to internal decision-making processes.

Furthermore, this research underscores the importance of effective communication with investors and stakeholders, especially in the context of reputational risk management. Understanding the intricacies of how reputational risks impact financial performance can empower banks to engage more transparently with their stakeholders. Transparent communication should not be just about disseminating information; it's about building trust and demonstrating a proactive approach to managing potential risks.

Banks that effectively communicate their risk management strategies, including how they handle reputational risks, may potentially foster stronger relationships with stakeholders. This openness will not only reinforce investor confidence but also enhance the bank's credibility in the public eye. In a financial landscape where trust is a pivotal currency, such transparency is key to maintaining and strengthening the bank's reputation.

In summary, this study highlights the need for banks to place a greater emphasis on internal training programs focused on ethics, crisis management, and communication. It also points out the importance of transparent communication as a vital tool in reputational risk management. These practical contributions provide a roadmap for banks to enhance their resilience against reputational risks and to maintain a robust relationship with their stakeholders, ultimately leading to a more stable and trustworthy banking environment.

V-3. Research strengths and limitations

The research carries several strengths that significantly contribute to the field of banking risk management, alongside limitations that offer avenues for future research.

V-3.1. Strengths of the research

The methodology and findings of this study present a range of notable strengths that considerably enhance the understanding of reputational risk in the banking sector. Key among these strengths, which collectively contribute to the study's depth and relevance, are the following:

Novel approach: The study introduces a novel approach to quantifying reputational loss, using end-of-year financial metrics like RoA. This method offers a more comprehensive understanding of the long-term financial implications of reputational risk.

Robust model: A key strength of this study is the robustness of the model employed. The statistical techniques and methodologies used are well-suited to the research questions, providing reliable and insightful results.

Statistical significance: The findings of the study are underpinned by statistically significant results, lending credibility and weight to the conclusions drawn. This statistical significance reinforces the validity of the research outcomes.

Theoretical contributions: The research makes substantial theoretical contributions, particularly in challenging existing perspectives, such as the Resource-Based Theory, and extending the understanding of the Unified Theory of Reaction in Assets Market.

Practical implications: The study's findings have significant practical implications, providing actionable insights for banks and financial institutions in enhancing their reputational risk management strategies.

V-3.2. Limitations of the research

While this study provides crucial insights into the dynamics of reputational risk in the banking sector, it is important to recognize certain limitations that frame the interpretation of its findings and pave the way for future research. Despite the robust statistical checks employed, it is acknowledged that various other factors could have influenced the banks' financial metrics. This recognition forms a set of limitations as follows:

V-3.2.a Unaddressed factors influencing financial metrics in reputational risk analysis:

One of the primary limitations of the study accounts for the complexities of financial operations meaning that metrics like RoA can be affected by a multitude of elements beyond reputational factors alone. These can include market fluctuations, regulatory changes, macroeconomic conditions, and internal operational shifts. As such, while the study offers a focused analysis of the impact of reputational risk on RoA, the potential influence of these additional factors remains an area that was not exhaustively explored in this research. This limitation underscores the need for future studies to consider a broader range of variables that could affect a bank's financial health, providing an even more comprehensive understanding of reputational risk and its implications in the banking industry.

V-3.2.b Limited sample size

Another limitation of this research is the constrained sample size, consisting of 77 operational losses across 53 banks. This was a deliberate methodological choice to focus on banks with unique operational losses in a specific year, aiming to minimize bias in accurately assessing the impact of these losses on reputational damage and financial performance. However, this focus inadvertently led to the exclusion of a considerable number of banks, particularly those with multiple or consecutive years of operational losses, from the study's sample.

This limitation highlights an important area for future research: the inclusion of banks experiencing operational losses over multiple years. Investigating these cases may be crucial for understanding the long-term and cumulative effects of reputational losses.

Banks that suffer repeated operational losses may face compounded reputational damage, potentially leading to more severe or enduring impacts on their financial performance and market standing.

Expanding the scope to include such banks would provide a more comprehensive view of the reputational risks associated with ongoing or repeated operational losses. It would enable a deeper understanding of how consecutive years of operational losses and subsequent reputational damage influence a bank’s financial health and operational strategies over time. This approach would significantly enhance the robustness and applicability of the research findings, offering broader insights into the dynamics of reputational risk management in the banking sector. Future studies incorporating a wider range of operational loss scenarios could thus contribute to a more nuanced and representative understanding of the long-term implications of reputational risks in banking.

V-3.2.c Focus on internal frauds

The decision to focus exclusively on internal frauds in this study was driven by their recognized potential for severe impact on a bank's financial performance. Internal frauds, often involving betrayal of trust from within the organization, can have particularly damaging repercussions on a bank’s reputation and financial stability. This focus was thus intended to provide detailed insights into the ramifications of such high-risk events on reputational loss and financial metrics.

However, this targeted approach has its limitations. By concentrating solely on internal frauds, the study may have overlooked the broader spectrum of operational risks that banks face. Other forms of operational risks, such as external fraud, system failures, or process management errors, can also have significant implications for a bank's reputation and financial health. Each of these risk types carries unique characteristics and potential impacts that could differently influence a bank's reputation and performance metrics.

Consequently, this focus on internal frauds narrows the study's scope, potentially limiting the applicability of its findings to other operational risk scenarios. Future research could benefit from a more inclusive approach that examines a variety of operational risks. Such an expansion would provide a more comprehensive understanding of the diverse ways in which different operational risks contribute to reputational loss and affect the overall financial health of banking institutions. By encompassing a broader range of operational risks, subsequent studies could offer more generalized insights, enhancing the understanding of reputational risk management across different risk types in the banking sector.

V-3.2.d Unexplored contagion effect of reputational loss

One notable limitation of this research is the lack of exploration into the contagion effect of reputational loss (Appendix 10). Specifically, the study did not investigate how reputational damage to one bank might indirectly impact neighboring banks that have not experienced any direct reputational loss. In the interconnected landscape of the banking sector, the fallout from a reputational crisis in one institution can potentially spill over to others, especially within the same geographical or economic region. This contagion effect, driven by perceptions, market sentiment, and interconnected financial relationships, can have significant implications for banks that are otherwise uninvolved in the initial reputational event. The study's focus on the direct impacts of reputational loss on individual banks means that these broader, network-level dynamics remain unexamined.

V-3.2.e Geographical scope

Although this study takes a commendable step in adopting a global perspective on reputational risk in banking, it is important to recognize the potential limitations regarding geographical coverage and the depth of regional nuances captured. The research makes significant strides in moving beyond the traditionally US and Europe-centric focus in reputational risk literature, yet it may not comprehensively encompass the full range of regional specificities and banking practices across the world.

Different regions have distinct banking environments, influenced by unique cultural, economic, regulatory, and political contexts. These factors can profoundly affect how reputational risk is perceived, managed, and manifested in various banking systems. While the study provides valuable insights into some of these regional dynamics, there might be gaps in fully capturing and understanding the subtleties and complexities inherent in each geographical area.

For instance, emerging markets or regions with less developed banking sectors may experience and respond to reputational risks differently compared to more established markets. The study's methodology and data sources might not fully account for these variations, potentially leading to an incomplete picture of the global landscape of reputational risk in banking.

V-3.2.f Temporal constraints

The temporal scope of this research, while extending beyond the conventional event window used in many studies, has its own limitations that need to be acknowledged. The methodology adopted in this study involves observing market reactions over several days and utilizes an annual metric to assess the impact of reputational damage. However, the primary focus of the research is on the immediate three years following a reputational loss event. While this timeframe allows for a detailed analysis of the short- to medium-term effects of reputational damage, it may not capture the full spectrum of long-term consequences and recovery patterns that can manifest over a more extended period.

Reputational damage in the banking sector can have enduring effects that persist well beyond the initial three-year window. The recovery from such incidents, or the evolution of the reputational impact, can unfold over several years, sometimes taking a decade or more to stabilize fully. Long-term effects can include sustained changes in customer behavior, lasting shifts in investor confidence, and ongoing adjustments in operational and strategic approaches. Additionally, the reputational impact might evolve or manifest differently over time, influenced by factors such as changes in management, evolving market conditions, regulatory interventions, and broader economic trends.

In summary, while the study's strengths lie in its innovative methodology, robust modeling, and significant theoretical and practical contributions, its limitations underscore areas for further research to deepen and broaden the understanding of reputational risk in the banking sector.

V-4. Recommendations for future research

The study's findings on reputational risk in the banking sector provide a solid foundation for further investigation. However, the limitations identified point to several areas where future research could be highly beneficial. These recommendations for future research are intended to expand the understanding of reputational risk and enhance risk management strategies in the banking sector.

V-4.1. Expanding data sources and integrating mixed approach

Future research in the field of reputational risk in banking would greatly benefit from a combined approach that integrates both quantitative and qualitative research methods. While quantitative analysis provides valuable statistical insights, incorporating qualitative methods such as in-depth interviews, focus groups, and case studies could significantly enrich the understanding of reputational risk.

Qualitative research could delve into the subjective experiences and perceptions of various stakeholders, including bank employees, customers, investors, and regulatory bodies. This approach would offer depth and context to the numerical data, especially in understanding complex dynamics like trust, stakeholder perceptions, and the strategic responses of banks to reputational crises. For instance, interviews with banking executives could provide insights into decision-making processes and risk management strategies that are not evident in quantitative data. Similarly, case studies of specific instances of reputational damage could reveal the nuances of how such events unfold and are managed within different banking contexts.

In conclusion, future research in this area would benefit significantly from a mixed-methods approach that combines quantitative and qualitative research techniques and expands the range of data sources used. This approach would provide a more holistic understanding of reputational risk in banking, capturing both the measurable impacts and the deeper, often unquantifiable aspects of reputational damage and management.

V-4.2. Exploring diverse operational risk types

The current study's focus on internal frauds, primarily due to their significant and lingering effects on banks' reputations and financial performance, provides a vital foundation for understanding one aspect of operational risk. However, there exists a rich opportunity for future research to expand this scope and encompass a broader array of operational risk types. By doing so, research can achieve a more comprehensive and holistic understanding of reputational risk in the banking sector.

Different operational risks, such as external fraud, system failures, compliance breaches, or process management errors, can each uniquely impact a bank's reputation and financial health. For instance, system failures or IT security breaches might elicit different stakeholder reactions and recovery patterns compared to issues of internal fraud. These variances in the nature and impact of different operational risks can significantly shape a bank's reputational risk profile and its subsequent financial implications.

Future studies should aim to investigate these diverse types of operational risks and their specific effects on banks' reputation and financial metrics. This expanded investigation could include an analysis of how different types of operational risks correlate with changes in RoA and other financial indicators, offering insights into the varying degrees of reputational damage and recovery processes associated with each risk type.

Such research would be instrumental in refining risk management strategies and policy formulations within banks. By understanding the distinct impacts of various operational risks on reputational and financial outcomes, banks can develop more targeted and effective risk management approaches. This approach would not only enhance the resilience of individual banks to diverse operational risks but also contribute to the overall stability and trustworthiness of the banking sector.

In summary, future research that broadens the examination to include various operational risk types would significantly deepen our understanding of reputational risk dynamics in banking. This approach promises to yield valuable insights that are crucial for developing robust, comprehensive, and nuanced reputational risk management strategies in the banking industry.

V-4.3. Regulatory implications and policies

The potential consideration of a capital charge for reputational risk in the banking sector presents a compelling avenue for future research, especially in the context of regulatory implications and policy formulation. This area of study is particularly vital given the profound impact that reputational issues can have on a bank's financial stability and integrity. Investigating the feasibility and practicality of implementing such a capital charge could significantly contribute to enhancing the risk management frameworks within the banking industry.

Research in this domain could focus on several key aspects. Firstly, it would be essential to assess the feasibility of introducing a capital charge for reputational risk. This assessment would involve further exploring methods for quantifying reputational risk, determining the appropriate levels of capital required, and understanding how such a measure could be integrated into existing regulatory frameworks. Additionally, it would be crucial to evaluate the potential impact of this measure on the overall risk profile of banks, considering how it might influence their operational and strategic decisions.

Moreover, such research would have substantial policy implications. It could provide valuable insights into how the introduction of a capital charge for reputational risk might affect banking practices, both at the individual bank level and across the sector. This includes examining the potential changes in banking products and services, as well as the strategic adjustments that banks might need to make to accommodate this additional capital requirement.

Furthermore, given the global nature of the banking industry, understanding the varied perspectives and approaches of different regulatory bodies and jurisdictions towards a capital charge for reputational risk becomes crucial. Comparative studies could shed light on the global regulatory landscape, offering a diverse range of perspectives and approaches.

Finally, investigating stakeholder reactions to the introduction of such a capital charge is essential. This includes understanding how investors, customers, and the broader market might perceive this change, and its potential impact on their confidence and trust in the banking system.

In summary, future research exploring the regulatory implications and the feasibility of a capital charge for reputational risk in banking would not only inform policy decisions but could also lead to significant enhancements in regulatory frameworks. This would ultimately contribute to a more resilient and stable banking sector, better equipped to manage the complexities of reputational risk.

V-4.4. Investigating contagion effects of the reputational loss

The occurrence of financial crises has led numerous researchers to conclude that the financial sector is susceptible to shocks. These shocks initially impact a specific area or institution before spreading and affecting the broader economy (Allen et al., 2010; Allen & Carletti, 2013). The contagion effect of reputational risk presents a compelling facet of systemic risk within the financial landscape. Reputational risk, while primarily affecting an individual institution, possesses the potential to trigger a domino effect across the broader financial system. This interconnectedness can magnify the repercussions of reputational damage, extending far beyond the originally affected institution (Eckert & Gatzert, 2019).

This warrants accurate examination. Following a methodology akin to that of Eckert & Gatzert (2019), with a significant adjustment, future studies could shift focus from the traditional market model perspective to an analysis based on deviations in annual financial metrics like RoA. This approach would allow for a more comprehensive understanding of how reputational damage in one bank can indirectly impact other banks within the same network or region.

Such a study would involve analyzing the RoA of banks before and after a significant reputational event in a neighboring institution. Such an approach, as proposed in Appendix 7, would provide insights into the indirect effects of reputational loss, offering a more holistic view of the reputational risk landscape. This line of inquiry is essential for developing a more nuanced understanding of reputational risk management in the banking sector. It could lead to the development of more robust risk management frameworks that account for both direct and indirect impacts of reputational crises. Furthermore, this research would provide valuable information for policymakers and regulatory bodies, aiding in the formulation of policies and regulations that consider the interconnected nature of reputational risks in the banking sector.

V-4.5. In-Depth Long-Term Impact Analysis

An essential direction for future research in the field of reputational risk in banking is the analysis of long-term impacts following reputational incidents. The current study, with its focus on the immediate three-year period post-reputational damage, offers valuable insights into the short to medium-term effects. However, a more extended temporal scope would enable a deeper understanding of the enduring consequences and recovery trajectories associated with such events.

Future studies should consider examining the long-term effects of reputational damage over an extended period, potentially spanning several years or even a decade. This approach would provide a more nuanced picture of how reputational damage evolves over time and its prolonged impacts on a bank's financial performance, market position, and overall strategic direction.

A long-term impact analysis could reveal patterns and trends that are not immediately apparent in the aftermath of a reputational incident. It might shed light on how banks navigate the process of rebuilding trust and restoring their reputational standing, as well as the effectiveness of various recovery strategies employed over time. Additionally, such an analysis could uncover the potential for lingering impacts – both positive and negative – that might manifest in the long run, influencing a bank's operational and financial health in ways that are not evident in the short term.

Extending the research timeframe would also allow for a more comprehensive understanding of the lifecycle of reputational risk events. It would offer insights into how banks adapt, respond, and potentially transform in the wake of reputational crises. This could include changes in risk management practices, shifts in corporate culture, and alterations in stakeholder engagement and communication strategies.

In summary, future research that focuses on the long-term impacts of reputational damage in the banking sector would be invaluable. It would not only enhance the current understanding of the duration and permanence of reputational impacts but also provide strategic insights into effective long-term recovery and resilience-building measures. This extended temporal perspective is crucial for a complete and in-depth understanding of reputational risk management and its implications in the banking industry.

V-4.6. Impact of digital and social media

In the context of an evolving digital landscape, the influence of social media and digital platforms on a bank's reputation has become increasingly pronounced. Future research should delve into how these digital channels contribute to shaping reputational risk. This includes examining the impact of social media narratives, online customer feedback, and digital news cycles on a bank's public image. Additionally, with the growing integration of Artificial Intelligence (AI) in digital communication and data analysis, it would be valuable to explore how AI tools can be utilized to monitor, analyze, and manage reputational risks online. Investigating the strategies banks employ to maintain and enhance their digital presence, manage crises, and engage with stakeholders on these platforms could provide crucial insights into effective online reputation management. This research would offer a comprehensive understanding of the digital dimensions of reputational risk and the technological innovations supporting its management in the banking sector.

By addressing these areas, future research can build upon the current study's findings, addressing its limitations and contributing further to the field of reputational risk management in banking. This continued research is essential for developing more effective strategies to protect and enhance the reputation of banks in an ever-changing financial landscape.

V-5. Conclusion

In concluding this research on reputational risk in the banking sector, it is imperative to recognize the broader implications and the substantial contributions it makes to both the academic world and the practical realm of financial risk management. This study has not only delved into the complex dynamics of reputational risk and its financial impacts but has also challenged and extended existing theoretical frameworks, particularly the Resource-Based Theory and the Unified Theory of Reaction in Assets Market. By adopting a novel approach to quantifying reputational loss using end-of-year financial metrics, the research has opened new avenues for understanding the long-term financial consequences of reputational risks in banking.

The findings of this study hold significant value for banking professionals, offering actionable insights for enhancing risk management strategies and tailoring them to different bank sizes and geographical contexts. However, the findings also highlight the need for further investigations, particularly in the context of integrating reputational risk within the banking sector's regulatory risk framework. The study's limitations pave the way for future scholarly work, which is crucial for a more comprehensive understanding and management of these risks. Key areas for future research include a deeper exploration into the potential of a reputational risk capital charge, which could be a groundbreaking step in banking regulation. Additionally, there is a need to examine the long-term effects of reputational damage, going beyond the immediate aftermath to understand the enduring impact on banks. Another promising area is the role of AI in managing digital reputational risks, which could revolutionize how banks monitor and respond to reputational threats in the digital age. These avenues of research are not only vital for advancing academic knowledge but also for informing practical approaches and regulatory policies in the banking sector.

Ultimately, this research contributes to a more nuanced understanding of reputational risk in the banking sector, highlighting its critical importance and the need for robust management strategies. It serves as a reminder of the interconnectedness of reputation, trust, and financial performance in banking, and the necessity for ongoing vigilance and adaptation in risk management practices. The insights gained from this study not only advance academic discourse but also have the potential to influence real-world practices, contributing to the resilience and sustainability of the banking industry in the face of reputational challenges.

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APPENDICES

Appendix 1: Descriptive statistics R's Script

```
#MY MAC SCRIPT
#STUDY DESCRIPTIVE STATISTICS

# Load required packages
library(readxl)
library(dplyr)
library(tidyr)
library(e1071)
library(tidyverse)
library(writexl)
library(openxlsx)
library(ggplot2)
library(reshape2)


# Load the dataset from Excel
data <- read_excel("/Users/senan/Library/CloudStorage/OneDrive-UniversityofCapeTown/UCT-PhD/GSB_MyThesis/Data Analysis/OL_DB271023.xlsx")


# Compute mean, median, and mode for the variables

# For RoA
roa_mean <- mean(data$RoA, na.rm = TRUE)
roa_median <- median(data$RoA, na.rm = TRUE)
roa_mode <- as.numeric(names(sort(table(data$RoA), decreasing = TRUE)[1]))
```

```
# For TotalAssets
totalAssets_mean <- mean(data$TotalAssets, na.rm = TRUE)
totalAssets_median <- median(data$TotalAssets, na.rm = TRUE)
totalAssets_mode <- as.numeric(names(sort(table(data$TotalAssets), decreasing = TRUE)[1]))

# For GDP_GrowthRate
gdpGrowthRate_mean <- mean(data$GDP_GrowthRate, na.rm = TRUE)
gdpGrowthRate_median <- median(data$GDP_GrowthRate, na.rm = TRUE)
gdpGrowthRate_mode <- as.numeric(names(sort(table(data$GDP_GrowthRate), decreasing = TRUE)[1]))

# For InflationRate
inflationRate_mean <- mean(data$InflationRate, na.rm = TRUE)
inflationRate_median <- median(data$InflationRate, na.rm = TRUE)
inflationRate_mode <- as.numeric(names(sort(table(data$InflationRate), decreasing = TRUE)[1]))

# Print the results
cat("RoA - Mean:", roa_mean, "Median:", roa_median, "Mode:", roa_mode, "\n")
cat("TotalAssets - Mean:", totalAssets_mean, "Median:", totalAssets_median, "Mode:", totalAssets_mode, "\n")
cat("GDP_GrowthRate - Mean:", gdpGrowthRate_mean, "Median:", gdpGrowthRate_median, "Mode:", gdpGrowthRate_mode, "\n")
cat("InflationRate - Mean:", inflationRate_mean, "Median:", inflationRate_median, "Mode:", inflationRate_mode, "\n")
```

```
#### CENTRAL TENDENCY BY REGION ####

# Define mode function
get_mode <- function(v) {
  uniqv <- unique(v)
  uniqv[which.max(tabulate(match(v, uniqv)))]
}

# Central Tendency Analysis by g2_Region
central_tendency_by_region <- data %>%
  group_by(g2_Region) %>%
  summarise(
    RoA_Mean = mean(RoA, na.rm = TRUE),
    RoA_Median = median(RoA, na.rm = TRUE),
    RoA_Mode = get_mode(RoA),
    TotalAssets_Mean = mean(TotalAssets, na.rm = TRUE),
    TotalAssets_Median = median(TotalAssets, na.rm = TRUE),
    TotalAssets_Mode = get_mode(TotalAssets),
    GDP_GrowthRate_Mean = mean(GDP_GrowthRate, na.rm = TRUE),
    GDP_GrowthRate_Median = median(GDP_GrowthRate, na.rm = TRUE),
    GDP_GrowthRate_Mode = get_mode(GDP_GrowthRate),
    InflationRate_Mean = mean(InflationRate, na.rm = TRUE),
    InflationRate_Median = median(InflationRate, na.rm = TRUE),
    InflationRate_Mode = get_mode(InflationRate)
  )

# Print the results
```

```
print(central_tendency_by_region)

write_xlsx(central_tendency_by_region, "central_tendency_by_region.xlsx")



##### CREATE BOXPLOT FOR RoA, TOTAL ASSETS, GDP GRTOWTH RATE AND INFLATION RATE #####



# Create the box plot for RoA by region

# Adjust region names for two-line display

data$g2_Region <- gsub(" ", "\n", data$g2_Region)

ggplot(data, aes(x = g2_Region, y = RoA)) +

  geom_boxplot(fill = "lightgrey", color = "black") +

  labs(title = "Box Plot of RoA by Region",

       y = "RoA",

       x = "Region") +

  theme_minimal() +

  theme(axis.text.x = element_text(size = 12, angle = 45, hjust = 1))  # Increase size of x labels



# Create the box plot for TotalAssets by region

# Adjust region names for two-line display

data$g2_Region <- gsub(" ", "\n", data$g2_Region)

ggplot(data, aes(x = g2_Region, y = TotalAssets)) +

  geom_boxplot(fill = "lightgrey", color = "black") +

  labs(title = "Box Plot of Banks' Total Assets by Region",

       y = "Banks' Total Assests",
```

```
     x = "Geographical location") +
  theme_minimal() +
  theme(axis.text.x = element_text(size = 12, angle = 45, hjust = 1))  # Increase size of x
labels


# Create the box plot for GDPGrowthRate by region
# Adjust region names for two-line display
data$g2_Region <- gsub(" ", "\n", data$g2_Region)
ggplot(data, aes(x = g2_Region, y = GDP_GrowthRate)) +
  geom_boxplot(fill = "lightgrey", color = "black") +
  labs(title = "Box Plot of GDP Growth Rate by Region",
     y = "GDP Growth Rate",
     x = "Geographical location") +
  theme_minimal() +
  theme(axis.text.x = element_text(size = 13, angle = 45, hjust = 1))  # Increase size of x
labels


# Create the box plot for InflationRate by region
# Adjust region names for two-line display
data$g2_Region <- gsub(" ", "\n", data$g2_Region)
ggplot(data, aes(x = g2_Region, y = InflationRate)) +
  geom_boxplot(fill = "lightgrey", color = "black") +
  labs(title = "Box Plot of Inflation Rate by Region",
     y = "Inflation Rate",
     x = "Geographical location") +
  theme_minimal() +
```

```
  theme(axis.text.x = element_text(size = 13, angle = 45, hjust = 1))  # Increase size of x labels


##### GENERATE A HEATMAP FOR REGIONAL CENTRAL TENDENCY DATA #####
# Define mode function
get_mode <- function(v) {
  uniqv <- unique(v)
  uniqv[which.max(tabulate(match(v, uniqv)))]
}


# Compute central tendency by g2_Region
central_tendency_by_region <- data %>%
  group_by(g2_Region) %>%
  summarise(
    RoA_Mean = mean(RoA, na.rm = TRUE),
    RoA_Median = median(RoA, na.rm = TRUE),
    RoA_Mode = get_mode(RoA),
    TotalAssets_Mean = mean(TotalAssets, na.rm = TRUE),
    TotalAssets_Median = median(TotalAssets, na.rm = TRUE),
    TotalAssets_Mode = get_mode(TotalAssets),
    GDP_GrowthRate_Mean = mean(GDP_GrowthRate, na.rm = TRUE),
    GDP_GrowthRate_Median = median(GDP_GrowthRate, na.rm = TRUE),
    GDP_GrowthRate_Mode = get_mode(GDP_GrowthRate),
    InflationRate_Mean = mean(InflationRate, na.rm = TRUE),
    InflationRate_Median = median(InflationRate, na.rm = TRUE),
    InflationRate_Mode = get_mode(InflationRate)
  )
```

```
# Reshape data for heatmap
heatmap_data <- melt(central_tendency_by_region, id.vars = "g2_Region")

# Generate heatmap
ggplot(heatmap_data, aes(x = variable, y = g2_Region, fill = value)) +
  geom_tile() +
  scale_fill_gradient(low = "white", high = "red") +
  labs(title = "Heatmap of Regional Central Tendency Data", x = "Variables", y = "Regions")
+
  theme_minimal()



#### CENTRAL TENDENCY FOR OPERATIONAL LOSS INTENSITY ####
filtered_data <- data %>% filter(EventIntensity != 0)
event_intensity_central_tendency <- list(
  Mean = mean(filtered_data$EventIntensity),
  Median = median(filtered_data$EventIntensity),
  Mode            =            as.numeric(names(sort(table(filtered_data$EventIntensity),
decreasing=TRUE)[1]))
)

# Central tendency for EventIntensity by g2_region and RiskCategory
regional_category_central_tendency <- filtered_data %>%
  group_by(g2_Region, RiskCategory) %>%
  summarise(
    Mean = mean(EventIntensity),
    Median = median(EventIntensity),
```

```
    Mode = as.numeric(names(sort(table(EventIntensity), decreasing=TRUE)[1]))
  )

# Display central tendency for EventIntensity
print("Central Tendency for EventIntensity (Ignoring values '0'):")
print(event_intensity_central_tendency)

# Display central tendency for EventIntensity by g2_region and RiskCategory
print("\nCentral Tendency for EventIntensity by g2_region and RiskCategory:")
print(regional_category_central_tendency)

# Calculating central tendency measures by g2_Region and RiskCategory
central_tendency_by_group <- data %>%
  filter(EventIntensity != 0) %>%
  group_by(g2_Region, RiskCategory) %>%
  summarise(
    Mean = mean(EventIntensity, na.rm = TRUE),
    Median = median(EventIntensity, na.rm = TRUE),
    Mode = mlv(EventIntensity, method = "mfv", na.rm = TRUE)
  )

# Export to Excel
write_xlsx(central_tendency_by_group,
"CentralTendency_by_Region_RiskCategory.xlsx")



### CENTRAL TENDENCY BY RISK CATEGORY ###
```

```
# Remove rows with NA in RiskCategory
data <- na.omit(data, cols = "RiskCategory")

# Define a function to calculate mode
getmode <- function(v) {
  uniqv <- unique(v)
  uniqv[which.max(tabulate(match(v, uniqv)))]
}

# Group by RiskCategory and calculate Mean, Median, and Mode
analysis <- data %>%
  group_by(RiskCategory) %>%
  summarise(
    Mean = mean(EventIntensity, na.rm = TRUE),
    Median = median(EventIntensity, na.rm = TRUE),
    Mode = getmode(EventIntensity)
  )

# View the result
print(analysis)



# create horizontal bar chart for operational losses mean by internal fraud category
# Adjust RiskCategory for multiline display
analysis$RiskCategory <- str_wrap(analysis$RiskCategory, width = 40)

# Create a horizontal bar chart for Mean values
```

```
ggplot(analysis, aes(y = reorder(RiskCategory, Mean), x = Mean)) +
 geom_bar(stat = "identity", fill = "darkgrey", width = 0.9) +
 geom_text(aes(label = sprintf("%.2f", Mean)),
      vjust = -0.3,
      color = "black") +
 labs(title = "Mean Operational Loss by Internal Fraud Category",
   y = "Internal Fraud Category",
   x = "Mean Operational Loss ($ million)") +
 theme(axis.text.y = element_text(angle = 0, size = 12))


### create horizontal bar chart for operational losses mean by geographical location (g2_Region)
# Calculate mean EventIntensity for each g2_Region
region_means <- data %>%
 group_by(g2_Region) %>%
 summarise(MeanEventIntensity = mean(EventIntensity, na.rm = TRUE))

# Create a horizontal bar chart with data labels
ggplot(region_means, aes(x = MeanEventIntensity, y = reorder(g2_Region, MeanEventIntensity))) +
 geom_bar(stat = "identity", fill = "darkgrey") +
 geom_text(aes(label = sprintf("%.2f", MeanEventIntensity)),
      hjust = 0.5,
      position = position_dodge(width = 0.9),
      color = "black") +
 labs(title = "Mean Operational Loss by geographical Location",
   x = "Mean Operational Loss ($ million)",
```

```
    y = "Geographical Location") +
  theme(axis.text.y = element_text(angle = 0, size = 11))




#### TABLE OF RISK CATEGORY BY REGION
# Calculating the frequency of risk categories by region only
risk_frequency_by_region <- data %>%
  filter(!is.na(RiskCategory) & !is.na(g2_Region)) %>%
  group_by(g2_Region, RiskCategory) %>%
  summarise(Count = n())

# Pivot the data to get regions in columns
risk_crosstab_region <- risk_frequency_by_region %>%
  pivot_wider(names_from = g2_Region, values_from = Count, values_fill = 0)

# Add a total column
risk_crosstab_region$Total <- rowSums(select(risk_crosstab_region, -RiskCategory))

# Calculate the global weight for each risk category
total_events <- sum(risk_crosstab_region$Total)
risk_crosstab_region$GlobalWeight <- (risk_crosstab_region$Total / total_events) * 100

# View the crosstab
print(risk_crosstab_region)

# Export the dataframe to an Excel file
```

```
write_xlsx(cross_tab, "RiskCategory_by_Region_Percentage_Pivot.xlsx")



# BUBBLE PLOT FOR RISK CATEGORY X REGION

# Calculating the frequency of risk categories by region
risk_frequency_by_region <- data %>%
  filter(!is.na(RiskCategory) & !is.na(g2_Region)) %>%
  count(g2_Region, RiskCategory)

# Wrap text for risk categories and regions
risk_frequency_by_region$RiskCategory <-
str_wrap(risk_frequency_by_region$RiskCategory, width = 30)
risk_frequency_by_region$g2_Region <-
str_wrap(risk_frequency_by_region$g2_Region, width = 20)

# Create a bubble plot with wrapped labels for risk categories and regions
ggplot(risk_frequency_by_region, aes(x = g2_Region, y = RiskCategory, size = n)) +
  geom_point(alpha = 0.6) +
  scale_size_continuous(range = c(3, 15)) +  # Adjust the range based on your data
  labs(title = "Risk Category Frequency by Region",
       x = "Region",
       y = "Risk Category",
       size = "Frequency") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 90, vjust = 0.5, hjust=1), # Rotate x labels for
clarity
```

```
    axis.text.y = element_text(angle = 0, hjust = 0, lineheight = 0.8)) +  # Adjust y label wrapping and line height
  geom_text(aes(label=n), hjust=-0.3, vjust=-0.3)  # Add counts labels




### BOX PLOT OF EVENT INTENSITY
#Event Intensity by Risk category
# Filter the data
filtered_data <- data %>%
  filter(!is.na(RiskCategory) & RiskCategory != "" & EventIntensity != 0) %>%
  mutate(RiskCategory = str_wrap(RiskCategory, width = 20))   # Wrapping the RiskCategory label

# Create the box plot
box_plot <- ggplot(filtered_data, aes(x = RiskCategory, y = EventIntensity)) +
  geom_boxplot() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1, vjust = 1)) +
  labs(title = "Box Plot of Size of the Operational loss by the type of Internal Fraud",
       x = "Category of Internal Fraud",
       y = "Size of the Operational Loss")

print(box_plot)



#Event Intensity by Region
# Filter the data
```

```
filtered_data <- data %>%
  filter(!is.na(g2_Region) & g2_Region != "" & EventIntensity != 0) %>%
  mutate(g2_Region = str_wrap(g2_Region, width = 20))  # Wrapping the g2_Region label

# Create the box plot
box_plot <- ggplot(filtered_data, aes(x = g2_Region, y = EventIntensity)) +
  geom_boxplot() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1, vjust = 1)) +
  labs(title = "Box Plot of Size of the Operational loss by the Geographical location",
       x = "Geograpgical Location",
       y = "Size of the Operational Loss")

print(box_plot)



### DISPERSION ANALYSIS ###

##### COMPARATIVE DISPERSION #####



# Filter out rows where 'RoA' and 'TotalAssets' are NA
data_cleaned <- data %>% filter(!is.na(RoA) & !is.na(TotalAssets))

# Dispersion by Region
dispersion_by_region <- data_cleaned %>%
  group_by(g2_Region) %>%
  summarise(
```

```
    RoA_Std_Dev = sd(RoA, na.rm = TRUE),
    RoA_Variance = var(RoA, na.rm = TRUE),
    RoA_Range = max(RoA, na.rm = TRUE) - min(RoA, na.rm = TRUE),
    TotalAssets_Std_Dev = sd(TotalAssets, na.rm = TRUE),
    TotalAssets_Variance = var(TotalAssets, na.rm = TRUE),
    TotalAssets_Range = max(TotalAssets, na.rm = TRUE) - min(TotalAssets, na.rm =
TRUE)
  )

# Dispersion by Risk Category
dispersion_by_risk_category <- data_cleaned %>%
  group_by(RiskCategory) %>%
  summarise(
    RoA_Std_Dev = sd(RoA, na.rm = TRUE),
    RoA_Variance = var(RoA, na.rm = TRUE),
    RoA_Range = max(RoA, na.rm = TRUE) - min(RoA, na.rm = TRUE),
    TotalAssets_Std_Dev = sd(TotalAssets, na.rm = TRUE),
    TotalAssets_Variance = var(TotalAssets, na.rm = TRUE),
    TotalAssets_Range = max(TotalAssets, na.rm = TRUE) - min(TotalAssets, na.rm =
TRUE)
  )

# Display results
print("Dispersion by Region:")
print(dispersion_by_region)

print("Dispersion by Risk Category:")
print(dispersion_by_risk_category)
```

```
#### VIOLON PLOT ####
# Wrap long region names onto multiple lines
data$g2_Region <- str_wrap(data$g2_Region, width = 15)

# Filter out NA values for accurate plotting
data <- data[!is.na(data$RoA) & !is.na(data$TotalAssets), ]

# Violin plot for RoA by g2_Region
ggplot(data, aes(x=g2_Region, y=RoA)) +
  geom_violin(trim=FALSE) +
  labs(title="Violin Plot of RoA by Geographical location",
       x = "Geographical Location",
       y="Return on Assets (RoA)") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  geom_boxplot(width=0.1)  # Adding a boxplot inside the violin plot for additional clarity




##### TIME SERIES ANALYSIS OF DISPERSION #####

# Filtering out rows with missing 'Year', 'RoA', or 'TotalAssets'
data_clean <- data %>% filter(!is.na(Year), !is.na(RoA), !is.na(TotalAssets))

# Calculating standard deviation and variance by year
```

```
dispersion_over_time <- data_clean %>%
  group_by(Year) %>%
  summarise(
    RoA_Std_Dev = sd(RoA, na.rm = TRUE),
    RoA_Variance = var(RoA, na.rm = TRUE),

  )

# Display results
print("dispersion_over_time:")
print(dispersion_over_time)

# Export to Excel
write_xlsx(dispersion_over_time, "dispersion_over_time.xlsx")



# Plotting time series for RoA with adjusted legend and axis text size
dispersion_over_time %>%
  ggplot(aes(x = Year)) +
  geom_line(aes(y = RoA_Std_Dev, color = "Standard Deviation")) +
  geom_line(aes(y = RoA_Variance, color = "Variance")) +
  scale_color_manual(values = c("Standard Deviation" = "grey", "Variance" = "black")) +
  labs(
    title = "Time Series Analysis of RoA Dispersion",
    y = "Value",
    x = "Year",
    color = "Metric"
```

```
  ) +
  scale_x_continuous(breaks = seq(min(dispersion_over_time$Year), max(dispersion_over_time$Year), by = 2)) +
  theme_minimal() +
  theme(
    legend.position = "bottom",
    legend.text = element_text(size = 12),
    axis.text.x = element_text(size = 12),
    axis.text.y = element_text(size = 12)
  )



##### DISPERSION OF OPERATIONAL LOSSES

# Exclude rows where EventIntensity is 0 and RiskCategory is blank
filtered_data <- data %>% filter(EventIntensity != 0, RiskCategory != "")

# Calculate dispersion measures for each risk category
dispersion_by_risk_category <- filtered_data %>%
  group_by(RiskCategory) %>%
  summarise(
    Mean = mean(EventIntensity, na.rm = TRUE),
    Median = median(EventIntensity, na.rm = TRUE),
    Std_Dev = sd(EventIntensity, na.rm = TRUE),
    Variance = var(EventIntensity, na.rm = TRUE),
```

```
    Range = max(EventIntensity, na.rm = TRUE) - min(EventIntensity, na.rm = TRUE)
  )

# Filter out rows with missing or zero values in 'EventIntensity'
data_filtered <- data %>%
  filter(!is.na(EventIntensity) & EventIntensity != 0)

# Sum up the EventIntensity for each year
yearly_intensity <- data_filtered %>%
  group_by(Year) %>%
  summarise(Total_EventIntensity = sum(EventIntensity))

# Plotting the total EventIntensity over the years
ggplot(yearly_intensity, aes(x=Year, y=Total_EventIntensity)) +
  geom_line(color="black") +
  geom_point() +
  labs(title="Total Event Intensity Over the Years",
       x="Year",
       y="Total Event Intensity") +
  theme_minimal()



# Print the dispersion measures by risk category
print(dispersion_by_risk_category)

# Visualize the spread of operational losses across risk categories using a box plot
# Read the data and filter out rows with EventIntensity as 0 or blank RiskCategory
```

```
filtered_data <- data %>% filter(EventIntensity != 0, RiskCategory != "")

# Generate the plot
ggplot(filtered_data, aes(x = str_wrap(RiskCategory, 15), y = EventIntensity)) +
  geom_boxplot() +
  labs(title = "Dispersion in Size of Operational loss by Type of Internal Fraud",
       y = "Size of the Operational loss",
       x = "Type of Internal Fraud") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 90, hjust = 1, size = 11))



##### CORRELATION ANALYSIS OF MEASURES OF DISPERSION #####

# Compute measures of dispersion for 'RoA' and 'TotalAssets'
dispersion_data <- data %>%
  summarise(
    RoA_Std_Dev = sd(RoA, na.rm = TRUE),
    RoA_Variance = var(RoA, na.rm = TRUE),
    TotalAssets_Std_Dev = sd(TotalAssets, na.rm = TRUE),
    TotalAssets_Variance = var(TotalAssets, na.rm = TRUE)
  )

# Calculate correlation between measures of dispersion for 'RoA' and 'TotalAssets'
correlation_std_dev <- cor(dispersion_data$RoA_Std_Dev,
dispersion_data$TotalAssets_Std_Dev, use = "complete.obs")
```

```
correlation_variance <- cor(dispersion_data$RoA_Variance, dispersion_data$TotalAssets_Variance, use = "complete.obs")


# Print the correlation values

cat("Correlation between Standard Deviation of RoA and TotalAssets:", correlation_std_dev, "\n")

cat("Correlation between Variance of RoA and TotalAssets:", correlation_variance, "\n")


# Plotting the correlation for better visualization

ggplot(dispersion_data, aes(x = RoA_Std_Dev, y = TotalAssets_Std_Dev)) +
 geom_point() +
 ggtitle("Scatterplot between Standard Deviation of RoA and TotalAssets") +
 xlab("Standard Deviation of RoA") +
 ylab("Standard Deviation of TotalAssets")


ggplot(dispersion_data, aes(x = RoA_Variance, y = TotalAssets_Variance)) +
 geom_point() +
 ggtitle("Scatterplot between Variance of RoA and TotalAssets") +
 xlab("Variance of RoA") +
 ylab("Variance of TotalAssets")




##### FREQUENCY ANALYSIS #####


# Filter out blank cells for relevant columns

data <- data %>%
```

```
  filter(!is.na(g2_Region) & g2_Region != ""
        )

# Filter out blank cells for relevant columns
data <- data %>%
  filter(!is.na(g2_Region) & g2_Region != "")

# 1. Analysis by Region
region_freq <- data %>%
  group_by(g2_Region) %>%
  summarize(Count = n()) %>%
  mutate(Percentage = (Count / sum(Count)) * 100)

# Print the results
print("Frequency Analysis by Region")
print(region_freq)

# Visualization for Analysis by Region
# Calculate percentages
region_freq <- region_freq %>%
  mutate(Percentage = Count / sum(Count) * 100)

# Visualization for Analysis by Region
ggplot(region_freq, aes(x=reorder(g2_Region, Percentage), y=Percentage)) +
  geom_bar(stat='identity') +
  geom_text(aes(label=sprintf("%.2f%%", Percentage)),
position=position_dodge(width=0.9), hjust=-0.1) +
```

```
  labs(title="Percentage of Banks in the sample by Region", x="Region", y="Percentage of Banks") +
  scale_y_continuous(breaks = seq(0, 100, 5), limits = c(0, 35)) +  # Adjust y-axis ticks and limits here
  coord_flip() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))




# 2. Analysis by Country
# Load the dataset from Excel
data <- read_excel("/Users/senan/Library/CloudStorage/OneDrive-UniversityofCapeTown/UCT-PhD/GSB_MyThesis/Data Analysis/OL_DB301023.xlsx")

# Filter out blank cells for relevant columns
data <- data %>%
  filter(!is.na(g1_country) & g1_country != "")

# Calculate frequency and percentage for each country
country_freq <- data %>%
  group_by(g1_country) %>%
  summarize(Count = n()) %>%
  mutate(Percentage = (Count / sum(Count)) * 100) %>%
  arrange(-Count) %>% # Reorder by Count in descending order
  slice_head(n = 10)  # Select the top 10 countries

# Print the results
print("Frequency Analysis by Country")
```

```
print(country_freq)

# Visualization for Analysis by Country (Top 10 countries for clarity)
top_10_countries <- country_freq %>%
  top_n(10, Percentage) %>%
  arrange(desc(Percentage))

# Plotting the bar chart
ggplot(top_10_countries, aes(x=reorder(g1_country, Percentage), y=Percentage)) +
  geom_bar(stat='identity', fill="darkgrey") +
  geom_text(aes(label=sprintf("%.2f%%", Percentage)), vjust=-0.5) +
  labs(title="Top 10 Countries by Percentage", x="Country", y="Percentage (%)") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1),
        axis.title.x = element_text(face="bold", size=12),
        axis.title.y = element_text(face="bold", size=12)) +
  coord_flip()



# 3. Cross-tabulation between Region and Country
region_country_crosstab <- data %>%
  group_by(g2_Region, g1_country) %>%
  summarize(Count = n())

# Print the results
print("Cross-tabulation between Region and Country")
print(region_country_crosstab)
```

```
## Analyzing the number of countries by region
# Filter out blank cells for relevant columns
data_filtered <- data %>%
  filter(!is.na(g2_Region) & g2_Region != "", !is.na(g1_country) & g1_country != "")

# Analyzing the number of countries by region
country_by_region <- data_filtered %>%
  group_by(g2_Region) %>%
  summarize(Num_of_Countries = n_distinct(g1_country)) %>%
  mutate(Percentage = (Num_of_Countries / sum(Num_of_Countries)) * 100)

# Print the results
print("Number of Countries by Region")
print(country_by_region)




# 4. Frequency Analysis of Risk Categories
risk_category_freq <- data %>%
  filter(!is.na(RiskCategory) & RiskCategory != "") %>%
  group_by(RiskCategory) %>%
  summarize(Count = n())

# Visualization for Frequency Analysis of Risk Categories
ggplot(risk_category_freq, aes(x=reorder(RiskCategory, Count), y=Count)) +
```

```
  geom_bar(stat='identity') +
  labs(title="Number of Events by Risk Category", x="Risk Category", y="Number of Events") +
  coord_flip()

# 5. Cross-tabulation between Region and Risk Category
region_risk_crosstab <- data %>%
  filter(!is.na(RiskCategory) & RiskCategory != "") %>%
  group_by(g2_Region, RiskCategory) %>%
  summarize(Count = n())

# Visualization for Cross-tabulation between Region and Risk Category
ggplot(region_risk_crosstab, aes(x=g2_Region, y=Count, fill=RiskCategory)) +
  geom_bar(stat="identity") +
  labs(title="Number of Events by Region and Risk Category", x="Region", y="Number of Events", fill="Risk Category") +
  theme_minimal() +
  theme(axis.text.x=element_text(angle=45, hjust=1))


##### SKEWNESS AND CURTOSIS #####

# Calculate skewness and kurtosis
skewness_value <- skewness(data$RoA, na.rm = TRUE)
kurtosis_value <- kurtosis(data$RoA, na.rm = TRUE)

# Print the results
cat("Skewness for RoA:", skewness_value, "\n")
```

```
cat("Kurtosis for RoA:", kurtosis_value, "\n")


# Histogram with Density Plot for 'RoA'
ggplot(data, aes(x=RoA)) +
  geom_histogram(aes(y=..density..), binwidth=0.5, fill="black", alpha=0.5) +
  geom_density(color="darkgrey") +
  labs(title="Distribution of RoA with Density Plot",
       x="RoA", y="Density") +
  theme_minimal()
```

Appendix 2: Study model R's script

```
# Load required packages

library(tidyverse)

library(readxl)

library(dplyr)

library(writexl)

library(openxlsx)

library(zoo)     # Required for plm

library(miscTools)     # Required for plm

library(plm)

library(lmtest)

library(car)

library(sandwich)

library(mvtnorm)

library(survival)

library(TH.data)

library(MASS)

library(multcomp)

library(stargazer)

library(ggplot2)
```

```
# Load the dataset from Excel

pdata <- read_excel("/Users/senan/Library/CloudStorage/OneDrive-UniversityofCapeTown/UCT-PhD/GSB_MyThesis/Data Analysis/OL_DB171023.xlsx")



# Convert the data to a pdata.frame

pdata <- pdata.frame(pdata, index = c("BankName", "Year"))



# Fit the random effects model

model_re_with_region_gdp <- plm(RoA ~ lag(RoA, 1:3) + lag(TotalAssets, 1:3) +
                   InflationRate + GDP_GrowthRate + factor(g2_Region),
                  data = pdata, model = "random")


# Display the summary of the model

summary(model_re_with_region_gdp)



### MODEL Coefficients Table:


# Define the function GEFCOEF to extract coefficients, standard error, and p-value
```

```
getcoef <- function(model, what) {
  if (what == "coefficients") {
    return(coef(model))
  } else if (what == "standard.error") {
    return(sqrt(diag(vcov(model))))
  } else if (what == "p.value") {
    return(2 * (1 - pnorm(abs(coef(model)/sqrt(diag(vcov(model))))))
  } else {
    stop("Unknown type")
  }
}


# Create the table
stargazer(model_re_with_region_gdp, type="text",
        title="Coefficients from Random Effects Model",
        align=TRUE,
        coef=list(cbind(getcoef(model_re_with_region_gdp, "coefficients"),
                        getcoef(model_re_with_region_gdp, "standard.error"),
                        getcoef(model_re_with_region_gdp, "p.value"))),
        column.labels=c("Coefficient", "Standard Error", "p-value"),
        star.cutoffs=c(0.05, 0.01, 0.001),
```

```
    notes=c("* p < 0.05", "** p < 0.01", "*** p < 0.001"))




### Export the COEFICIENT TABLE TO EXCEL

# Extract coefficients, standard errors, and p-values from the model summary

coefficients <- summary(model_re_with_region_gdp)$coefficients


# Convert the coefficients matrix to a data frame

coeff_df <- as.data.frame(coefficients)


# Export the data frame to an Excel file

write.xlsx(coeff_df, "Random_model_summary.xlsx", row.names = TRUE)




write.xlsx(model_re_with_region_gdp, "Random_model_summary.xlsx", row.names =
FALSE)
```

```
### CREATE AN EFFECT SIZE BAR FOR THE RANDOM EFFECT MODEL COEFICIENTS

# Extract coefficients and variables
coefficients <- coef(model_re_with_region_gdp)
variables <- names(coefficients)

# Create a data frame
df <- data.frame(Variable = variables, Coefficient = coefficients)

# Filter out insignificant predictors (based on p-value, for instance)
# Note: Extract p-values from the model summary and add them to the data frame to filter by significance.
# Note: Only show variables with coefficient values with threshold matching
threshold <- 0.05
df <- df[abs(df$Coefficient) > threshold,]

# Plot the effect sizes
ggplot(df, aes(x = reorder(Variable, Coefficient), y = Coefficient)) +
  geom_bar(stat = "identity", fill = "darkgrey") +
  coord_flip() +
  ggtitle("Significant Predictors on RoA") +
```

```
  xlab("Independent Variables") +
  ylab("Coefficient Value") +
  theme_minimal()



#GENERATE THE PREDICTED RoA POST EVENT
# Extract coefficients from the model
coefficients <- coef(model_re_with_region_gdp)

# Compute predicted RoA
pdata$predicted_RoA <- with(pdata,
                    coefficients["(Intercept)"] +
                      coefficients["lag(RoA, 1:3)1"] * lag(RoA, 1) +
                      coefficients["lag(RoA, 1:3)2"] * lag(RoA, 2) +
                      coefficients["lag(RoA, 1:3)3"] * lag(RoA, 3) +
                      coefficients["lag(TotalAssets, 1:3)1"] * lag(TotalAssets, 1) +
                      coefficients["lag(TotalAssets, 1:3)2"] * lag(TotalAssets, 2) +
                      coefficients["lag(TotalAssets, 1:3)3"] * lag(TotalAssets, 3) +
                      coefficients["InflationRate"] * InflationRate +
                      coefficients["GDP_GrowthRate"] * GDP_GrowthRate
)
```

```
colnames(post_event_data)

# Extract the post-event data and predictions
post_event_data <- pdata[pdata$PostEvent == 1, ]
post_event_predicted_RoA <- post_event_data[, c("BankName", "Year", "predicted_RoA")]

# Print the predicted RoA post-event for each bank
print(post_event_predicted_RoA)

# Write the data to an Excel file
write.xlsx(post_event_data, "Predicted_RoA_Output.xlsx", rowNames = FALSE)

#CALCULATE THE ABNORMAL RoA (AR)
# Calculate Abnormal Return
post_event_data$Abnormal_Return <- post_event_data$RoA - post_event_data$predicted_RoA

# View the data
head(post_event_data[, c("BankName", "Year", "RoA", "predicted_RoA", "Abnormal_Return")])

# Calculate Monetary Value of Abnormal Return
```

```
post_event_data$Monetary_Abnormal_Return <- post_event_data$Abnormal_Return * post_event_data$TotalAssets / 100

# View the data
head(post_event_data[, c("BankName", "Year", "RoA", "predicted_RoA", "Abnormal_Return", "Monetary_Abnormal_Return")])

#ADD ABNORMAL RETURN OF RoA AND ITS VALUE TO DATASET
# Calculate Abnormal Return and its Monetary Value
pdata$Abnormal_Return <- pdata$RoA - pdata$predicted_RoA
pdata$Monetary_Abnormal_Return <- pdata$Abnormal_Return * pdata$TotalAssets / 100

# Export to Excel
write_xlsx(pdata, "OL_mAR.xlsx")

##### ABNORMAL RETURN ANALYSIS ######
# Load the dataset from Excel
data <- read_excel("/Users/senan/Library/CloudStorage/OneDrive-UniversityofCapeTown/UCT-PhD/GSB_MyThesis/Data Analysis/OL-PostEvent_DB311023.xlsx")
```

```
# Descriptive statistics for AR values
overall_stats <- summary(data$AR)
yearwise_stats <- data %>% group_by(PostEvent_Year) %>% summarise(
  Count = n(),
  Mean = mean(AR, na.rm = TRUE),
  Median = median(AR, na.rm = TRUE),
  SD = sd(AR, na.rm = TRUE),
  Min = min(AR, na.rm = TRUE),
  Max = max(AR, na.rm = TRUE)
)

print(overall_stats)
print(yearwise_stats)


# Summary of AR statistics
calculate_stats <- function(df) {
  data.frame(
    Metric = c("Count", "Mean", "Standard Deviation", "Min", "25th Percentile",
               "Median (50th Percentile)", "75th Percentile", "Max"),
```

```
  Value = c(nrow(df), mean(df$AR, na.rm = TRUE), sd(df$AR, na.rm = TRUE),
            min(df$AR, na.rm = TRUE), quantile(df$AR, 0.25, na.rm = TRUE),
            median(df$AR, na.rm = TRUE), quantile(df$AR, 0.75, na.rm = TRUE),
            max(df$AR, na.rm = TRUE))
 )
}

# Calculate statistics for overall AR and each year
overall_stats <- calculate_stats(data)
year1_stats <- calculate_stats(filter(data, PostEvent_Year == 1))
year2_stats <- calculate_stats(filter(data, PostEvent_Year == 2))
year3_stats <- calculate_stats(filter(data, PostEvent_Year == 3))

# Bind the statistics into a single data frame
stats_data <- cbind(overall_stats, year1_stats$Value, year2_stats$Value, year3_stats$Value)
colnames(stats_data) <- c("Metric", "Overall", "Year1", "Year2", "Year3")

# Write the data frame to an Excel file
write_xlsx(stats_data, "AR_Summary_Statistics.xlsx")

# Print the table for verification
```

```
print(stats_data)




# Visualizing distribution of AR values
ggplot(data, aes(x = factor(PostEvent_Year), y = AR)) +
  geom_boxplot(fill = "lightgrey", color = "black") +
  labs(title = "Distribution of Abnormal Return (AR) by Post-Event Year",
       x = "Post-Event Year",
       y = "Abnormal Return (AR)") +
  theme_minimal()


# Analysis of negative AR values
negative_ar <- data %>% filter(AR < 0)
negative_counts <- table(negative_ar$PostEvent_Year)
negative_means <- negative_ar %>% group_by(PostEvent_Year) %>% summarise(
  Mean_Negative_AR = mean(AR, na.rm = TRUE)
)

print(negative_counts)
print(negative_means)
```

```
# Comparative analysis of mean and median AR values
mean_median_ar <- data %>% group_by(PostEvent_Year) %>% summarise(
  Mean_AR = mean(AR, na.rm = TRUE),
  Median_AR = median(AR, na.rm = TRUE)
)

ggplot(mean_median_ar, aes(x = factor(PostEvent_Year))) +
  geom_line(aes(y = Mean_AR, group = 1, color = "Mean AR"), size = 1) +
  geom_point(aes(y = Mean_AR, color = "Mean AR")) +
  geom_line(aes(y = Median_AR, group = 1, color = "Median AR"), linetype = "dashed",
size = 1) +
  geom_point(aes(y = Median_AR, color = "Median AR")) +
  geom_hline(yintercept = 0, linetype = "dashed", size = 1.2) +
  labs(title = "Mean and Median Abnormal Return (AR) Across Post-Event Years",
       x = "Post-Event Year",
       y = "Abnormal Return (AR)") +
  scale_color_manual(values = c("Mean AR" = "black", "Median AR" = "dark grey")) +
  theme_minimal() +
  theme(legend.title = element_blank())

# Chart with legend at the bottom
```

```
ggplot(mean_median_ar, aes(x = factor(PostEvent_Year))) +
  geom_line(aes(y = Mean_AR, group = 1, color = "Mean AR"), size = 1) +
  geom_point(aes(y = Mean_AR, color = "Mean AR")) +
  geom_line(aes(y = Median_AR, group = 1, color = "Median AR"), linetype = "dashed", size = 1) +
  geom_point(aes(y = Median_AR, color = "Median AR")) +
  geom_hline(yintercept = 0, linetype = "dashed", size = 1.2) +
  labs(title = "Mean and Median Abnormal Return (AR) Across Post-Event Years",
       x = "Post-Event Year",
       y = "Abnormal Return (AR)") +
  scale_color_manual(values = c("Mean AR" = "black", "Median AR" = "dark grey")) +
  theme_minimal() +
  theme(legend.title = element_blank(),
        legend.position = "bottom")



### Boehmer et al. (1991) test statistic Z

# Load the dataset from Excel

data <- read_excel("/Users/senan/Library/CloudStorage/OneDrive-UniversityofCapeTown/UCT-PhD/GSB_MyThesis/Data Analysis/OL-PostEvent_DB311023.xlsx")
```

```
# Compute the CAR for each bank by summing up the AR over the post-event years
CAR_by_bank <- data %>%
  group_by(BankName) %>%
  summarise(CAR = sum(AR, na.rm = TRUE))

# Merge the CAR data back to the original dataset
data_with_CAR <- left_join(data, CAR_by_bank, by = "BankName")

# Calculate the standard deviation of AR for each bank over the post-event years
sd_AR_by_bank <- data %>%
  group_by(BankName) %>%
  summarise(sd_AR = sd(AR, na.rm = TRUE))

# Merge the standard deviation data back to the dataset
data_with_CAR_and_sd <- left_join(data_with_CAR, sd_AR_by_bank, by =
"BankName")

# Calculate the standardized abnormal returns (SR) for each observation
data_with_CAR_and_sd$SR <- data_with_CAR_and_sd$CAR /
data_with_CAR_and_sd$sd_AR

# Compute the Boehmer et al. (1991) test statistic Z
```

```
N <- nrow(data_with_CAR_and_sd)

Z <- sqrt(N) * (mean(data_with_CAR_and_sd$SR, na.rm = TRUE) / sd(data_with_CAR_and_sd$SR, na.rm = TRUE))


# Print the Z statistic

print(paste("Boehmer et al. (1991) Z statistic:", Z))




### Boehmer et al. (1991) test statistic Z (ONLY BANKS WITH AT LEAST A NEGATIVE AR)

# Filter only banks with at least one negative AR in the post-event period

banks_with_negative_AR <- data %>%

  group_by(BankName) %>%

  filter(any(AR < 0)) %>%

  ungroup()


# Calculate CAR for each bank

banks_with_negative_AR <- banks_with_negative_AR %>%

  group_by(BankName) %>%

  mutate(CAR = cumsum(AR)) %>%

  ungroup()
```

```
# Calculate SR using the Boehmer et al. formula

SR <- sum(banks_with_negative_AR$AR / sqrt(banks_with_negative_AR$CAR^2 + 1))


# Calculate the Z statistic

N <- n_distinct(banks_with_negative_AR$BankName)  # Total number of banks with at least one negative AR

Z <- SR / sqrt(N)


# Print the Z statistic

print(paste("Boehmer et al. (1991) Z statistic:", Z))


##### REPUTATIONAL LOSS ANALYSIS ######


# Calculate the monetary abnormal return (mAR) and Reputational loss (Rl)

data$mAR <- (data$AR * data$TotalAssets)/100

data$Rl <- data$mAR - data$EventIntensity
```

```
# Load the dataset from Excel

data <- read_excel("/Users/senan/Library/CloudStorage/OneDrive-UniversityofCapeTown/UCT-PhD/GSB_MyThesis/Data Analysis/OL-PostEvent_DB311023.xlsx")



# Overall summary statistics for 'Rl'

overall_stats <- summary_stats(data, "Rl")


# Summary statistics by year for 'Rl'

yearly_stats <- data %>%
  group_by(PostEvent_Year) %>%
  summarise(
    Count = n(),
    Mean = mean(Rl, na.rm = TRUE),
    Std_Dev = sd(Rl, na.rm = TRUE),
    Min = min(Rl, na.rm = TRUE),
    `25th_Percentile` = quantile(Rl, 0.25, na.rm = TRUE),
    Median = median(Rl, na.rm = TRUE),
    `75th_Percentile` = quantile(Rl, 0.75, na.rm = TRUE),
    Max = max(Rl, na.rm = TRUE)
  )
```

```
# Print the results
print("Overall Statistics:")
print(overall_stats)
print("Yearly Statistics:")
print(yearly_stats)


# Overall summary statistics for 'Rl'
overall_stats <- summary_stats(data, "Rl")

# Summary statistics by year for 'Rl'
yearly_stats <- data %>%
  group_by(PostEvent_Year) %>%
  do(summary_stats(., "Rl"))

# Write to Excel
write.xlsx(list(Overall = overall_stats, Yearly = yearly_stats),
"Rl_summary_statistics.xlsx")


# Visualizing distribution of Rl values
```

```
ggplot(data, aes(x = factor(PostEvent_Year), y = Rl)) +
  geom_boxplot(fill = "darkgrey") +
  geom_hline(yintercept = 0, linetype = "dashed", size = 1.2, color = "black") +
  labs(title = "Distribution of Reputational Loss (Rl) by Post-Event Year",
       x = "Post-Event Year",
       y = "Reputational Loss (Rl)") +
  theme_minimal()

# Analysis of negative Rl values
negative_rl <- data %>% filter(Rl < 0)
negative_counts <- table(negative_rl$PostEvent_Year)
negative_means <- negative_rl %>% group_by(PostEvent_Year) %>% summarise(
  Mean_Negative_Rl = mean(Rl, na.rm = TRUE)
)

# Comparative analysis of mean and median Rl values
mean_median_rl <- data %>% group_by(PostEvent_Year) %>% summarise(
  Mean_Rl = mean(Rl, na.rm = TRUE),
  Median_Rl = median(Rl, na.rm = TRUE)
)

ggplot(mean_median_rl, aes(x = factor(PostEvent_Year))) +
```

```
  geom_line(aes(y = Mean_Rl, group = 1, color = "Mean Rl"), size = 1) +
  geom_point(aes(y = Mean_Rl, color = "Mean Rl")) +
  geom_line(aes(y = Median_Rl, group = 1, color = "Median Rl"), linetype = "dashed", size
= 1) +
  geom_point(aes(y = Median_Rl, color = "Median Rl")) +
  labs(title = "Mean and Median Reputational Loss (Rl) Across Post-Event Years",
       x = "Post-Event Year",
       y = "Reputational Loss (Rl)") +
  scale_color_manual(values = c("Mean Rl" = "black", "Median Rl" = "darkgrey")) +
  theme_minimal() +
  theme(legend.title = element_blank(), legend.position = "bottom")

# Compile the statistics into a table
stats_data <- rbind(overall_stats, yearwise_stats)
write_xlsx(stats_data, "Rl_Summary_Statistics.xlsx")




###### BANKS WITH RL AND BANKS WITH NO RL


# Load the dataset from Excel
```

```
data <- read_excel("/Users/senan/Library/CloudStorage/OneDrive-UniversityofCapeTown/UCT-PhD/GSB_MyThesis/Data Analysis/OL-PostEvent_DB311023.xlsx")



# Identify banks with at least one negative Rl in any post-event year

banks_with_negative_rl <- data %>%

  group_by(BankName) %>%

  summarise(NegativeCount = sum(Rl < 0)) %>%

  filter(NegativeCount > 0) %>%

  pull(BankName)


# Percentage of banks with at least one negative Rl over total banks

percentage_negative_rl <- (length(unique(banks_with_negative_rl)) / length(unique(data$BankName))) * 100


# Summary statistics for banks with at least one negative Rl

summary_negative_rl <- data %>%

  filter(BankName %in% banks_with_negative_rl) %>%

  summarise(

    Count = n(),

    Mean = mean(Rl, na.rm = TRUE),

    Median = median(Rl, na.rm = TRUE),
```

```
    SD = sd(Rl, na.rm = TRUE),
    Min = min(Rl, na.rm = TRUE),
    Max = max(Rl, na.rm = TRUE)
  )

# Summary statistics for banks with no negative Rl in all post-event years
summary_no_negative_rl <- data %>%
  filter(!BankName %in% banks_with_negative_rl) %>%
  filter(Rl >= 0) %>%
  summarise(
    Count = n(),
    Mean = mean(Rl, na.rm = TRUE),
    Median = median(Rl, na.rm = TRUE),
    SD = sd(Rl, na.rm = TRUE),
    Min = min(Rl, na.rm = TRUE),
    Max = max(Rl, na.rm = TRUE)
  )

# Print the results
print(paste("Percentage of banks with at least one negative Rl: ", round(percentage_negative_rl, 2), "%"))
print(summary_negative_rl)
```

```
print(summary_no_negative_rl)



# Calculate the number of banks with negative Rl for each post-event year
# Total number of unique banks in the dataset
total_banks <- n_distinct(data$BankName)

# Calculate the number and percentage of banks with negative Rl for each post-event year
negative_rl_by_year <- data %>%
  filter(Rl < 0) %>%
  group_by(PostEvent_Year) %>%
  summarise(
    Num_Banks_With_Negative_Rl = n_distinct(BankName),
    Percentage_of_Total_Banks = (Num_Banks_With_Negative_Rl / total_banks) * 100
  )

# Print the results
print(negative_rl_by_year)



#PLOT OF RL DISTRIBUTION POST-EVENT
```

```
# Filter for only negative Rl values
negative_rl_data <- data %>%
  filter(Rl < 0)


# Generate the boxplot
ggplot(negative_rl_data, aes(x = as.factor(PostEvent_Year), y = Rl)) +
  geom_boxplot(fill = "darkgrey", outlier.color = "black", outlier.shape = 16) +
  labs(title = "Distribution of Reputational Loss (Rl) Across Post-Event Years",
       x = "Post-Event Year",
       y = "Reputational Loss (Rl in $ million)") +
  theme_minimal() +
  theme(axis.text = element_text(size = 13),
        axis.title = element_text(size = 13),
        plot.title = element_text(size = 12, hjust = 0.5))


###### MODEL VALIDITY AND ROBUSTNESS CHECKS ######


# Load the dataset from Excel
```

```
pdata <- read_excel("/Users/senan/Library/CloudStorage/OneDrive-UniversityofCapeTown/UCT-PhD/GSB_MyThesis/Data Analysis/OL_DB271023.xlsx")


# 1. Check for Multicollinearity
# Calculate Variance Inflation Factor (VIF)
vif_values <- vif(model_re_with_region_gdp)
print(vif_values)
# Rule of thumb: A VIF value greater than 10 suggests high multicollinearity.



# 2. Check for Heteroskedasticity
# White's Test
coeftest(model_re_with_region_gdp, vcov = vcovHC(model_re_with_region_gdp, type = "HC3"))


# Get the coefficients with robust standard errors
coeftest_results <- coeftest(model_re_with_region_gdp, vcov = vcovHC(model_re_with_region_gdp, type = "HC3"))


# Convert to data frame
coeftest_df <- as.data.frame(coeftest_results)


# Convert to data frame if it's not already
```

```
if(!is.data.frame(coeftest_results)) {
  coeftest_df <- as.data.frame.matrix(coeftest_results)
}

# Rename the columns
names(coeftest_df) <- c("Estimate", "Std. Error", "t value", "Pr(>|t|)")

# Get the variable names from the model and add them as a new column
variable_names <- names(coef(model_re_with_region_gdp))
coeftest_df$Variable <- variable_names

# Create significance codes
signif_codes <- c("***", "**", "*", ".", "")
p_values <- coeftest_df$`Pr(>|t|)`
signif_stars <- symnum(p_values, corr = FALSE, na = FALSE, cutpoints = c(0, 0.001, 0.01, 0.05, 0.1, 1), symbols = signif_codes)

coeftest_df$Signif <- as.character(signif_stars)

# Reorder the dataframe to have Variable as the first column
coeftest_df <- coeftest_df[, c("Variable", "Estimate", "Std. Error", "t value", "Pr(>|t|)", "Signif")]
```

```
# Export the dataframe to an Excel file

write.xlsx(coeftest_df, file = "WhiteTest_Results.xlsx")



# Now perform White's test

white_test <- bptest(model_re_with_region_gdp, ~ fitted(model_re_with_region_gdp) + I(fitted(model_re_with_region_gdp)^2))

# Print the test results

print(white_test)



# Breusch-Pagan test

bp_test <- bptest(model_re_with_region_gdp, studentize = TRUE)

print(bp_test)

# A significant p-value suggests the presence of heteroskedasticity.



# 3. Check for Autocorrelation
```

```
# Wooldridge test for autocorrelation

wooldridge_test <- pbgtest(model_re_with_region_gdp)

print(wooldridge_test)

# A significant p-value suggests the presence of autocorrelation.



##### RQ2: CORRELATION BETWEEN OPERATIONAL LOSS INTENSITY AND THE REPUTATIONAL LOSS #####


# Load the dataset from Excel

data <- read_excel("/Users/senan/Library/CloudStorage/OneDrive-UniversityofCapeTown/UCT-PhD/GSB_MyThesis/Data Analysis/OL-PostEvent_DB311023.xlsx")


# Group by bank and sum Rl for each bank across the three post-event years

sum_Rl_by_bank <- data %>%

  group_by(BankName) %>%

  summarise(Total_Rl_3years = sum(Rl, na.rm = TRUE))


# Merge to get EventIntensity for each bank

correlation_data <- data %>%

  select(BankName, EventIntensity) %>%
```

```
  distinct() %>%
  left_join(sum_Rl_by_bank, by = "BankName")

# Calculate the Pearson correlation coefficient
correlation_coefficient <- cor(correlation_data$EventIntensity, correlation_data$Total_Rl_3years)

#Print results
correlation_coefficient

### CORRELATION BY BANK
# Function to calculate Pearson correlation coefficient
calculate_correlation <- function(df) {
  cor(df$EventIntensity, df$Total_Rl_3years, use = "complete.obs")
}

# Calculate and print the Pearson correlation coefficient for each BankName
correlation_by_bank <- correlation_data %>%
  group_by(BankName) %>%
  do(correlation = calculate_correlation(.))

# Print Results
```

```
print(correlation_by_bank)

# Export the correlation to an Excel file
write.xlsx(correlation_by_bank, file = "CorrCoef_OpL_Rl.xlsx")



# Plot the correlation - scatter plot with a linear regression line
plot <- ggplot(data = correlation_data, aes(x = EventIntensity, y = Total_Rl_3years)) +
  geom_point(alpha = 0.6) +  # Display data points with some transparency
  geom_smooth(method = "lm", se = FALSE, color = "darkgrey") +  # Add linear regression
line
  labs(title = "Correlation between Ol and Total Rl (3 years post-event)",
       x = "Operational Losse size (Ol)",
       y = "Total Reputational Loss (Rl, 3 years post-event)",
       caption = paste("Regression Equation: y =",
                       round(coef(lm(Total_Rl_3years ~ EventIntensity, data =
correlation_data))[2], 3),
                       "x +",
                       round(coef(lm(Total_Rl_3years ~ EventIntensity, data =
correlation_data))[1], 3),
                       "\nR-squared:",
```

```
          round(summary(lm(Total_Rl_3years ~ EventIntensity, data = correlation_data))$r.squared, 3))) +
  theme_minimal()

# Display the plot
print(plot)



##### RQ3 CORRELATION BETWEEN TOTAL ASSETS AND REPUTATIONAL LOSS

# Load the dataset from Excel
data <- read_excel("/Users/senan/Library/CloudStorage/OneDrive-UniversityofCapeTown/UCT-PhD/GSB_MyThesis/Data Analysis/OL-PostEvent_DB311023.xlsx")

# Function to compute correlation for each group
compute_correlation <- function(df) {
  cor_value <- cor(df$TotalAssets, df$Rl, method = "pearson")
  return(data.frame(correlation = cor_value))
}

# Group by BankName and compute correlation
```

```
A_Rl_correlation_results <- data %>%
  group_by(BankName) %>%
  do(compute_correlation(.))

# Print the results
print(A_Rl_correlation_results)

# Write the results to an Excel file
write_xlsx(list("A_Rl Correlation" = A_Rl_correlation_results, "A_Rl_correlation" = df), "A_Rl_correlation_results.xlsx")

# Compute the global correlation TotalAssets and Rl
global_correlation <- cor(data$TotalAssets, data$Rl, method = "pearson", use = "complete.obs")

# Check the result
if (is.na(global_correlation)) {
  cat("Global correlation between TotalAssets and Rl could not be computed. Check data for issues.\n")
} else {
  cat("Global correlation between TotalAssets and Rl:", global_correlation, "\n")
```

```
}



# Compute the correlation TotalAssets and Rl grouped by BankSize
# Exclude rows with missing values in TotalAssets or Rl
data_clean <- data[complete.cases(data$TotalAssets, data$Rl), ]

# Group by BankSize and compute correlation
correlation_results <- data_clean %>%
  group_by(BankSize) %>%
  summarise(correlation = cor(TotalAssets, Rl, method = "pearson"))

# Print the results
print(correlation_results)



#GLOBAL CORRELATION SCATTER PLOT
data <- read_excel("/Users/senan/Library/CloudStorage/OneDrive-UniversityofCapeTown/UCT-PhD/GSB_MyThesis/Data Analysis/OL-PostEvent_DB311023.xlsx")
```

```
# Fit linear model
model <- lm(Rl ~ TotalAssets, data = data)


# Extract coefficients and R-squared value
equation <- paste("y = ", round(coef(model)[2], 2), "x + ", round(coef(model)[1], 2),
                  "\n", "R^2 = ", round(summary(model)$r.squared, 2))


# Create scatter plot with regression line
ggplot(data, aes(x = TotalAssets, y = Rl)) +
  geom_point() +
  geom_smooth(method = "lm", se = FALSE, color = "darkgrey", formula = y ~ x) +
  annotate("text", x = min(data$TotalAssets), y = max(data$Rl), label = equation, hjust = 0,
vjust = 1) +
  labs(title = "Scatter plot of TotalAssets vs. Rl",
       x = "Total Assets (A)",
       y = "Reputational Loss Intensity (Rl)",
       caption = equation) +
  theme(legend.position = "bottom")




##### RQ4: GEOGRAPHICAL VARIATIONS OF REPUTATIONAL LOSS
```

```
# Perform ANOVA
anova_result <- aov(Rl ~ g2_Region, data = data)

# Print the summary of the ANOVA
summary(anova_result)



# Convert g2_Region to a factor
data$g2_Region <- as.factor(data$g2_Region)

# Perform ANOVA
anova_result <- aov(Rl ~ g2_Region, data = data)

# Perform Tukey's HSD post-hoc test
tukey_result <- TukeyHSD(anova_result, "g2_Region")

# Print the summary of the Tukey's HSD test
print(tukey_result)

# Write the results to an Excel file
# Convert the Tukey's HSD result to a data frame
```

```
tukey_df <- as.data.frame(tukey_result$g2_Region)

# Add the region comparisons as a new column
tukey_df$Region_Comparison <- rownames(tukey_df)

# Write the data frame to an Excel file (ADD TABLE TO APPENDICES)
write.xlsx(tukey_df, "Tukey_HSD_Results.xlsx")
```

Appendix 3: Descriptive statistics: Central tendency

Overall Results

Metric	Mean	Median	Mode
RoA (%)	1.23	0.94	0.00
Total Assets (US $ Million)	108,421.96	20,663.58	0.00
GDP Growth Rate (%)	4.47	4.70	2.30
Country Inflation Rate (%)	5.09	3.35	4.90
Operational loss (US $ Million)	60.03	2.76	0.99

Regional Results: RoA (%)

Region	Mean	Median	Mode
Central America	0.86	0.93	0.93
Eastern Africa	3.29	3.51	2.11
Eastern Asia	1.69	0.86	1.09
Eastern Europe	0.05	0.53	0.12
Northern America	0.85	0.94	1.33
Northern Europe	0.80	0.37	0.00
South-Eastern Asia	1.62	1.44	1.36
Southern Asia	0.21	0.53	0.63
Western Africa	4.79	2.01	6.11
Western Asia (incl. Middle East)	1.46	1.27	1.10

Regional Results: Total Assets (US $ Million)

Region	**Mean**	**Median**	**Mode**
Central America	74,645.78	77,197.58	79,757.50
Eastern Africa	3,119.54	2,527.20	2,571.02
Eastern Asia	850,872.56	787,850.46	27,897.02
Eastern Europe	16,874.95	5,796.93	4,692.08
Northern America	155,185.51	119,078.24	774,603.65
Northern Europe	465,311.00	62,233.96	52,564.47
South-Eastern Asia	55,829.32	71,301.17	79,374.76
Southern Asia	30,623.12	21,148.00	19,055.13
Western Africa	6,278.80	5,671.75	1,362.11
Western Asia (incl. Middle East)	7,509.61	5,826.48	13,538.82

Regional Results: Country GDP Growth Rate (%)

Region	**Mean**	**Median**	**Mode**
Central America	2.90	3.05	3.70
Eastern Africa	3.88	3.95	5.00
Eastern Asia	4.13	4.35	7.80
Eastern Europe	0.22	2.05	0.00
Northern America	2.11	2.25	2.30
Northern Europe	1.91	1.85	2.40
South-Eastern Asia	4.44	4.95	2.70
Southern Asia	6.59	6.60	6.40
Western Africa	5.42	6.20	8.00
Western Asia (incl. Middle East)	6.71	4.45	5.60

Regional Results: Inflation Rate (%)

Region	Mean	Median	Mode
Central America	3.47	3.60	3.40
Eastern Africa	4.85	4.85	9.20
Eastern Asia	1.41	1.50	2.60
Eastern Europe	6.54	1.70	0.30
Northern America	1.51	1.50	2.10
Northern Europe	2.04	2.15	3.90
South-Eastern Asia	2.38	2.20	2.20
Southern Asia	7.16	6.70	4.90
Western Africa	9.95	9.00	10.80
Western Asia (incl. Middle East)	8.31	2.25	2.90

Operational loss (US $ Million) by risk category

Region	Mean	Median	Mode
Bribes Accepted by Employee	3.23	3.23	
Embezzlement and Internal Fraud Schemes	22.49	2.41	
Fraudulent Internal Credit Application for a Fictitious Customer	1.56	1.69	
Fraudulent Internal Credit Application for an Existing Customer	6.70	6.70	
Identity Misuse	162.00	162.00	
Intentional Disclosure of Confidential Corporate Information	0.11	0.11	
Internal Credit Approval Fraud or Abuse	134.27	15.25	
Internal Identity Theft without System Intrusion	0.12	0.12	
Pilferage and Physical Theft	56.73	0.40	
Bribes Accepted by Employee	3.23	3.23	

Appendix 4: Descriptive statistics: Dispersion Analysis

RoA (%) Dispersion by risk category

Risk category	Std Dev	Variance	rage
Bribes Accepted by Employee	0.05	0.00	0.07
Embezzlement and Internal Fraud Schemes	5.08	25.79	25.24
Fraudulent Internal Credit Application for a Fictitious Customer	1.44	2.07	2.87
Fraudulent Internal Credit Application for an Existing Customer			0.00
Identity Misuse			0.00
Intentional Disclosure of Confidential Corporate Information			0.00
Internal Credit Approval Fraud or Abuse	1.30	1.68	5.05
Internal Identity Theft without System Intrusion			0.00
Pilferage and Physical Theft	1.03	1.05	2.53
	2.86	8.17	32.74

Total Assets (US $ Million) Dispersion by risk category

Risk category	Std Dev	Variance	rage
Bribes Accepted by Employee	21.99	483,730.75	31.10
Embezzlement and Internal Fraud Schemes	373.97	139,850,711.50	1,658.40
Fraudulent Internal Credit Application for a Fictitious Customer	3.44	11,865.39	6.08
Fraudulent Internal Credit Application for an Existing Customer	0.00	0.00	0.00
Identity Misuse	0.00	0.00	0.00
Intentional Disclosure of Confidential Corporate Information	0.00	0.00	0.00
Internal Credit Approval Fraud or Abuse	47.45	2,251,186.76	149.37
Internal Identity Theft without System Intrusion	0.00	0.00	0.00
Pilferage and Physical Theft	34.87	1,216,236.46	82.08
	300.92	90,552,288.65	1,873.85

RoA (%) Dispersion by region

Region	Std Dev	Variance	rage
Central America	0.28	0.08	0.78
Eastern Africa	0.88	0.78	2.57
Eastern Asia	3.00	9.02	10.83
Eastern Europe	2.59	6.73	11.25
Northern America	0.42	0.18	1.67
Northern Europe	1.12	1.26	4.84
South-Eastern Asia	1.18	1.38	7.03
Southern Asia	1.27	1.60	8.65
Western Africa	7.57	57.25	32.72
Western Asia (incl. Middle East)	1.54	2.38	5.93

Total Assets (US $ Million) Dispersion by region

Region	Std Dev	Variance	rage
Central America	12.57	158,063.35	34.01
Eastern Africa	1.13	1,266.29	3.34
Eastern Asia	854.20	729,658,528.14	1,845.95
Eastern Europe	16.99	288,597.47	40.62
Northern America	224.86	50,564,057.20	819.20
Northern Europe	635.69	404,102,440.62	1,511.08
South-Eastern Asia	34.10	1,162,559.76	97.23
Southern Asia	28.83	831,399.21	117.80
Western Africa	3.21	10,313.61	11.78
Western Asia (incl. Middle East)	7.17	51,452.11	18.20

Appendix 5: Descriptive statistics: Frequency Analysis

Frequency of banks by region in the study dataset

Region	Count	Percentage
Central America	1	1.89
Eastern Africa	2	3.77
Eastern Asia	2	3.77
Eastern Europe	3	5.66
Northern America	10	18.87
Northern Europe	3	5.66
South-Eastern Asia	7	13.21
Southern Asia	17	32.08
Western Africa	5	9.43
Western Asia (incl. Middle East)	3	5.66

Frequency of banks by countries (Top 10)

Region	Count	Percentage
India	14	26.42
United States of America	8	15.09
Nigeria	4	7.55
Thailand	4	7.55
Canada	2	3.77
Czech Republic	2	3.77
Pakistan	2	3.77
United Kingdom	2	3.77
Bangladesh	1	1.89
China	1	1.89

Count of banks by countries by region

Region	Country	Number of banks
Central America	Mexico	1
Eastern Africa	Kenya	1
Eastern Africa	Zimbabwe	1
Eastern Asia	China	1
Eastern Asia	Japan	1
Eastern Europe	Czech Republic	2
Eastern Europe	Ukraine	1
Northern America	Canada	2
Northern America	United States of America	8
Northern Europe	Norway	1
Northern Europe	United Kingdom	2
South-Eastern Asia	Indonesia	1
South-Eastern Asia	Malaysia	1
South-Eastern Asia	Philippines	1
South-Eastern Asia	Thailand	4
Southern Asia	Bangladesh	1
Southern Asia	India	14
Southern Asia	Pakistan	2
Western Africa	Liberia	1
Western Africa	Nigeria	4
Western Asia (incl. Middle East)	Iraq	1
Western Asia (incl. Middle East)	Saudi Arabia	1
Western Asia (incl. Middle East)	United Arab Emirates	1

Frequency of risk categories

Region	Count	Percentage
Bribes Accepted by Employee	2	3.77
Embezzlement and Internal Fraud Schemes	22	41.51
Fraudulent Internal Credit Application for a Fictitious Customer	3	5.66
Fraudulent Internal Credit Application for an Existing Customer	1	1.89
Identity Misuse	1	1.89
Intentional Disclosure of Confidential Corporate Information	1	1.89
Internal Credit Approval Fraud or Abuse	17	32.08
Internal Identity Theft without System Intrusion	1	1.89
Pilferage and Physical Theft	5	9.43
	53	100.00

Appendix 6: Projected RoA (eRoA) results

BankName	Year	g1_country	InflationRate	RoA	eRoA
Access Bank Plc	2009	Nigeria	12.50	23.96	**17.20**
Access Bank Plc	2010		13.70	14.84	**11.13**
Access Bank Plc	2011		10.80	13.35	**9.96**
Al-Baraka Bank	2015	Pakistan	2.50	0.66	**0.84**
Al-Baraka Bank	2016		3.80	0.58	**0.88**
Al-Baraka Bank	2017		4.10	0.48	**0.84**
Allahabad Bank	2014	India	6.70	0.56	**1.03**
Allahabad Bank	2015		4.90	0.27	**0.71**
Allahabad Bank	2016		4.90	-0.31	**0.31**
Banco Nacional de México (Citibanamex)	2014	Mexico	4.00	0.71	**0.97**
Banco Nacional de México (Citibanamex)	2015		2.70	1.07	**1.12**
Banco Nacional de México (Citibanamex)	2016		2.80	0.94	**1.06**
Bangkok Bank	2016	Thailand	0.20	1.07	**0.95**
Bangkok Bank	2017		0.70	1.06	**0.96**
Bangkok Bank	2018		1.10	1.14	**1.04**
Bank AlJazira	2015	Saudi Arabia	1.20	1.27	**1.18**
Bank AlJazira	2016		2.10	1.09	**1.14**
Bank AlJazira	2017		-0.80	1.27	**1.09**
Bank of Baroda	2016	India	4.90	-0.71	**0.00**
Bank of Baroda	2017		3.30	0.25	**0.55**
Bank of Baroda	2018		3.90	-0.27	**0.25**
Bank of Maharashtra	2015	India	4.90	0.33	**0.75**
Bank of Maharashtra	2016		4.90	0.08	**0.58**
Bank of Maharashtra	2017		3.30	-0.85	**-0.14**
Bank Rakyat Indonesia	2015	Indonesia	6.40	3.02	**2.68**
Bank Rakyat Indonesia	2016		3.50	2.78	**2.31**
Bank Rakyat Indonesia	2017		3.80	2.72	**2.29**
BBVA USA	2014	USA	1.60	0.43	**0.24**
BBVA USA	2015		0.10	0.40	**0.09**
BBVA USA	2016		1.30	0.50	**0.27**
Canadian Western Bank	2015	Canada	1.10	0.99	**1.02**
Canadian Western Bank	2016		1.40	0.81	**0.91**
Canadian Western Bank	2017		1.60	0.94	**0.99**
Central Bank of India	2015	India	4.90	0.22	**0.66**

BankName	Year	g1_country	InflationRate	RoA	eRoA
Central Bank of India	2016		4.90	-0.47	**0.20**
Central Bank of India	2017		3.30	-0.77	**-0.10**
China CITIC Bank International	2016	China	2.00	0.87	**0.92**
China CITIC Bank International	2017		1.60	0.86	**0.89**
China CITIC Bank International	2018		2.10	0.85	**0.92**
Czech Export Bank	2015	Czech Republic	0.30	-0.15	**0.16**
Czech Export Bank	2016		0.70	0.49	**0.65**
Czech Export Bank	2017		2.50	0.36	**0.65**
Dar Es Salaam Bank	2007	Iraq	-10.10	3.60	**2.03**
Dar Es Salaam Bank	2008		12.70	2.84	**2.98**
Dar Es Salaam Bank	2009		6.90	3.09	**2.80**
Dena Bank	2015	India	4.90	0.21	**0.67**
Dena Bank	2016		4.90	-0.71	**0.05**
Dena Bank	2017		3.30	-0.66	**-0.01**
Dhanlaxmi Bank	2014	India	6.70	-1.77	**-0.52**
Dhanlaxmi Bank	2015		4.90	-1.66	**-0.58**
Dhanlaxmi Bank	2016		4.90	-1.11	**-0.21**
European Bank for Reconstruction and Development (EBRD)	2013	United Kingdom	2.30	1.84	**1.64**
European Bank for Reconstruction and Development (EBRD)	2014		1.50	-1.43	**-0.63**
European Bank for Reconstruction and Development (EBRD)	2015		0.40	0.82	**0.82**
Fifth Third Bank	2014	USA	1.60	1.19	**1.10**
Fifth Third Bank	2015		0.10	1.11	**0.94**
Fifth Third Bank	2016		1.30	0.95	**0.92**
First City Monument Bank (FCMB)	2013	Nigeria	8.50	1.67	**1.92**
First City Monument Bank (FCMB)	2014		8.00	2.03	**2.13**
First City Monument Bank (FCMB)	2015		9.00	0.41	**1.14**
First Security Bank	2015	USA	0.10	0.81	**0.82**
First Security Bank	2016		1.30	0.57	**0.75**
First Security Bank	2017		2.10	0.46	**0.73**
General Motors Acceptance Corporation (GMAC)	2014	USA	1.60	0.76	**0.81**
General Motors Acceptance Corporation (GMAC)	2015		0.10	0.83	**0.75**
General Motors Acceptance Corporation (GMAC)	2016		1.30	0.66	**0.72**
Global Bank	2013	Liberia	7.60	1.99	**2.06**
Global Bank	2014		9.90	1.60	**2.03**
Global Bank	2015		7.70	1.56	**1.86**

BankName	Year	g1_country	InflationRate	RoA	eRoA
Guaranty Trust Bank (GTBank)	2013	Nigeria	8.50	4.66	**3.93**
Guaranty Trust Bank (GTBank)	2014		8.00	4.21	**3.60**
Guaranty Trust Bank (GTBank)	2015		9.00	4.04	**3.59**
Home Capital Group Inc.	2015	Canada	1.10	1.41	**1.30**
Home Capital Group Inc.	2016		1.40	1.28	**1.24**
Home Capital Group Inc.	2017		1.60	0.14	**0.46**
ICB Islamic Bank	2015	Bangladesh	6.20	-1.05	**-0.07**
ICB Islamic Bank	2016		5.50	-2.07	**-0.81**
ICB Islamic Bank	2017		5.70	-3.28	**-1.60**
Indian Bank	2012	India	9.50	1.34	**1.77**
Indian Bank	2013		10.00	1.06	**1.60**
Indian Bank	2014		6.70	0.68	**1.11**
Kasikornbank	2012	Thailand	3.00	1.86	**1.64**
Kasikornbank	2013		2.20	1.95	**1.69**
Kasikornbank	2014		1.90	1.97	**1.70**
KCB Bank	2012	Kenya	9.40	3.49	**3.23**
KCB Bank	2013		5.70	3.77	**3.18**
KCB Bank	2014		6.90	3.83	**3.29**
Komercni Banka	2012	Czech Republic	3.30	1.81	**1.72**
Komercni Banka	2013		1.40	1.52	**1.39**
Komercni Banka	2014		0.30	1.43	**1.23**
Kotak Mahindra Bank	2016	India	4.90	1.78	**1.72**
Kotak Mahindra Bank	2017		3.30	1.91	**1.71**
Kotak Mahindra Bank	2018		3.90	2.01	**1.82**
Krungthai Bank	2013	Thailand	2.20	2.54	**2.13**
Krungthai Bank	2014		1.90	3.30	**2.64**
Krungthai Bank	2015		-0.90	3.61	**2.64**
Lloyds Bank	2014	United Kingdom	1.50	0.23	**-0.23**
Lloyds Bank	2015		0.40	0.19	**-0.24**
Lloyds Bank	2016		1.00	0.34	**0.00**
M&T Bank	2015	USA	0.10	1.04	**0.91**
M&T Bank	2016		1.30	1.09	**1.03**
M&T Bank	2017		2.10	1.21	**1.16**
NMB Bank	2016	Zimbabwe	-1.50	3.28	**2.40**
NMB Bank	2017		0.90	1.82	**1.54**
NMB Bank	2018		10.60	1.89	**2.23**
Oppenheimer & Co. (investment bank)	2015	USA	0.10	0.07	**0.32**

BankName	Year	g1_country	InflationRate	RoA	eRoA
Oppenheimer & Co. (investment bank)	2016		1.30	-0.05	**0.33**
Oppenheimer & Co. (investment bank)	2017		2.10	0.98	**1.07**
Public Bank	2013	Malaysia	2.10	1.40	**1.28**
Public Bank	2014		3.10	1.39	**1.32**
Public Bank	2015		2.10	1.43	**1.30**
Punjab & Sind Bank	2014	India	6.70	0.34	**0.89**
Punjab & Sind Bank	2015		4.90	0.13	**0.62**
Punjab & Sind Bank	2016		4.90	0.34	**0.76**
Punjab National Bank (PNB)	2013	India	10.00	1.01	**1.53**
Punjab National Bank (PNB)	2014		6.70	0.65	**1.06**
Punjab National Bank (PNB)	2015		4.90	0.53	**0.85**
Regions Bank	2016	USA	1.30	0.99	**0.96**
Regions Bank	2017		2.10	1.03	**1.04**
Regions Bank	2018		2.40	1.33	**1.26**
Rizal Commercial Banking Corp. (RCBC)	2016	Philippines	1.30	0.78	**0.83**
Rizal Commercial Banking Corp. (RCBC)	2017		2.90	0.74	**0.91**
Rizal Commercial Banking Corp. (RCBC)	2018		5.30	0.71	**1.06**
Russian Standard Bank	2016	Ukraine	13.90	-0.82	**0.65**
Russian Standard Bank	2017		14.40	0.75	**1.74**
Russian Standard Bank	2018		11.00	2.68	**2.80**
Siam Commercial Bank	2015	Thailand	-0.90	1.71	**1.31**
Siam Commercial Bank	2016		0.20	1.67	**1.36**
Siam Commercial Bank	2017		0.70	1.45	**1.23**
Silkbank	2013	Pakistan	7.70	-1.28	**-0.09**
Silkbank	2014		7.20	0.09	**0.79**
Silkbank	2015		2.50	-1.45	**-0.56**
Sparebanken Hedmark	2014	Norway	2.00	2.13	**1.84**
Sparebanken Hedmark	2015		2.20	1.76	**1.61**
Sparebanken Hedmark	2016		3.60	1.39	**1.46**
State Bank of Bikaner and Jaipur (SBBJ)	2015	India	4.90	0.80	**1.08**
State Bank of Bikaner and Jaipur (SBBJ)	2016		4.90	0.80	**1.07**
State Bank of Bikaner and Jaipur (SBBJ)	2017		3.30	0.00	
Sumitomo Mitsui Financial Group	2016	Japan	-0.10	0.97	**0.00**
Sumitomo Mitsui Financial Group	2017		0.50	1.00	**-0.01**
Sumitomo Mitsui Financial Group	2018		1.00	0.37	**-0.45**
SunTrust Bank	2016	USA	1.30	0.94	**0.89**
SunTrust Bank	2017		2.10	1.03	**0.99**
SunTrust Bank	2018		2.40	1.34	**1.21**

BankName	Year	g1_country	InflationRate	RoA	eRoA
Syndicate Bank	2015	India	4.90	0.55	**0.89**
Syndicate Bank	2016		4.90	-0.54	**0.15**
Syndicate Bank	2017		3.30	0.12	**0.50**
Union Bank of Nigeria	2014	Nigeria	8.00	2.55	**2.48**
Union Bank of Nigeria	2015		9.00	1.39	**1.81**
Union Bank of Nigeria	2016		15.70	1.36	**2.28**
United Arab Bank	2015	UAE	4.10	-0.74	**0.00**
United Arab Bank	2016		1.60	-2.33	**-1.23**
United Arab Bank	2017		2.00	0.08	**0.48**
United Bank of India	2014	India	6.70	-1.01	**-0.02**
United Bank of India	2015		4.90	0.21	**0.67**
United Bank of India	2016		4.90	-0.22	**0.38**
Vijaya Bank	2013	India	10.00	0.57	**1.27**
Vijaya Bank	2014		6.70	0.34	**0.88**
Vijaya Bank	2015		4.90	0.31	**0.74**

Appendix 7: Reputational losses (Rl) results

BankName	Year	g1_country	AR	mAR	Rl
Access Bank Plc	2009	Nigeria	6.76	324.19	446.00
Access Bank Plc	2010		3.71	196.34	196.34
Access Bank Plc	2011		3.39	340.31	340.31
Al-Baraka Bank	2015	Pakistan	(0.19)	(46.48)	(45.96)
Al-Baraka Bank	2016		(0.29)	(68.31)	(68.31)
Al-Baraka Bank	2017		(0.36)	(90.41)	(90.41)
Allahabad Bank	2014	India	(0.47)	(172.40)	(171.41)
Allahabad Bank	2015		(0.43)	(158.45)	(158.45)
Allahabad Bank	2016		(0.62)	(225.38)	(225.38)
Banco Nacional de México (Citibanamex)	2014	Mexico	(0.26)	(195.51)	204.49
Banco Nacional de México (Citibanamex)	2015		(0.06)	(39.62)	(39.62)
Banco Nacional de México (Citibanamex)	2016		(0.12)	(66.14)	(66.14)
Bangkok Bank	2016	Thailand	0.12	98.94	99.28
Bangkok Bank	2017		0.10	92.79	92.79
Bangkok Bank	2018		0.10	95.78	95.78
Bank AlJazira	2015	Saudi Arabia	0.09	15.83	16.23
Bank AlJazira	2016		(0.05)	(8.57)	(8.57)
Bank AlJazira	2017		0.18	32.96	32.96
Bank of Baroda	2016	India	(0.71)	(745.38)	(689.63)
Bank of Baroda	2017		(0.30)	(337.84)	(337.84)
Bank of Baroda	2018		(0.51)	(589.77)	(589.77)
Bank of Maharashtra	2015	India	(0.42)	(99.13)	10.11
Bank of Maharashtra	2016		(0.50)	(122.07)	(122.07)
Bank of Maharashtra	2017		(0.71)	(174.60)	(174.60)
Bank Rakyat Indonesia	2015	Indonesia	0.34	218.60	221.19
Bank Rakyat Indonesia	2016		0.47	347.36	347.36
Bank Rakyat Indonesia	2017		0.43	360.16	360.16
BBVA USA	2014	USA	0.19	1,458.61	1,459.71
BBVA USA	2015		0.31	2,556.81	2,556.81
BBVA USA	2016		0.23	1,784.66	1,784.66
Canadian Western Bank	2015	Canada	(0.03)	(5.66)	(2.74)
Canadian Western Bank	2016		(0.11)	(20.04)	(20.04)
Canadian Western Bank	2017		(0.06)	(11.61)	(11.61)
Central Bank of India	2015	India	(0.44)	(222.37)	(221.93)

BankName	Year	g1_country	AR	mAR	RI
Central Bank of India	2016		(0.67)	(308.83)	(308.83)
Central Bank of India	2017		(0.67)	(345.34)	(345.34)
China CITIC Bank International	2016	China	(0.06)	(22.54)	121.03
China CITIC Bank International	2017		(0.03)	(11.91)	(11.91)
China CITIC Bank International	2018		(0.07)	(30.41)	(30.41)
Czech Export Bank	2015	Czech Republic	(0.31)	(11.02)	10.50
Czech Export Bank	2016		(0.16)	(4.91)	(4.91)
Czech Export Bank	2017		(0.29)	(8.65)	(8.65)
Dar Es Salaam Bank	2007	Iraq	1.57	0.62	282.62
Dar Es Salaam Bank	2008		(0.14)	(0.05)	(0.05)
Dar Es Salaam Bank	2009		0.28	0.15	0.15
Dena Bank	2015	India	(0.46)	(96.66)	(62.33)
Dena Bank	2016		(0.76)	(153.38)	(153.38)
Dena Bank	2017		(0.65)	(130.06)	(130.06)
Dhanlaxmi Bank	2014	India	(1.24)	(30.52)	(7.40)
Dhanlaxmi Bank	2015		(1.08)	(24.98)	(24.98)
Dhanlaxmi Bank	2016		(0.90)	(16.99)	(16.99)
European Bank for Reconstruction and Development (EBRD)	2013	United Kingdom	0.21	138.98	140.38
European Bank for Reconstruction and Development (EBRD)	2014		(0.79)	(503.95)	(503.95)
European Bank for Reconstruction and Development (EBRD)	2015		0.00	1.36	1.36
Fifth Third Bank	2014	USA	0.09	118.08	130.08
Fifth Third Bank	2015		0.16	231.68	231.68
Fifth Third Bank	2016		0.02	30.72	30.72
First City Monument Bank (FCMB)	2013	Nigeria	(0.25)	(15.76)	(15.57)
First City Monument Bank (FCMB)	2014		(0.10)	(6.54)	(6.54)
First City Monument Bank (FCMB)	2015		(0.74)	(42.80)	(42.80)
First Security Bank	2015	USA	(0.01)	(0.06)	0.32
First Security Bank	2016		(0.18)	(1.14)	(1.14)
First Security Bank	2017		(0.26)	(1.57)	(1.57)
General Motors Acceptance Corporation (GMAC)	2014	USA	(0.05)	(72.33)	(65.33)
General Motors Acceptance Corporation (GMAC)	2015		0.08	133.32	133.32
General Motors Acceptance Corporation (GMAC)	2016		(0.06)	(96.14)	(96.14)
Global Bank	2013	Liberia	(0.07)	(2.53)	(2.23)
Global Bank	2014		(0.43)	(19.16)	(19.16)
Global Bank	2015		(0.30)	(16.15)	(16.15)

BankName	Year	g1_country	AR	mAR	RI
Guaranty Trust Bank (GTBank)	2013	Nigeria	0.73	95.88	100.84
Guaranty Trust Bank (GTBank)	2014		0.61	78.92	78.92
Guaranty Trust Bank (GTBank)	2015		0.45	57.18	57.18
Home Capital Group Inc.	2015	Canada	0.10	15.39	1,526.56
Home Capital Group Inc.	2016		0.05	6.99	6.99
Home Capital Group Inc.	2017		(0.32)	(45.13)	(45.13)
ICB Islamic Bank	2015	Bangladesh	(0.99)	(1.61)	74.17
ICB Islamic Bank	2016		(1.27)	(1.98)	(1.98)
ICB Islamic Bank	2017		(1.68)	(2.39)	(2.39)
Indian Bank	2012	India	(0.42)	(117.78)	(117.49)
Indian Bank	2013		(0.54)	(161.46)	(161.46)
Indian Bank	2014		(0.43)	(134.89)	(134.89)
Kasikornbank	2012	Thailand	0.22	150.08	150.19
Kasikornbank	2013		0.26	180.80	180.80
Kasikornbank	2014		0.27	195.93	195.93
KCB Bank	2012	Kenya	0.26	11.10	11.31
KCB Bank	2013		0.59	26.85	26.85
KCB Bank	2014		0.54	29.41	29.41
Komercni Banka	2012	Czech Republic	0.09	36.40	113.14
Komercni Banka	2013		0.13	56.11	56.11
Komercni Banka	2014		0.19	80.99	80.99
Kotak Mahindra Bank	2016	India	0.06	21.42	26.48
Kotak Mahindra Bank	2017		0.20	84.01	84.01
Kotak Mahindra Bank	2018		0.19	99.78	99.78
Krungthai Bank	2013	Thailand	0.41	6.53	7.12
Krungthai Bank	2014		0.66	10.97	10.97
Krungthai Bank	2015		0.97	16.28	16.28
Lloyds Bank	2014	United Kingdom	0.46	6,107.48	6,107.60
Lloyds Bank	2015		0.43	5,107.37	5,107.37
Lloyds Bank	2016		0.34	3,392.20	3,392.20
M&T Bank	2015	USA	0.13	161.87	168.57
M&T Bank	2016		0.06	70.05	70.05
M&T Bank	2017		0.04	52.72	52.72
NMB Bank	2016	Zimbabwe	0.88	20.00	20.35
NMB Bank	2017		0.28	6.92	6.92
NMB Bank	2018		(0.34)	(8.37)	(8.37)
Oppenheimer & Co. (investment bank)	2015	USA	(0.25)	(6.78)	28.22

BankName	Year	g1_country	AR	mAR	RI
Oppenheimer & Co. (investment bank)	2016		(0.38)	(8.51)	(8.51)
Oppenheimer & Co. (investment bank)	2017		(0.10)	(2.33)	(2.33)
Public Bank	2013	Malaysia	0.12	111.14	111.43
Public Bank	2014		0.06	63.64	63.64
Public Bank	2015		0.13	107.46	107.46
Punjab & Sind Bank	2014	India	(0.55)	(86.66)	(86.37)
Punjab & Sind Bank	2015		(0.49)	(77.40)	(77.40)
Punjab & Sind Bank	2016		(0.42)	(65.47)	(65.47)
Punjab National Bank (PNB)	2013	India	(0.52)	(458.61)	(457.75)
Punjab National Bank (PNB)	2014		(0.41)	(373.92)	(373.92)
Punjab National Bank (PNB)	2015		(0.32)	(305.95)	(305.95)
Regions Bank	2016	USA	0.03	32.70	42.90
Regions Bank	2017		(0.01)	(11.01)	(11.01)
Regions Bank	2018		0.08	96.94	96.94
Rizal Commercial Banking Corp. (RCBC)	2016	Philippines	(0.05)	(5.32)	156.68
Rizal Commercial Banking Corp. (RCBC)	2017		(0.17)	(19.14)	(19.14)
Rizal Commercial Banking Corp. (RCBC)	2018		(0.35)	(42.88)	(42.88)
Russian Standard Bank	2016	Ukraine	(1.47)	(81.19)	(48.07)
Russian Standard Bank	2017		(0.99)	(54.26)	(54.26)
Russian Standard Bank	2018		(0.12)	(5.55)	(5.55)
Siam Commercial Bank	2015	Thailand	0.39	304.12	349.88
Siam Commercial Bank	2016		0.32	256.11	256.11
Siam Commercial Bank	2017		0.23	208.97	208.97
Silkbank	2013	Pakistan	(1.18)	(10.30)	(9.04)
Silkbank	2014		(0.70)	(7.15)	(7.15)
Silkbank	2015		(0.89)	(11.28)	(11.28)
Sparebanken Hedmark	2014	Norway	0.29	19.24	21.85
Sparebanken Hedmark	2015		0.15	9.56	9.56
Sparebanken Hedmark	2016		(0.07)	(7.64)	(7.64)
State Bank of Bikaner and Jaipur (SBBJ)	2015	India	(0.27)	(44.64)	(33.33)
State Bank of Bikaner and Jaipur (SBBJ)	2016		(0.27)	(45.05)	(45.05)
State Bank of Bikaner and Jaipur (SBBJ)	2017		0.00		
Sumitomo Mitsui Financial Group	2016	Japan	0.97	16,029.41	16,039.55
Sumitomo Mitsui Financial Group	2017		1.01	17,979.40	17,979.40
Sumitomo Mitsui Financial Group	2018		0.82	15,294.65	15,294.65
SunTrust Bank	2016	USA	0.06	114.47	115.83
SunTrust Bank	2017		0.04	76.44	76.44
SunTrust Bank	2018		0.13	279.54	279.54

BankName	**Year**	**g1_country**	**AR**	**mAR**	**Rl**
Syndicate Bank	2015	India	(0.34)	(163.98)	(162.07)
Syndicate Bank	2016		(0.69)	(320.92)	(320.92)
Syndicate Bank	2017		(0.38)	(177.00)	(177.00)
Union Bank of Nigeria	2014	Nigeria	0.07	3.62	7.25
Union Bank of Nigeria	2015		(0.42)	(21.92)	(21.92)
Union Bank of Nigeria	2016		(0.92)	(36.61)	(36.61)
United Arab Bank	2015	UAE	(0.74)	(47.68)	(46.00)
United Arab Bank	2016		(1.10)	(63.77)	(63.77)
United Arab Bank	2017		(0.39)	(22.24)	(22.24)
United Bank of India	2014	India	(0.99)	(206.43)	(191.18)
United Bank of India	2015		(0.47)	(91.82)	(91.82)
United Bank of India	2016		(0.60)	(117.80)	(117.80)
Vijaya Bank	2013	India	(0.71)	(143.63)	(143.26)
Vijaya Bank	2014		(0.55)	(125.65)	(125.65)
Vijaya Bank	2015		(0.43)	(97.95)	(97.95)

Appendix 8: Pearson correlation results for size and reputational losses

BankName	Pearson Coef.	g1_country	g2_Region
Access Bank Plc	0.00196	Nigeria	Western Africa
Al-Baraka Bank	(0.40659)	Pakistan	Southern Asia
Allahabad Bank	0.63751	India	Southern Asia
Banco Nacional de México (Citibanamex)	0.83927	Mexico	Central America
Bangkok Bank	(0.82219)	Thailand	South-Eastern Asia
Bank AlJazira	0.28530	Saudi Arabia	Western Asia (incl. Middle East)
Bank of Baroda	0.40466	India	Southern Asia
Bank of Maharashtra	(0.99645)	India	Southern Asia
Bank Rakyat Indonesia	0.92791	Indonesia	South-Eastern Asia
BBVA USA	0.98745	United States of America	Northern America
Canadian Western Bank	(0.45619)	Canada	Northern America
Central Bank of India	(0.02987)	India	Southern Asia
China CITIC Bank International	(0.97586)	China	Eastern Asia
Czech Export Bank	0.98994	Czech Republic	Eastern Europe
Dar Es Salaam Bank	(0.35036)	Iraq	Western Asia (incl. Middle East)
Dena Bank	0.89076	India	Southern Asia
Dhanlaxmi Bank	0.30312	India	Southern Asia
European Bank for Reconstruction and Development (EBRD)	0.23552	United Kingdom	Northern Europe
Fifth Third Bank	(0.31272)	United States of America	Northern America
First City Monument Bank (FCMB)	0.99734	Nigeria	Western Africa
First Security Bank	(0.38569)	United States of America	Northern America
General Motors Acceptance Corporation (GMAC)	(0.03814)	United States of America	Northern America
Global Bank	(0.71302)	Liberia	Western Africa
Guaranty Trust Bank (GTBank)	0.99995	Nigeria	Western Africa
Home Capital Group Inc.	0.19738	Canada	Northern America
ICB Islamic Bank	0.76134	Bangladesh	Southern Asia
Indian Bank	(0.50307)	India	Southern Asia
Kasikornbank	0.96793	Thailand	South-Eastern Asia
KCB Bank	0.76120	Kenya	Eastern Africa
Komercni Banka	(0.87281)	Czech Republic	Eastern Europe
Kotak Mahindra Bank	0.90780	India	Southern Asia
Krungthai Bank	0.90063	Thailand	South-Eastern Asia

Lloyds Bank	0.99620	United Kingdom	Northern Europe
M&T Bank	0.51139	United States of America	Northern America
NMB Bank	(0.88262)	Zimbabwe	Eastern Africa
Oppenheimer & Co. (investment bank)	0.95728	United States of America	Northern America
Public Bank	(0.74971)	Malaysia	South-Eastern Asia
Punjab & Sind Bank	(0.99446)	India	Southern Asia
Punjab National Bank (PNB)	0.99278	India	Southern Asia
Regions Bank	0.77687	United States of America	Northern America
Rizal Commercial Banking Corp. (RCBC)	(0.81373)	Philippines	South-Eastern Asia
Russian Standard Bank	(0.98843)	Ukraine	Eastern Europe
Siam Commercial Bank	(0.89999)	Thailand	South-Eastern Asia
Silkbank	(0.65874)	Pakistan	Southern Asia
Sparebanken Hedmark	(0.88479)	Norway	Northern Europe
State Bank of Bikaner and Jaipur (SBBJ)		India	Southern Asia
Sumitomo Mitsui Financial Group	(0.21281)	Japan	Eastern Asia
SunTrust Bank	0.96199	United States of America	Northern America
Syndicate Bank	0.42793	India	Southern Asia
Union Bank of Nigeria	0.84957	Nigeria	Western Africa
United Arab Bank	(0.24524)	United Arab Emirates	Western Asia (incl. Middle East)
United Bank of India	(0.92905)	India	Southern Asia
Vijaya Bank	0.78474	India	Southern Asia

Appendix 9: Tukey HSD Post Hoc results

No	Regions Comparison	difference	Lower	Upper	p adj
1	Eastern Africa-Central America	-188.65776	-7946.6481	7569.33253	1
2	Eastern Asia-Central America	7875.80395	117.813662	15633.7942	0.04404147
3	Eastern Europe-Central America	-179.29602	-7493.5994	7135.00737	1
4	Northern America-Central America	135.925528	-6507.6204	6779.4715	1
5	Northern Europe-Central America	1885.45737	-5428.846	9199.76075	0.99692874
6	South-Eastern Asia-Central America	-47.948145	-6819.6772	6723.78095	1
7	Southern Asia-Central America	-339.09829	-6857.1139	6178.91728	1
8	Western Africa-Central America	-97.229128	-7036.1866	6841.72833	1
9	Western Asia (incl. Middle East)-Central America	-120.20342	-7434.5068	7194.09997	1
10	Eastern Asia-Eastern Africa	8064.46171	1730.08917	14398.8343	0.00406896
11	Eastern Europe-Eastern Africa	9.36174168	-5773.1028	5791.82629	1
12	Northern America-Eastern Africa	324.583289	-4582.0006	5231.16716	0.99999997
13	Northern Europe-Eastern Africa	2074.11513	-3708.3494	7856.57968	0.96905489
14	South-Eastern Asia-Eastern Africa	140.709616	-4938.0872	5219.50644	1
15	Southern Asia-Eastern Africa	-150.44053	-4885.6691	4584.788	1
16	Western Africa-Eastern Africa	91.4286332	-5208.2877	5391.14494	1
17	Western Asia (incl. Middle East)-Eastern Africa	68.4543419	-5714.0102	5850.91889	1
18	Eastern Europe-Eastern Asia	-8055.1	-13837.565	-2272.6354	0.00120719
19	Northern America-Eastern Asia	-7739.8784	-12646.462	-2833.2945	0.00017159
20	Northern Europe-Eastern Asia	-5990.3466	-11772.811	-207.88203	0.0369216
21	South-Eastern Asia-Eastern Asia	-7923.7521	-13002.549	-2844.9553	0.00020666
22	Southern Asia-Eastern Asia	-8214.9022	-12950.131	-3479.6737	3.0916E-05
23	Western Africa-Eastern Asia	-7973.0331	-13272.749	-2673.3168	0.000375
24	Western Asia (incl. Middle East)-Eastern Asia	-7996.0074	-13778.472	-2213.5428	0.00134152
25	Northern America-Eastern Europe	315.221547	-3854.5729	4485.01603	0.9999999
26	Northern Europe-Eastern Europe	2064.75338	-3107.2401	7236.74691	0.94046897
27	South-Eastern Asia-Eastern Europe	131.347874	-4239.7845	4502.48021	1
28	Southern Asia-Eastern Europe	-159.80227	-4126.5402	3806.93568	1
29	Western Africa-Eastern Europe	82.0668915	-4543.9047	4708.03853	1
30	Western Asia (incl. Middle East)-Eastern Europe	59.0926003	-5112.9009	5231.08613	1
31	Northern Europe-Northern America	1749.53184	-2420.2627	5919.32633	0.9208748
32	South-Eastern Asia-Northern America	-183.87367	-3305.4865	2937.7392	0.99999999
33	Southern Asia-Northern America	-475.02382	-2999.4404	2049.39276	0.99974321
34	Western Africa-Northern America	-233.15466	-3702.6334	3236.32408	0.99999997
35	Western Asia (incl. Middle East)-Northern America	-256.12895	-4425.9234	3913.66554	0.99999998
36	South-Eastern Asia-Northern Europe	-1933.4055	-6304.5378	2437.72682	0.8945326
37	Southern Asia-Northern Europe	-2224.5557	-6191.2936	1742.1823	0.68805389
38	Western Africa-Northern Europe	-1982.6865	-6608.6581	2643.28515	0.91098716
39	Western Asia (incl. Middle East)-Northern Europe	-2005.6608	-7177.6543	3166.33274	0.94987701
40	Southern Asia-South-Eastern Asia	-291.15015	-3135.8454	2553.54507	0.99999857
41	Western Africa-South-Eastern Asia	-49.280982	-3758.3098	3659.7478	1
42	Western Asia (incl. Middle East)-South-Eastern Asia	-72.255274	-4443.3876	4298.87706	1
43	Western Africa-Southern Asia	241.869166	-2980.724	3464.46232	0.99999991
44	Western Asia (incl. Middle East)-Southern Asia	218.894875	-3747.8431	4185.63283	0.99999999
45	Western Asia (incl. Middle East)-Western Africa	-22.974291	-4648.9459	4602.99735	1

Appendix 10: Perspectives for an adjusted approach for assessing spillovers effects.

Introduction

Understanding the spillover effects of operational and reputational events is crucial, not only for the affected institution but also for stakeholders of other banks that might indirectly feel the tremors of such events. To address this concern, we preliminary aim to explore how the RoA of neighboring banks might be influenced following a reputational setback experienced by a particular commercial bank.

Eckert & Gatzert, (2019b) developed a model to assess the spillover effects, particularly in the context of stock market data. Their approach is grounded in the understanding that operational losses in financial institutions can have ramifications beyond the affected institution itself. They model these effects using Cumulative Abnormal Returns (CARs) which act as a measure of the spillover effect.

In their model:

- Spillover effects are stochastic in nature, and the severity best fits a Laplace distribution.
- The cumulative abnormal return follows a Laplace distribution with parameters determined by the average CAR and its standard deviation in the sample.
- Their methodology accommodates both competitive and contagion effects and explicitly recognizes that abnormal returns can differ across firms.
- The CAR from spillover effects is modeled based on three different approaches, with one of the approaches focusing on integrating influencing factors like firm sizes and geographical distance between firms.

Eckert and Gatzert's original framework predominantly focuses on stock market data. However, with the perspective of investigating the effects on year-end financial metrics, the aim is to tailor their model to scrutinize the ripple effects within the purview of historical RoA data. Upon establishing the extent of reputational damage (**$Rl_{i,t}$**) for banks that have experienced operational losses, the subsequent steps outlined below would facilitate the evaluation of potential spillover effects on neighboring banks, ensuring they have not been influenced by any direct operational losses or other intervening events:

Quantify the Spillover Impact on Neighboring Banks

The first step aims to evaluate, for each bank that has experienced an operational loss, its potential influence on the RoA of neighboring banks. This is a direct adaptation of the CAR mechanism from Eckert and Gatzert's model but is tailored to RoA. The spillover effect for a neighboring bank 'l' due to an operational loss event in bank 'i' would be captured as:

$$Sp_l = \sum_{i=1}^{I_l} \sum_{u=1}^{U} Z_{l;i,u}$$

$\boldsymbol{Sp_l}$: represents the spillover effect on the RoA of a neighboring bank 'l' due to an operational loss event in bank 'i'. It's essential to determine how an operational loss in one bank may influence the RoA in another, capturing the interbank dynamic within the financial sector. This is an adaptation of the CAR (Cumulative Abnormal Returns) concept from Eckert and Gatzert's model, which shifted from stock returns to RoA for the study's analysis.

$\boldsymbol{\sum_{i=1}^{I_l}}$ **:** This summation term iterates over all banks 'I' that have experienced operational loss events and potentially influence bank 'l'. It acknowledges that multiple banks' operational loss events could influence a single neighboring bank, making a cumulative assessment vital.

$\boldsymbol{\sum_{i=1}^{I_l}}$: This term sums over all operational loss events of type 'u' in each bank 'i'. A single bank could experience multiple types or instances of internal frauds or other operational event types in a single year, each possibly having its distinct spillover effect. Thus, accounting for each type ensures granularity in the assessment.

$\boldsymbol{Z_{l;i,u}}$**:** Represents the deviation in RoA in bank 'l' due to a specific operational loss event of type 'u' in bank 'i'. This component would capture the essence of the spillover: quantifying how an event in one bank impacts another. We would consider this as the RoA counterpart to the abnormal stock return in Eckert and Gatzert's model.

Incorporation of influential determinants

In adapting Eckert and Gatzert's foundational model to the specific context of year-end financial metrics like RoA, it becomes imperative to embed additional determinants that could potentially moderate the spillover effects. Specifically, variables such as 'Bank's size' and 'Geographical location' are integrated into the model, resonating with the original model's emphasis on the significance of firm size and geographical proximity. By leveraging regression analysis, this enhanced model aims to capture not just the direct repercussions of spillover effects but also the nuanced influences exerted by these pivotal variables.

To understand how the spillover effects vary contingent on the bank's size (s) and geographical location (g) of the banks, a moderated regression analysis could be performed where the spillover effect on RoA (Sp_l) serves as the dependent variable. The size (s) and geographical location (g) of the bank would be the moderating variables.

$$\boldsymbol{Sp_l} = \beta_0 + (\beta_1 \times \text{e}_i) + (\beta_2 \times s_l) + (\beta_3 \times g_l) + \epsilon_l$$

Where:

$\boldsymbol{\beta_0}$ is the intercept, representing the expected mean value of the dependent variable when all independent variables are set to zero.

e_i is the primary independent variable and represents the specific internal fraud event in bank '*i*'. β_1 is its coefficient, indicating the change in the RoA deviation for bank '*l*' for every one-unit change in the operational loss event, keeping other factors constant.

s_l This independent variable captures the size of the bank '*l*'. β_2 is its coefficient, reflecting the change in the RoA deviation for bank '*l*' for every one-unit change in bank size, with other variables held constant.

g_l This represents the geographical region of bank '*l*' and is another independent variable. β_3 is its coefficient, signifying the change in the RoA deviation for bank '*l*' for every one-unit change in the region variable while keeping other factors constant.

ϵ_l is the error term for bank '*l*' accounting for the variation in the dependent variable not explained by the independent variables.

In essence, this regression model aims to decipher the relationship between the RoA deviation experienced by a bank and the operational loss event of another bank, while also accounting for the size and geographical region of the bank in question. The coefficients β_1, β_2 and β_3 provide insight into the magnitude and direction (positive or negative) of these relationships.

Validation of spillover effects

To ensure the robustness of the spillover effects analysis, it will be essential to statistically validate the relationship between the RoA deviations in neighboring banks '*l*' and the operational loss '*u*' events in the focal bank '*i*'.

Specifically, the coefficient $Z_{l;i,u}$ would represent the magnitude of the spillover effect. Its statistical significance will provide evidence as to whether an operational loss event '*u*' in one bank '*i*' has a meaningful impact on the RoA of a neighboring bank '*l*'. The validation would cover:

- Estimate the Coefficient: Using regression analysis, determine the value of $Z_{l;i,u}$, which quantifies the RoA deviation in a neighboring bank '*l*' due to an operational loss event '*u*' in bank '*i*'.

- Hypothesis Testing: Test hypothesis of spillover effects implying that $Z_{l;i,u} = 0$ (null hypothesis) or $Z_{l;i,u} \neq 0$ (alternative hypothesis).

- Significance Test: Examining the p-value associated with $Z_{l;i,u}$, will determine if the observed relationship is statistically significant. A p-value less than the chosen significance level (commonly 0.05) would lead to rejecting the null hypothesis in favor of the alternative, suggesting a significant spillover effect.
- Confidence Intervals: Besides the p-value, compute confidence intervals for $Z_{l;i,u}$. If the interval does not contain zero, it will provide further evidence of a significant spillover effect.

Comparative analysis with unaffected banks

To bolster the robustness of the model on the spillover effects, it will be beneficial to juxtapose the RoA trajectory of potentially influenced banks against those that remained untouched by such operational loss events. By drawing this comparison, we aim to:

- Establish a baseline: Unaffected banks serve as a control group, allowing to establishment of a baseline RoA trajectory. This "business-as-usual" trajectory provides a reference point against which the RoA deviations of potentially influenced banks can be measured.

- Quantify the magnitude: By contrasting the two trajectories, quantify the magnitude of the deviation attributable to spillover effects. Such a quantified difference offers a clear representation of the real-world impact of the reputational damage events on neighboring banks.

- Enhance credibility: Establishing that the deviations in RoA are unique to banks in close proximity to the focal banks (those with operational loss events, and subsequent reputational damage) and not observed in unaffected banks will strengthen the credibility of the findings.

Longitudinal examination of spillover impacts

Understanding the temporal evolution of the spillover effects is important for capturing their sustained impacts on neighboring banks. Drawing inspiration from the cumulative dimension of CARs in Eckert and Gatzert's model, future studies could extend the analysis to trace the RoA trajectory of neighboring banks over multiple years following the operational loss event (3 years similarly and above). This longitudinal approach would serve several purposes:

- Depth of impact: Provide a nuanced understanding of how deep the repercussions of the reputational damage are felt by neighboring banks.
- Duration and decay: By monitoring RoA over an extended period, ascertain the duration for which the spillover effects persist. Additionally, it will allow us to identify any potential decay or intensification in the effects as time progresses.
- Patterns of recovery: The temporal analysis could potentially reveal patterns in how neighboring banks recover (or further decline) in the aftermath of the event, shedding light on the resilience and adaptability of these institutions.

In sum, this longitudinal examination won't just quantify the spillover effects but will also paint a comprehensive picture of their lifecycle, from onset to potential recovery or exacerbation, providing a holistic view of the event's ripple effects through the banking ecosystem.