The Effect of Risk Management on the Efficiency of Financial Institutions

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DOCTORAL THESIS

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UTJECAJ UPRAVLJANJA RIZICIMA NA EFIKASNOST FINANCIJSKIH INSTITUCIJA

DOKTORSKI RAD

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Dedicated to Marijan Petrović (1963–2023)

ABSTRACT

Financial institutions, particularly banks and insurance companies, play a pivotal role in the modern economy by providing services that reduce risks, allocate capital, and enhance financial stability. A well-functioning financial system is essential for economic growth, making efficiency in financial institutions crucial. Efficiency traditionally relies on metrics like ROA and ROE, but recent decades have shifted towards assessing input-output optimization using parametric and nonparametric models. Despite extensive research on banks and, to a lesser extent, insurance companies, consensus is lacking on key efficiency determinants, optimal evaluation models, and the impact of risk management practices.

This doctoral dissertation systematically analyses the efficiency of financial institutions, focusing on the effect of risk management. It synthesizes prior research and defines a theoretical framework through three interconnected scientific articles. The first paper reviews the methods, variables, and approaches to efficiency, with an emphasis on risk management. Building on these insights, the second and third papers develop Risk Management Indices (RMI) using the constrained Data Envelopment Analysis (DEA) Benefit of the Doubt (BoD) model on longitudinal samples of 589 banks (2015–2021) and 744 insurers (2012–2021) from the Obris database. The RMIs were used to test the effect of risk management on efficiency via robust panel data models.

The results indicate that risk management positively impacts efficiency, more significantly in insurers than banks. Key drivers include capital adequacy and management efficiency for banks, with solvency and capital adequacy for insurers. This research highlights the importance of integrating risk management into efficiency assessments, advancing theory and practice.

Key words: efficiency, risk management, financial institutions, composite indices, banks, insurance companies, risk-adjusted efficiency, composite risk management index, DEA BoD

JEL classification codes: C14, C61, D24, G21, G22

SAŽETAK

Financijske institucije, poput banaka i osiguravajućih društava, ključne su za razvoj moderne ekonomije, obnašajući funkcije financijskih posrednika u svrhu smanjenja transakcijskih troškova, alokacije kapitala i smanjenja rizika vezanih uz imovinu i ulaganja. Njihova efikasnost, često mjerena pokazateljima profitabilnosti poput povrata na imovinu (ROA) i povrata na kapital (ROE), ima značajan utjecaj na ekonomsku stabilnost i rast. Efikasnost se definira kao optimizacija resursa, a istraživanja posljednjih desetljeća fokusiraju se na procjenu operativne učinkovitosti putem parametarskih i ne parametarskih modela.

Predmet ovog doktorskog rada je analiza dosadašnjih istraživanja u svrhu definiranja teorijskog okvira i metoda procjene efikasnosti financijskih institucija, s posebnim naglaskom na utjecaj upravljanja rizicima. Rad se temelji na tri povezana znanstvena rada, od kojih prvi sistematizira metode i najčešće korištene varijable u procjeni efikasnosti. Daljnji radovi razvijaju indekse upravljanja rizicima (RMI) koristeći DEA BoD model na uzorcima 589 banaka u razdoblju od 2015. do 2021. i 744 osiguravajućih društava u razdoblju od 2012. do 2021. prikupljenih iz Orbis baze. Rezultati istraživanja pokazuju da upravljanje rizicima pozitivno utječe na efikasnost, osobito kod osiguravajućih društava, pri čemu su ključni pokazatelji adekvatnost kapitala i efikasnost managementa kod banaka te solventnost i adekvatnost kapitala kod osiguranja.

Ovo istraživanje doprinosi razumijevanju utjecaja upravljanja rizicima na efikasnost te naglašava važnost daljnjih istraživanja i razvoja kompozitnih indeksa poput RMI-ja. Također upućuje na potrebu za uključivanjem upravljanja rizicima u strategije financijskih institucija radi postizanja veće stabilnosti i efikasnosti sustava.

Ključne riječi: efikasnost, upravljanje rizicima, financijske institucije, kompozitni indeksi, banke, osiguravajuća društva, indeks upravljanja rizicima, DEA BoD

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PROŠIRENI SAŽETAK

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kategorizirati kao ulazne i izlazne varijable prilikom procijene efikasnosti financijskih institucija. Usprkos brojnim empirijskim istraživanjima, utjecaj aktivnosti upravljanja rizicima na efikasnost financijskih institucija još uvijek nije definiran što predstavlja područje interesa ovog doktorskog rada. Rezultati bibliografske analize ukazuju na novi trend razvijanja kompozitnih indeksa u cilju evaluacije utjecaja aktivnosti upravljanja rizicima na efikasnost kao i na stabilnost financijskih institucija. Stoga zaključci bibliografske analize predlažu razvoj kompozitnog indeksa upravljanja rizicima (eng. *Risk Management Index – RMI*) u cilju procjene rizikom prilagođene (*risk-adjusted*) efikasnosti financijskih institucija.

Sistematski pregled literature usmjerio je odabir metode i varijabli u za razvoj RMI za banke i osiguravajuća društva zasebno. Drugi znanstveni rad usmjerava se na razvoj RMI s ciljem procjene efikasnosti uzimajući u obzir utjecaj upravljanja rizicima na efikasnost banaka. Kako bi se postigao navedeni cilj, implementirana je CAMEL (*Capital Adequacy, Asset Quality, Management Efficiency, Earnings, Liquidity)* klasifikacija pomoću koje se definiralo 5 pod-indeksa (adekvatnost kapitala, kvaliteta imovine, efikasnost menadžmenta, prihoda i likvidnosti) koji zajedno formiraju RMI. RMI je konstruiran od 16 financijskih pokazatelja korištenjem ograničenog DEA BoD (*Data Envelopment Analysis Benefit of the Doubt)* modela čija je prednost alokacija težinskog pondera na temelju podataka, čime se uklanja subjektivnost. RMI izračunat je i ekonometrijski testiran na međunarodnom longitudinalnom uzorku od 589 banaka u razdoblju od 2015. do 2021. godine.

Iako banke i osiguravajuća društva dijele brojne sličnosti kao financijski posrednici, u suštini se razlikuju po svojim operativnim aktivnostima. Temeljem navedenog, treći znanstveni rad fokusira se na razvoj RMI za osiguravajuća društva. RMI sastavlja se od 15 financijskih pokazatelja specifičnih za osiguravajuća društva, podjednako podijeljenih u pet pod-indikatora: adekvatnost kapitala (*Capital Adequacy*), kvaliteta imovine (*Asset Quality*), efikasnost managementa (*Management Efficiency*), prihodi (*Earnings*) i solventnost (*Solvency*) što na engleskome čini kraticu CAMES u odnosu na CAMEL klasifikaciju kod banaka, ističući važnost solventnosti kod osiguravajućih društava. Korištenjem ograničenog DEA BoD modela RMI je izračunat i ekonometrijski testiran na međunarodnom longitudinalnom uzorku od 744 osiguravajućih društava u razdoblju od 2012. do 2021. godine.

Rezultati istraživanja u ovom doktorskom radu pokazuju da upravljanje rizicima pozitivno utječe na efikasnost, osobito kod osiguravajućih društava, pri čemu su ključni pokazatelji adekvatnost kapitala, efikasnost managementa kod banaka, te solventnost i adekvatnost kapitala kod osiguravajućih društava. Ovo istraživanje doprinosi razumijevanju utjecaja upravljanja rizicima na efikasnost te naglašava važnost daljnjih istraživanja i razvoja kompozitnih indeksa poput RMI-ja. Rezultati ističu potrebu za uključivanjem upravljanja rizicima u strategije financijskih institucija radi postizanja veće efikasnosti, održivosti, stabilnosti i razvoja financijskog sustava.

Ostatak doktorskog rada sistematiziran je na sljedeći način. Nakon uvoda koji detaljnije razlaže problem i predmet istraživanja, ali i ciljeve doktorskog rada, slijedi kratki pregled literature korištene u znanstvenim radovima koji su sastavni dio ovog doktorskog rada. U nastavku se detaljnije razlaže korištena metodologija te se prikazuju rezultati istraživanja. Rad završava zaključnim razmatranjima. Usprkos brojnim empirijskim istraživanjima na temu efikasnosti financijskih institucija, determinante efikasnosti još uvijek nisu jasno definirane. Današnja empirijska istraživanja usmjeruju se prvenstveno na utjecaj regulacije i konsolidacije financijskog sustava na efikasnost financijskih institucija. Recentni pregledi literature ukazuju na formiranje novih područja istraživanja, poput egzogenih (okolišnih) utjecaja, utjecaja društvenog odgovornog poslovanja, te utjecaja rizika i aktivnosti upravljanja rizicima na efikasnost financijskih institucija. Pregled relevantnih istraživanja s posebnim naglaskom na utjecaj upravljanja rizicima na efikasnost financijskih institucija i primjenu kompozitnih indeksa nalazi se u drugom poglavlju. Pregled literature ističe prednosti i nedostatke metoda procjene efikasnosti te buduća područja od interesa za istraživače.

Temeljem navedenog, neistraženost utjecaja upravljanja rizicima na efikasnost financijskih institucija glavni je problem, odnosno tema ovog doktorskog rada s obzirom da nedorečenost utjecaja upravljanja rizicima na efikasnost financijskih institucija zahtijeva dodatna teorijska i empirijska razmatranja. U cilju utvrđivanja spomenutog efekta definirane su četiri hipoteze, grupirane po dvije za vrednovanje utjecaja upravljanja rizikom na efikasnost banka razvojem RMI za banke i isto tako po dvije za evaluaciju utjecaja upravljanja rizikom na efikasnost osiguravajućih društava razvojem njima adekvatnim RMI. Ovaj doktorski rad, kao konceptualne ciljeve predlaže teorijski okvir za procjenu efikasnosti financijskih institucija uzimajući u obzir utjecaj upravljanja rizicima. Navedeno definira metodološke odrednice, poput odabira modela i varijabli prilikom razvoja RMI-ijeva s ciljem empirijskog ispitivanja utjecaja upravljanja rizicima na efikasnost financijskih institucija.

Treće poglavlje doktorskog rada posvećeno je metodologiji istraživanja. U istome navodi se *Web of Science* baza kao izvor podataka za sistematski pregled literature te Orbis baza za izvor podataka korištenih u razvoju indeksa upravljanja rizicima (RMI). Kombinacija teorijskog i konceptualnog istraživanja je korištena u ovom radu, uključujući induktivnu i deduktivnu metodu, metode analize i sinteze, klasifikacije i deskripcije koje su korištene u teorijskom dijelu istraživanja prožete kroz postupke PRISMA metode za izradu strukturnog pregleda literature. Nadalje, ovo poglavlje detaljnije pojašnjava metodologiju korištenu u empirijskim dijelu rada, odnosno navode se specifičnosti DEA BoD metodologije korištene za razvoj RMI-ija za banke i za osiguranja.

Detaljan prikaz rezultata istraživanja dan je u četvrtom poglavlju rada. Prethodno ekonometrijskoj analizi, prikazani su rezultati RMI-ijeva zasebno za banke i za osiguravajuća društva. Kod RMI banaka ističu se pod-indikatori kvaliteta imovine, efikasnost managementa i likvidnost najvećim prosječnim težinskim ponderima. Pod-indikatori RMI-a s najvećim prosječnim težinskim ponderima za osiguranja su adekvatnost kapitala i solventnost. U ovom poglavlju prikazuju se rezultati ekonometrijskih testova hipoteza vezane uz postojanje veze između razvijenog RMI-a za banke i njegovih pod-indikatora s zaključkom kako su svi pod-indikatori pozitivni i signifikantni, te se temeljem navedenog odbija nul-hipoteza. Također se testira veza između razvijenog RMI-a za banke i efikasnosti banaka. Rezultati pokazuju kako postoji slaba, ali pozitivna veza između RMI banaka i efikasnosti, dok je veza između zarade i efikasnosti negativna i statistički značajna. Analogno navedenome, prikazuju se rezultati testiranja hipoteze koje se odnose na postojanje veze RMI-a razvijenog za osiguravajuća društva i njegovih pod-indikatora. Rezultati pokazuju kako postoji pozitivna i statistički značajna veza između razvijenog RMI-a i pod-indikatora. Također, testirajući posljednju hipotezu, koja se odnosi na utvrđivanje veze između razvijenog RMI-a i efikasnosti osiguravajućih društava. Rezultati analize potvrđuju snažnu pozitivnu vezu između razvijenog RMI-a i efikasnosti osiguravajućih društava, dok je za pod-indikatore RMI-a zabilježena negativna, statistički značajna veza s efikasnošću, osim u slučaju pod-indikatora solventnost za koji je veza pozitivna i statistički značajna.

Zaključak u petom poglavlju kroz diskusiju o rezultatima provedenog istraživanja u odnosu na postavljene hipoteze i ciljeve zaokružuje ovaj doktorski rad u jednu koherentnu cjelinu. U ovom poglavlju razmatraju se prednosti, ali i ograničenja metodologije korištene u istraživanju, ističući načine kako u budućim istraživanjima otkloniti ta ograničenja. U nastavku se kratko opisuju relevantna recentna istraživanja u cilju usporedbe rezultata i zaključaka dobivenih u ovom doktorskom radu. Pojašnjavaju se sličnosti i razlike između prethodnih istraživanja, te se ističe doprinos cjelokupnog istraživanja u području procijene efikasnosti financijskih institucija korištenjem razvijenih RMI-ijeva, na temelju kojih se predlažu smjernice i preporuke za buduća istraživanja.

Ključne riječi: efikasnost, upravljanje rizicima, financijske institucije, kompozitni indeksi, banke, osiguravajuća društva, DEA BoD

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1. INTRODUCTION

Financial institutions, particularly banks and insurance companies, play a pivotal role in the modern economy by providing services that mitigate risks, allocate capital, and enhance financial stability. A well-functioning financial system is essential for economic growth, making efficiency in financial institutions crucial. Traditionally, efficiency has been measured using metrics such as Return on Assets (ROA) and Return on Equity (ROE). However, recent decades have seen a shift towards evaluating input-output optimization through parametric and nonparametric models. Despite extensive research on banks and, to a lesser extent, insurance companies, there is a lack of consensus regarding key determinants of efficiency, optimal evaluation models, and the impact of risk management practices.

This doctoral dissertation systematically analyses the efficiency of financial institutions, with a particular focus on the impact of risk management. It synthesizes prior research and establishes a theoretical framework through three interconnected studies. The first study reviews various methods, variables, and approaches to efficiency, emphasizing the role of risk management. Building on these insights, the second and third studies develop Risk Management Indices (RMI) utilizing the constrained Data Envelopment Analysis “Benefit of the Doubt” (DEA BoD) model, applied to a longitudinal sample of 589 banks (2015–2021) and 744 insurers (2012–2021) sourced from the Obris database. The RMIs were employed to assess the effect of risk management on efficiency using robust panel data models.

Results indicate that risk management positively impacts efficiency, with a more significant effect observed in insurers compared to banks. The key drivers for banks include management efficiency, asset quality and capital adequacy, while for insurers, they are solvency, capital adequacy and asset quality. This research underscores the importance of integrating risk management into efficiency assessments, thereby advancing both theory and practice.

1.1 THE PROBLEM AND THE SUBJECT OF THE THESIS

Inadequate risk management practices often lead to financial instability, particularly as the financial industry becomes increasingly interconnected and consolidated. Policymakers remain vigilant regarding systemic risk, since the failure of a single large institution can trigger a cascade of bankruptcies, resulting in financial and economic crises. While various internal and external factors contribute to the failure of financial institutions, management holds the primary responsibility for minimizing these risks. Effective risk management strategies are designed to reduce the exposure of financial institutions to both internal and external threats. However, implementing these practices requires additional resources, which can increase operational costs. Measures such as maintaining adequate capital reserves, establishing funds for potential losses (e.g., loan loss reserves for banks and technical reserves for insurance companies), and designating staff for risk management roles enhance stability but may compromise efficiency.

Despite decades of research on the efficiency of financial institutions, the effect of risk management on efficiency remains insufficiently explored. This gap highlights the challenge of balancing effective risk management with maintaining efficiency, a critical issue for both financial institutions and the broader economy.

Mester (1996) was one of the first to advocate for the incorporation of risk management into efficiency estimations, arguing that risk-adjusted efficiency yields more accurate and insightful results. Neglecting the influence of risk management may result in the misclassification of institutions with inadequate practices as efficient, thereby impairing decision-making processes.

Financial institutions encounter a wide range of risks. External factors include market risk, economic shocks, political instability, wars, and pandemics, all of which are challenging to hedge against. In contrast, internal risks are frequently associated with operational decision-making. Berger & DeYoung (1997) classified these risks as "bad luck" (external factors) and "bad management" (internal factors), highlighting the essential role of management in mitigating internal risks. The recent failure of Silicon Valley Bank in 2023 exemplifies the consequences of inadequate and insufficient risk management practices. In such situations, government intervention is often necessary to avert further financial instability and economic losses. These occurrences emphasize the need for additional research into the relationship between risk management and operational efficiency. The purpose of risk management activities is to eliminate or reduce the risk exposures of financial institutions. However, this often comes at the expense of efficiency. Risk-adjusted efficiency takes into account the costs associated with these practices while measuring output, providing a nuanced understanding of institutional performance. Assaf et al. (2019) found that cost efficiency during stable periods helps banks mitigate risks and reduce the probability of failure, while during financial crises, it enhances profitability. They suggest that cost efficiency may be a better indicator of management quality, as high profit efficiency might result from riskier investments during normal periods.

The subject of this doctoral dissertation is to gain a deeper understanding of the effect of risk management on the efficiency of financial institutions. This necessitates a systematic analysis of existing theoretical and empirical studies examining the efficiency of financial institutions, with a particular emphasis on the influence of risk management. Additionally, this dissertation aims to develop RMIs specifically designed for banks and insurance companies to assess their risk-adjusted efficiency and to explore the relationship between risk management and efficiency. This novel methodology aims to facilitate benchmarking and comparison among financial institutions while identifying those with exemplary risk management practices. By offering actionable insights, these indices will serve as valuable tools for policymakers and practitioners seeking to enhance the stability and efficiency of the financial system.

1.2 THESIS' HYPOTHESES

The main hypothesis of this doctoral dissertation is: *There is significant relationship between risk management and the efficiency of financial institutions*.

Over the past three decades, significant attention has been devoted to studying the efficiency of financial institutions. However, there has been comparatively less empirical research focused on the effects of risk management practices on efficiency. While theoretical contributions underscore the importance of risk management in financial institutions (Berger & DeYoung, 1997; Kim & Santomero, 1988; Mester, 1996; Oldfield & Santomero, 1970; Santomero, 1997; Santomero & Babbel, 1997), empirical evidence addressing its impact on efficiency remains limited. This dissertation aims to fill this gap by investigating the relationship between risk management and efficiency. To guide this research, the following three research questions (RQs) were proposed in the first appended scientific paper (Petrović & Karanović, 2024), which examines the current state of efficiency among financial institutions:

RQ1: What are the most used methods employed in studies on the efficiency of financial institutions?

RQ2: What are the most used variables for measuring the efficiency of financial institutions?

RQ3: What are the most used measures of risk and efficiency for evaluating the impact of risk management on operational efficiency? Are composite indices utilized in the efficiency assessment of financial institutions?

The purpose of these questions is to provide a comprehensive overview of the prevailing methods, variables, and measures in the literature concerning the efficiency of financial institutions. Additionally, they aim to explore the effect of risk management practices on efficiency and propose the development of composite indices specific to banks and insurance companies for estimating risk-adjusted efficiency.

Building on this foundation, four hypotheses were formulated to investigate the relationship between risk management and efficiency. Two of these hypotheses concentrate on the risk-adjusted efficiency of banks, while two pertain to the risk-adjusted efficiency of insurance companies.

The hypotheses concerning banks were tested in the second scientific paper (Petrović et al. 2025a) appended to this doctoral dissertation:

H1: There is a significant relationship between bank specific risks (CAMEL) and the composite risk management index.

H2: There is a significant relationship between risk management index and bank's efficiency.

In the second scientific paper (Petrović et al., 2025a), a novel RMI was proposed, developed based on the CAMEL framework, which includes Capital Adequacy, Asset Quality, Management Efficiency, Earnings, and Liquidity. This innovative approach offers a robust methodology for evaluating the efficiency of banks, enabling benchmarking and comparison of risk-adjusted efficiency across institutions. The RMI aids in identifying banks with effective risk management practices and provides insights into the factors that contribute to successful risk management. Utilizing the proposed RMI, the second hypothesis (H2) assesses the relationship between risk management practices and bank efficiency, offering empirical insights into how risk management impacts operational performance.

The hypotheses focusing on insurance companies were tested in the third scientific paper (Petrović et al., 2025b) appended to this doctoral dissertation:

H3: There is a significant relationship between insurance company specific risks (capital, assets, operational, liquidity, and solvency) and the composite risk management index.

H4: There is a significant relationship between risk management index and insurance company efficiency.

Inspired by the development of the Risk Management Index (RMI) for banks, the third scientific paper (Petrović et al., 2025b), proposes an RMI specifically for insurance companies, based on a framework analogous to CAMEL, but tailored to the insurance sector. This framework incorporates sub-indicators such as Capital Adequacy, Asset Quality, Management Efficiency, Earnings, and Solvency (CAMES), with a particular emphasis on solvency as a critical risk factor for insurance companies.

The RMI for insurance companies offers a distinctive methodology for measuring risk-adjusted efficiency, facilitating benchmarking and comparisons across institutions. Additionally, it identifies companies with effective risk management practices and the factors that contribute to successful risk management. Utilizing this index, the fourth hypothesis (H4) assesses the relationship between risk management and efficiency within the insurance sector.

1.3 PURPOSE AND OBJECTIVES OF THE THESIS

The purpose of this doctoral dissertation is to identify the main models, approaches, and variables used to estimate the efficiency of financial institutions, with a particular emphasis on risk management and its effect on efficiency—termed risk-adjusted efficiency. By synthesizing the existing body of knowledge regarding the efficiency of financial institutions, this research seeks to examine the influence of risk management practices on operational efficiency.

The primary objectives of this research are to develop a model for estimating the risk-adjusted efficiency of financial institutions and to identify the determinants of effective risk management within these efficient entities. This doctoral study utilizes extensive international samples of banks and insurance companies to comprehensively address these objectives. In accordance with the purpose and scope of this doctoral dissertation, several conceptual objectives were established:

1. Synthesize the relevant theoretical literature on the efficiency of financial institutions and to propose a theoretical framework for estimating efficiency, while taking into account the effects of risk management activities.
2. Describe and define the concept of risk-adjusted efficiency.
3. Examine and define the most commonly used models, approaches, and variables employed in the estimation of efficiency within financial institutions.
4. Examine the relevant literature on composite indices and their applicability in assessing the risk-adjusted efficiency of financial institutions.
5. Propose a novel approach for estimating the risk-adjusted efficiency of financial institutions through the use of composite indices.

The primary aim of these objectives is to establish a theoretical foundation for analysing the efficiency of financial institutions. This includes assessing the impact of risk management, and identifying the most commonly used models, approaches, and variables in developing composite indices. Given the extensive and diverse literature on the efficiency of financial institutions, achieving these objectives lays the groundwork for subsequent empirical research.

The outlined objectives were addressed in the first scientific paper (Petrović & Karanović, 2024) appended to this doctoral dissertation, which involved conducting a systematic literature review. The findings from this review formed the basis for the empirical research in the subsequent appended scientific papers by providing an overview of the field and identifying prevalent models, approaches, and variables. The first appended scientific paper, Petrović & Karanović (2024) contributes a theoretical framework and introduces a novel methodology for estimating risk-adjusted efficiency, addressing a significant gap in the literature, while enhancing comparability across studies and reducing heterogeneity in the field.

Insights from the conceptual part of this dissertation, presented in the first paper, significantly influenced the empirical objectives, which are outlined as follows:

1. Develop a composite RMI utilizing the CAMEL (Capital Adequacy, Asset Quality, Management Efficiency, Earnings, and Liquidity) framework for a large, international, longitudinal sample of 589 banks from 2015 to 2021, with the aim of estimating their risk-adjusted efficiency and identifying its primary drivers.
2. Examine the effect of risk management on the efficiency of banks by applying the developed RMI to the same sample of 589 banks (2015–2021).
3. Develop a composite RMI based on the CAMES (Capital Adequacy, Asset Quality, Management Efficiency, Earnings, and Solvency) framework for a large, international,

longitudinal sample of 744 insurance companies from 2012 to 2021, to estimate their risk-adjusted efficiency and identify its primary drivers.

4. Examine the effect of risk management on the efficiency of insurance companies by applying the developed RMI on the same sample of 744 insurance companies (2012–2021).
5. Compare the results with previous research and to provide recommendations for future research.

The theoretical framework presented in the first appended scientific paper (Petrović & Karanović, 2024) guided the selection of models, methodologies, and variables used to develop the RMIs for banks and insurance companies. These RMIs facilitate the estimation of financial institutions' risk-adjusted efficiency and the identification of key factors that contribute to effective risk management. By employing RMIs, this research evaluates the impact of risk management on the efficiency of banks and insurance companies. It proposes a model for risk-adjusted efficiency that facilitates direct benchmarking and comparison across institutions. The proposed approach is characterized by its simplicity and adaptability, making it applicable to smaller sample sizes and various fields of study.

Moreover, the RMIs facilitate comparisons of risk-adjusted efficiency between individual banks and insurance companies, and across studies when this approach is adopted. This contributes to reducing heterogeneity in the field of estimating financial institution efficiency, as advocated by Henriques et al. (2020). Finally, the empirical results are compared with relevant studies in the literature to provide broader insights and directions for future research.

2. LITERATURE REVIEW

The literature on the efficiency of financial institutions is extensive and diverse. To provide a comprehensive overview of this large body of knowledge, the first scientific paper (Petrović & Karanović, 2024) appended to this dissertation conducted a systematic literature review (SLR). The SLR employed the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework, as outlined by Page et al. (2021). This review was conducted using the Web of Science (WoS) database from September to December 2023, adhering to widely recognized quality standards (Ali et al., 2023; Ali & Wilson, 2023; de Abreu et al., 2019; Walker et al., 2019), such as focusing on studies published in journals in 3, 4, and 4* ranks of the Academic Journal Guide (AJG) published by ABS (2021).

The SLR employed a targeted keyword search strategy, using combinations such as: *"index OR composite index AND CAMEL (Capital Adequacy, Asset Quality, Management Efficiency, Earnings, Liquidity) AND risk management literature review OR survey AND efficiency OR* *efficiency ratio AND financial institutions OR banks OR insurance companies, as well as methodological terms DEA AND/OR Benefit of Doubt OR BoD"* (Petrović & Karanović, 2024, p. 415). After excluding duplicate and irrelevant studies, the search yielded a final sample of 173 studies, which included 138 empirical studies and 35 theoretical studies. A detailed analysis of these findings is presented in the first appended scientific paper (Petrović & Karanović, 2024), with a summary provided in the following tables.

The seminal study by Berger & Humphrey (1997) highlighted that parametric methods, particularly Stochastic Frontier Analysis (SFA), and non-parametric methods, primarily Data Envelopment Analysis (DEA), are employed almost equally in studies on the efficiency of financial institutions. This observation is further corroborated by the findings of the SLR presented in the first appended paper (Petrović & Karanović, 2024).

Table 1 outlines the key characteristics, advantages, and limitations of the SFA and DEA models, along with the number of studies that have employed these methods to estimate the efficiency of financial institutions. The remaining studies have implemented econometric models.

Table 1 Parametric and non-parametric models used in studies of financial institution efficiency as determined in a literature review

Model	Number of studies	Definition	Banks	Insurance Companies	Context
SFA	22/138 (15.94%)	SFA is the most widely used parametric method for estimating efficiency. Described by Berger & Humphrey (1997) as an econometric frontier approach it was introduced by Aigner et al. (1977), Battese & Corra (1977), and Meeusen & van Den Broeck (1977). This method is frequently modelled using a	Agliardi et al. (2012), Altunbas et al. (2007), Barra et al. (2022), Berger et al. (2009), Bolt & Humphrey (2010), Bonin et al. (2005), Bos & Kool (2006), Dong et al. (2017), Fries & Taci (2005), Gang et al. (2018), Kalyvas & Mamatzakis (2014), Mamatzakis (2015), Mamatzakis &	Mamatzakis et al. (2023)	The primary limitation of the SFA is the need for a functional form and the relationships involving costs, profits, or production in relation to inputs, outputs, and environmental factors (Berger & Humphrey, 1997). Defining these relationships is relatively straightforward for goods producers, though it becomes more complex for service providers, particularly in the financial sector. Depending on the model employed, variables such as deposits in

		Cobb-Douglas production function (Williams & Gardener, 2003).	Bermpei (2014), Maudos et al. (2002), Mester (1996), Safiullah & Shamsuddin (2019), Shamshur & Weill (2019), Sun & Chang (2011), Williams (2004), Williams & Gardener (2003), Zamore et al. (2023)		banking or incurred claims in insurance may be classified as inputs, outputs, or both (Učkar & Petrović, 2021). SFA necessitates compliance with sample size and distribution axioms due to its stochastic nature.
DEA	32/138 (23.19%)	DEA is a linear programming approach designed to optimize input-output efficiency. First introduced by Charnes et al. (1978) under the assumption of constant returns to scale (CRS), known as the CCR model. Banker et al. (1984) extended the model to account for variable returns to scale (VRS), also known as the BCC model.	Asmild & Zhu (2016), Ayadi et al. (2016), Barth et al. (2013), Boussemart et al. (2019), Canhoto & Dermine (2003), Chan et al. (2013), Chang (1999), Chortareas et al. (2016), Chortareas et al. (2012), Eling & Jia (2018), Fukuyama & Tan (2022), Gaganis et al. (2021), Gonzalez (2009), Hadad et al. (2011), Lartey et al. (2021), Maudos et al. (2002), McKee & Kagan (2018), Mohsin et al. (2021), Nippani & Ling (2021), Pessarossi &	Cummins et al. (1999), Eling & Jia (2018), Huang et al. (2011)	DEA methodology is widely utilized across disciplines, including finance, due to its simplicity, versatility, and minimal assumptions regarding the inputs and outputs of decision-making units (DMUs). It is particularly well-suited for smaller sample sizes (Emrouznejad & Yang, 2018). Its primary limitation is the absence of a random error term, making it highly sensitive to inaccurate data. Inaccuracies are classified as DMU inefficiency rather than statistical noise. Consequently, studies typically employ a two-stage procedure or an econometric approach to further validate their results.

	Weill (2015), Proaño-Rivera & Feria-Dominguez (2023), Spokeviciute et al. (2019)		

Source: Appended scientific paper 1: Petrović, D., & Karanović, G. (2024). Financial institutions efficiency: a systematic literature review. Zbornik Radova Ekonomskog Fakulteta u Rijeci / Proceedings of Rijeka Faculty of Economics, 42(2), 411–446. https://doi.org/10.18045/zbefri.2024.2.11 (page 421)

Furthermore, the SLR conducted by Petrović & Karanović (2024) revealed that the selection of variables in studies on the efficiency of financial institutions largely depends on the chosen approach. The intermediation approach, which is most widely used, employs variables derived from the balance sheets of financial institutions. This approach highlights the role of financial institutions as intermediaries within the economy. The operating approach, which ranks as the second most popular, concentrates on the operational aspects of financial institutions and relies on variables extracted from profit and loss statements.

An overview of the most commonly used input and output variables for banks and insurance companies, along with relevant studies employing the parametric SFA model and non-parametric DEA model, is presented in Table 2. This table is based on the findings of the SLR (Petrović & Karanović, 2024, p. 423). Similar trends in banking were identified by Radojicic et al. (2018), who reported that the most frequently used inputs include labour/personnel expenses (administrative expenses), capital, deposits, fixed assets, and the number of employees. Conversely, the most common outputs are loans, non-interest income, other placements/earning assets, investments, and investment income (Radojicic et al., 2018, p. 1591).

Table 2 Most common input and output variables used in studies of financial institution efficiency as determined in a literature review

Model	Studies	Inputs	Outputs
SFA	Altunbas et al. (2007), Barra et al. (2022), Gang et al. (2018), Kalyvas & Mamatzakis (2014), Mamatzakis et al. (2023), Mamatzakis & Bermpei (2014), Pessarossi & Weill (2015), Williams & Gardener (2003), Zamore et al. (2023), Bolt & Humphrey (2010), Bos & Kool	*Banks:* Loan-loss reserves; interest rate spread/3-year government bonds; operating expenses/total assets; number of employees; number of branches; loan loss reserves/ gross loans (as proxy for risk);	*Banks:* ROA; ROE; current assets/ current liabilities; loans (differentiated by type); services; securities; net claims paid; total investments;

	(2006), Mester (1996), Ruinan (2019), Safiullah & Shamsuddin (2019), Shamshur & Weill (2019), Srairi (2010), Williams (2004).	nonperforming loans; labour expenses; administrative expenses; interest expenses; non-interest expenses; total cost; administration expenses/ total assets; net technical provisions/total assets; equity; assets; personnel expenses/total assets; total earning assets, total operating expenses/fixed assets; interest expenses/total assets; book value of equity/total assets; operating costs or overhead *Insurance companies:* Total equity, total investments, operating costs, investment costs, claims incurred	customer deposits; non-interest income; ordinary profits/sum of equity and reserves; net loans/total assets; ln (total assets); *Insurance companies: ROA; ROE;* earned premiums, investment income
DEA	Boussemart et al. (2019), Chan et al. (2013), Chortareas et al. (2016), Chortareas et al. (2012), Eling & Jia (2018), Hadad et al. (2011), Lartey et al. (2021), McKee & Kagan (2018), Mohsin et al. (2021), Nippani & Ling (2021), Pessarossi & Weill (2015), Proaño-Rivera & Feria-Dominguez (2023), Barth et al. (2013), Canhoto & Dermine (2003), Chang (1999), Cummins et al. (1999), Gonzalez (2009), L.-Y. Huang et al. (2011), Ruinan (2019), Spokeviciute et al. (2019)		

Source: Appended scientific paper 1: Petrović, D., & Karanović, G. (2024). Financial institutions efficiency: a systematic literature review. Zbornik Radova Ekonomskog Fakulteta u Rijeci / Proceedings of Rijeka Faculty of Economics, 42(2), 411–446. https://doi.org/10.18045/zbefri.2024.2.11 (page 423)

The SLR conducted by Petrović & Karanović (2024) identifies key themes and trends in the literature regarding the efficiency of financial institutions, with a particular emphasis on the effect of risk management. A significant focus of this body of work is the consolidation of financial institutions through mergers and acquisitions (M&A). Research in this area generally supports the idea that larger institutions formed through M&A achieve greater efficiency due to economies of scale; however, some studies indicate no significant effect or even the presence of diseconomies of scale. Over the past three decades, research in this field has expanded into several new areas, including the effects of regulation and deregulation, external and environmental influences, sustainability (Environmental, Social, and Governance—ESG), and risk management practices on efficiency.

The vast and diverse nature of this literature has been the subject of several reviews. Berger & Humphrey (1997) conducted one of the earliest and most comprehensive reviews, highlighting the predominance of studies on bank efficiency while noting the lesser focus on insurance companies. They also documented the widespread application of parametric models, such as SFA, and non-parametric models, such as DEA, a point later elaborated upon by Murillo-Zamorano (2004). A systematic literature review by Bhatia et al. (2018) focused exclusively on bank efficiency and productivity, identifying 11 major themes, including deregulation, risk, and methodological advancements. Aiello & Bonanno (2018) underscored the heterogeneity of the field, while de Abreu et al. (2019) highlighted the lack of consensus on the determinants of efficiency, emphasizing how different methodological approaches yield varying results. Ahmad et al. (2020) contributed by conducting a citation-based review that identified key journals, authors, and methods within the field. More recently, Ardia et al. (2023) examined trends in finance literature over the past three decades, noting that risk management and banking remain pivotal topics. These reviews collectively demonstrate the diversity of approaches and themes within the literature, further justifying the focus of this doctoral dissertation on the efficiency of financial institutions, with an emphasis on the impact of risk management.

The SLR (Petrović & Karanović, 2024) proposed a theoretical framework for the efficiency of financial institutions, grounded in key economic theories. Microeconomic production theory underpins the optimal use of inputs (cost minimization) and outputs (profit maximization), while the theory of financial intermediation (Allen & Santomero, 1997; Merton, 1995; Scholtens & van Wensveen, 2000; Seward, 1990) emphasizes efficient capital allocation and risk reduction. Additionally, the theory of the firm Coase (1937) highlights the importance of maximizing shareholder value through resource optimization and effective risk management.

Specific to financial institutions, the efficient structure hypothesis outlined by Demsetz (1973) suggests that more efficient institutions achieve greater profitability and market share. Additionally, banks and insurance companies are significantly impacted by agency theory (Jensen & Meckling, 1976; Stulz, 1984), which emphasizes the necessity of thorough screening and monitoring of clients and associated risks. Furthermore, the theory of risk capital by Erel et al. (2015) highlights the critical importance of maintaining sufficient capital and reserves to protect against defaults and claims payouts.

The significance of risk management is emphasized by Knight (1921), who introduced the concept of risk, and Markowitz (1952), who developed modern diversification tools. The role of financial institutions in promoting economic stability is highlighted by Oldfield & Santomero (1970) and Herring & Santomero (1995). Stulz (2023) argues that effective risk management strategies enhance operational efficiency and financial resilience, thereby mitigating the impact of crises.

In the banking sector, credit risk is the primary focus of risk management, with non-performing loans (NPLs) serving as a key metric that impacts performance, reserves, and capital (Kim & Santomero, 1988). Santomero (1984, 1997) examine the evolution of risk management in banks, underscoring credit risk as a central concern. In contrast, insurance companies prioritize risk pooling, diversification, and hedging, as they manage risks transferred through their policies, as described by Santomero & Babbel (1997). The importance of effective risk and capital management in the insurance industry is emphasized by Bomhard (2005) and de Castries (2005).

Despite the extensive research on the efficiency of financial institutions, this dissertation focuses specifically on a novel area: the impact of risk management on efficiency. Although previous reviews by Bhatia et al. (2018), de Abreu et al. (2019), and Ahmad et al. (2020) identified risk management as an emerging area of interest, there is still need for further synthesis and clarity in this field.

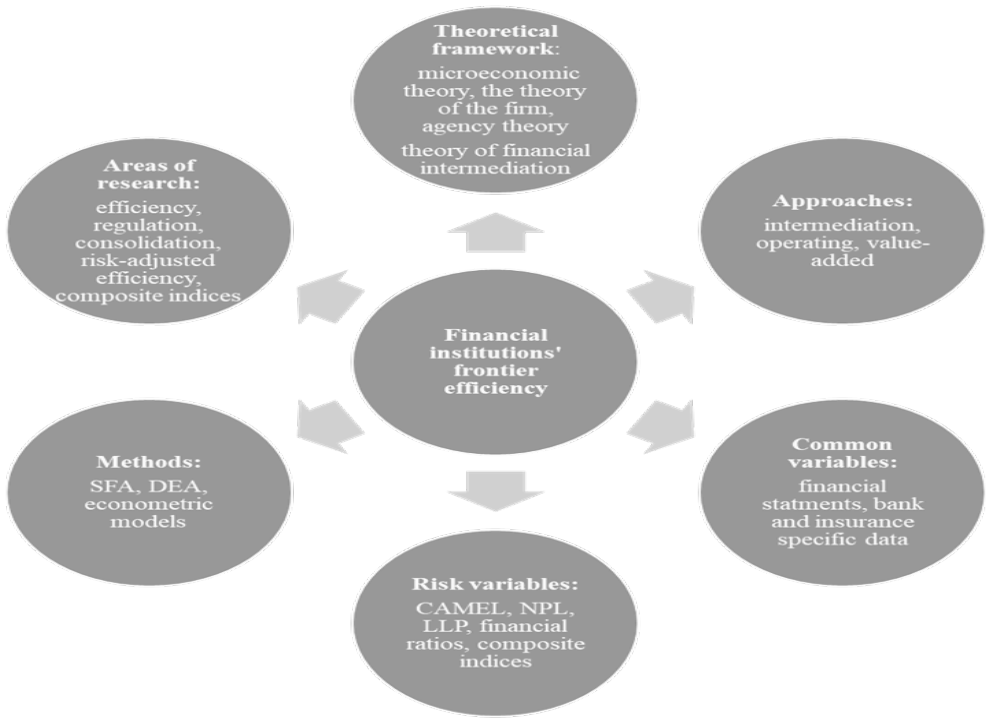
Mester (1996) was the first to highlight the risks associated with neglecting the impact of risk management on efficiency estimates, which can mislead stakeholders. Following this, Berger & Mester (1997) explained the differences in the efficiencies of financial institutions. Aiello & Bonanno (2018) observed the sources of heterogeneity in the banking efficiency literature, attributing this to a lack of consensus regarding the best approaches, models, and variables used in estimating the efficiency of financial institutions. Hughes & Mester (2008) focused on the theory, practice and evidence of banking efficiency, while Murillo-Zamorano (2004) outlined the efficiency and frontier techniques, emphasizing the widespread use of parametric models (predominantly SFA) and non-parametric models (DEA). These observations align with the seminal survey conducted by Berger & Humphrey (1997), which noted the predominance of studies on banking efficiency, while research on insurance companies was less prevalent. The heterogeneity of results in efficiency studies is well documented by Henriques et al. (2020) who advocate for the application of consistent methodologies to enhance comparability between studies.

To address these gaps, Petrović & Karanović (2024) conducted a systematic literature review to identify the most effective approaches, models, and variables for estimating risk-adjusted efficiency in financial institutions. The results were categorized into six key areas, as illustrated in Figure 1 (Petrović & Karanović, 2024, p. 425).

The theoretical framework for this dissertation is outlined above, highlighting the necessity of defining and categorizing variables into inputs and outputs in studies of financial institution efficiency. This process parallels the methodology employed for producers of physical goods, where inputs are generally classified as capital and labour, and outputs as goods and services. However, defining inputs and outputs for financial institutions is more intricate due to the multifaceted nature of financial services. This complexity has led to the development of various approaches for classifying variables to estimate frontier efficiency in financial institutions.

The intermediation approach classifies variables based on intermediation activities, primarily utilizing data derived from the balance sheets of financial institutions. In the case of banks, common inputs include total assets, equity, deposits, the number of employees, and other liabilities, while outputs typically encompass total loans, investments, securities, and deposits. For insurance companies, inputs such as total equity, total investments, the number of employees, and total assets are identified, with outputs include total earned premiums and investment income.

Figure 1 Financial institutions' frontier efficiency estimation framework



Source: Appended scientific paper 1: Petrović, D., & Karanović, G. (2024). Financial institutions efficiency: a systematic literature review. Zbornik Radova Ekonomskog Fakulteta u Rijeci / Proceedings of Rijeka Faculty of Economics, 42(2), 411–446. https://doi.org/10.18045/zbefri.2024.2.11 (page 425)

The operating approach emphasizes operational activities, deriving variables primarily from profit and loss statements. In the banking sector, inputs include interest and non-interest expenses, labour costs, and administrative expenses, while outputs typically consist of interest and non-interest income. Similarly, for insurance companies, inputs encompass operating costs, investment expenses, and claims incurred, while outputs include earned premiums, investment income, and, occasionally, claims incurred.

The value-added approach provides more flexibility in the classification of variables and allows for all liability and asset categories to have some output characteristics. This approach focuses on the "value added" of financial institutions services, and attempts to resolve classification problems for variables that can be classified as both inputs and outputs.

It is necessary to point out that the classification of variables, such as deposits in banking and claims incurred in insurance companies, pose a conundrum for which no wide-accepted consensus has been achieved. Recent literature reviews from Bhatia et al. (2018), de Abreu et al. (2019) and Ahmad et al. (2020) indicate that the intermediation approach remains the most widely used, followed by the operating and value-added approaches.

Efficiency studies frequently incorporate financial ratios such as ROA and ROE, in addition to institution-specific data (e.g., ownership structure, branch type, life versus non-life insurance), external factors (e.g., GDP, inflation rates, risk premiums), and environmental variables (Lozano-Vivas et al., 2002; Pastor et al., 1997). Recent trends have seen the adoption of the CAMEL framework (Pekkaya & Demir, 2018), which includes specific proxies such as total capital to risk-weighted assets (capital adequacy), non-performing loans (NPLs) to gross loans (asset quality), cost-to-income ratio (management efficiency), ROA (earnings), and net loans to total deposits (liquidity). Kumar et al. (2022) denote total capital to risk-weighted ratio as a proxy for capital adequacy, the ratio of NPLs to gross loans as a proxy for asset quality, the cost to income ratio as a proxy for management efficiency, while earnings were proxied by ROA, and liquidity was proxied by the ratio of net loans to total deposits. Similar proxies have been utilized (de Abreu & de Camargos, 2022; Muhmad & Hashim, 2015; Shaddady & Moore, 2019; Sloan Swindle, 1995). Safiullah & Shamsuddin (2019) expanded upon this by investigating risk-adjusted efficiency and corporate governance in both Islamic and conventional banks. They employed proxies such as the standard deviation of ROA for operational risk, along with various indicators for credit risk, including NPL ratios, loan loss provisions (LLPs), and loan loss reserves (LLRs).

These metrics facilitate the estimation of current and future risks, enabling institutions to effectively manage revenue, liquidity, and capital. This dissertation adopts a similar methodology for insurance companies, utilizing proxies such as gross provisions to gross written premiums, solvency ratios, and retention ratios to evaluate solvency.

The selection of an appropriate model for estimating frontier efficiency is crucial. As identified in the SLR conducted for this dissertation, similar to earlier reviews, as the one of the earliest by Berger & Humphrey (1997), both parametric and non-parametric models are frequently employed. As noted earlier, SFA is the most widely used parametric model, while DEA is the predominant non-parametric model (Ahmad et al., 2020; Aiello & Bonanno, 2018; Bhatia et al., 2018; de Abreu et al., 2019; Murillo-Zamorano, 2004). SFA incorporates an error term, distinguishing it from DEA, which attributes all deviations from the frontier to inefficiency. Despite the limitations of DEA, such as its sensitivity to statistical noise, its simplicity and suitability for smaller sample sizes contribute to its widespread popularity. Modifications, including stochastic DEA and slack-based DEA, address these limitations and enhance efficiency estimates. For example, Henriques et al. (2020) advocate for the application of consistent methodologies, such as a two-step slack-based model, to improve comparability and reduce heterogeneity in cross-geographic studies.

To ensure robustness, both parametric and non-parametric studies often utilize econometric models, including static models such as ordinary least squares (OLS) and dynamic models like the generalized method of moments (GMM) or panel data analysis. This approach is especially prevalent in DEA studies to validate and enhance their findings.

Table 3 presents a categorized summary and exemplar studies on the efficiency of financial institutions, organized into the five distinct research areas outlined in Figure 1. These studies serve as the foundation for this dissertation, which aims to build upon previous research by examining the impact of risk management on the efficiency of financial institutions.

Table 3 Overview of studies on financial institutions efficiency sorted in five research areas

Research area	Authors	Title	Financial institutions	Model	Findings
Efficiency	Shamshur & Weill (2019)	Does bank efficiency influence the cost of credit?	Large sample of 240,000 banks and companies	SFA with OLS robustness checks	Higher bank efficiency is associated with lower cost of credit.
	Eling & Jia (2018)	Business failure, efficiency, and volatility: Evidence from the European insurance industry	2,060 insurers from 16 countries	DEA for technical efficiency estimation, econometric business failure and robustness models	There is a negative correlation between technical efficiency and the probability of insurer failure.
	McKee & Kagan (2018)	Community bank structure an x-efficiency approach	2,058 US banks with assets < USD 1 billion	x-efficiency using SFA Distribution-Free Approach (DFA); DEA, OLS for robustness	Asset efficiency is not readily converted into loans
	Mamatzakis et al. (2023)	Measuring the efficiency and productivity of U.K. insurance market	U.K. insurers	SFA; DFA; Thick Frontier Approach (TFA), econometric, GMM	Insurers can improve performance by 40% by improving cost efficiency and about 70% by

					improving profit efficiency
Regulation	Mohsin et al. (2021)	The evaluation of efficiency and value addition of IFRS endorsement towards earnings timeliness disclosure	Pakistani banking sector	Input and output oriented CCR and BCC DEA models, OLS for robustness tests	Mandatory adoption of International Financial Reporting standards (IFRS) increased earnings timeliness of information in all banks.
	Pessarossi & Weill (2015)	Do capital requirements affect cost efficiency? Evidence from China	100 Chinese banks	SFA and econometric methods in the second step, DEA and GMM as robustness check	The increase of regulatory changes in capital ratios has a beneficial effect on cost efficiency, it also strengthens financial stability by providing a larger capital buffer
	Barra et al. (2022)	Basel accords and banking inefficiency: Evidence from the Italian local market	Italian banks	SFA econometric robustness tests	Basel II and Basel III had asymmetric effects on the efficiency of the Italian banking system.
	Ayadi et al. (2016)	Does Basel compliance matter for bank performance?	863 banks from a broad cross-section of countries	Double bootstrap DEA, econometric robustness tests	Compliance with Basel or any of its individual chapters has no association with bank efficiency.
	Chortareas et al. (2016)	Credit Market Freedom and Cost Efficiency	3,809 US banks from 48 states in the period 1987-2012	DEA, econometric robustness tests	There is a clear positive association between the credit market

					counterparts of the economic freedom indices and bank cost efficiency, thus excessive government interference in financial institution activities may adversely affect the efficient operation of banks.
Consolidation (mergers and acquisitions)	Mühlnickel & Weiss (2015)	Consolidation and systemic risk in the international insurance industry	394 transactions (M&A) and 88 reinsurers	Marginal external shortfall (MES) and lower tail dependence (LTD) econometric robustness checks	There is a strong positive relationship between consolidation in the insurance industry and moderate systemic risk in the insurance and banking sector–mergers in the insurance industry can have a destabilizing effect on both the insurance and banking sectors.
	Choi & Weiss (2005)	An empirical investigation of market structure, efficiency, and performance in property-liability insurance	NIAC reporting property-liability insurers 1992–1998	GMM, econometric robustness checks	The results corroborate the efficient structure hypothesis – higher concentration reduces prices and increases profits of large

					property - liability insurers
	Proaño-Rivera & Feria-Dominguez (2023)	Are Ecuadorian banks enough technically efficient for growth? A clinical study	24 Ecuadorian banks for the years 2015–2019	DEA econometric robustness checks	Large banks have higher levels of efficiency indicating the presence of scale efficiency, thus possible improvements in efficiency of medium and small banks.
	Chortareas et al. (2012)	Bank supervision, regulation, and efficiency: Evidence from the European Union	Banks from 22 European countries over the period 2000–2008	DEA econometric robustness checks	Larger banks operating in countries with less concentrated and more developed systems tend to have higher levels of efficiency while capital requirements and supervisory power are positively associated with improved bank performance.
Risk-adjusted efficiency	Safiullah & Shamsuddin (2019)	Risk-adjusted efficiency and corporate governance: Evidence from Islamic and conventional banks	188 Islamic banks from 28 countries over the period 2003–2014	SFA meta – frontier	Islamic banks have higher risk-adjusted cost efficiency, but lower risk-adjusted profit efficiency relative to conventional banks.
	Aouini & Abdennadher (2022)	Performance in the Insurance Industry (Islamic versus	9 insurance companies over the	Cobb-Douglas cost function, robustness checks using	Risk premium and size are significantly positively related

		Conventional) and Risk Management	period 2000–2013	Tobit DEA, OLS and other econometric models (GMM, AR)	to the performance (efficiency) of insurance whether conventional or Islamic.
	Pastor (1999)	Efficiency and risk management in Spanish banking: a method to decompose risk	Spanish banks over the period 1985–1995	Sequential DEA	Banks' risk management efficiency significantly improved between 1985–1992 indicating that in 1992 competition had a negative impact on efficiency, while larger banks achieve greater risk management efficiency due to greater diversification opportunities.
	Rayeni & Saljooghi (2016)	Examining the effect of risk on bank performance by using data envelopment analysis	14 branches of Saderat banks	Three stage network DEA model	Intense market competition reduces the market power of banks, compelling them to improve technical efficiency which is positively associated with risk taking.
Composite indices	Gulati et al. (2020)	A non-parametric index of corporate governance in the banking industry: An application to Indian data	40 Indian banks in 2017	DEA Benefit-of-the-doubt model	Results show that for the last decade, considerable efforts have been made by banks in

					adhering to corporate governance regulations in India.
	Gulati et al. (2023)	Developing a New Multidimensional Index of Bank Stability and Its Usage in the Design of Optimal Policy Interventions	76 Indian banks over the period 2014–2018	DEA meta-BoD framework	Indian banks on average operate below the stability frontier and have opportunities for improving their stability performance. Domestic banks are more stable than foreign banks, prioritising the asset quality and profitability, followed by management efficiency.
	Gulati (2023)	Beyond the Z-score: A novel measure of bank stability for effective policymaking	21 Indian banks in 2018	Constrained DEA BoD model	The empirical evidence clearly shows that the computed bank-wise dimensional and overall indices of bank stability enable benchmarking and ranking the sampled banks.
	Akin et al. (2016)	The composite risk-sharing finance index: Implications for Islamic finance	135 countries and 51 indicators	Distance to the frontier, factor analysis	There is a direct association between having a better risk-sharing friendly environment and per capita income.

Source: PhD candidate's compilation based on the results of the appended scientific paper 1: Petrović, D., & Karanović, G. (2024). Financial institutions efficiency: a systematic literature review. Zbornik Radova Ekonomskog Fakulteta u Rijeci / Proceedings of Rijeka Faculty of Economics, 42(2), 411–446. https://doi.org/10.18045/zbefri.2024.2.11

The field of financial institution efficiency continues to evolve across various areas of study. Despite the extensive theoretical and empirical research conducted over the past three decades, the impact of risk management on the efficiency of financial institutions remains underexplored. This gap underscores the motivation behind this doctoral dissertation, which aims to develop risk management indices for banks and insurance companies. These indices will serve as a foundation for establishing and analysing the relationship between risk management practices and the operational efficiency of financial institutions.

3. METHODOLOGY

In this doctoral dissertation, both theoretical and empirical research methodologies were employed to test the set hypotheses. The theoretical research utilized both inductive and deductive reasoning, along with methods such as analysis, synthesis, classification, and description. The objective of the theoretical research was to provide a comprehensive overview of the existing theoretical and empirical literature, which served as the foundation for the subsequent empirical investigation and the development of a robust theoretical framework.

The first scientific paper included in this dissertation (Petrović & Karanović, 2024) presents a SLR conducted using the PRISMA methodology on the Web of Science (WoS) database. This approach was employed to address the proposed research questions and to establish a comprehensive understanding of the research field.

The second (Petrović et al., 2025a) and third (Petrović et al., 2025b) scientific paper included in this dissertation applied quantitative research methodologies using data from the Orbis database. Longitudinal samples were extracted, excluding banks or insurance companies that were acquired, merged, or exited the market during the observed period, as well as those with incomplete data for the 16 variables (for banks) and 15 variables (for insurance companies) used in constructing the respective risk management indices.

The second paper focuses on a dataset comprising 589 banks from 34 countries over the period from 2015 to 2021, while the third paper examines 744 insurance companies from 31 countries during the period from 2012 to 2021. These datasets facilitate a comprehensive quantitative analysis of the relationship between risk management and the efficiency of financial institutions, which is a critical component of this doctoral research.

3.1 RESEARCH DESIGN

The initial step of this research involved conducting a systematic literature review (SLR), as detailed in the first appended scientific paper (Petrović & Karanović, 2024). This review utilized the PRISMA framework (Page et al., 2021) to examine the intersection of risk management and the application of composite indices in assessing the efficiency of financial institutions.

A combination of specific keywords was employed to refine the scope of the review, including: *"index OR composite index AND CAMEL (Capital Adequacy, Asset Quality, Management Efficiency, Earnings, Liquidity) AND risk management literature review OR survey AND efficiency OR efficiency ratio AND financial institutions OR banks OR insurance companies, as well as methodological terms such as DEA AND/OR Benefit-of-the-Doubt OR BoD"* (Petrović & Karanović, 2024, p. 415). This targeted approach focused the research on studies within the Web of Science (WoS) database, specifically those addressing the risk management, efficiency, and the development and application of composite indices in financial institutions.

The findings from this SLR significantly influenced the research design of the second and third scientific papers included in this dissertation. Most notably, they informed the selection of variables and the application of non-parametric DEA BoD models for developing the proposed RMI. The variables included in the proposed RMI for banks were categorized using the CAMEL framework, as illustrated in Figure 2.

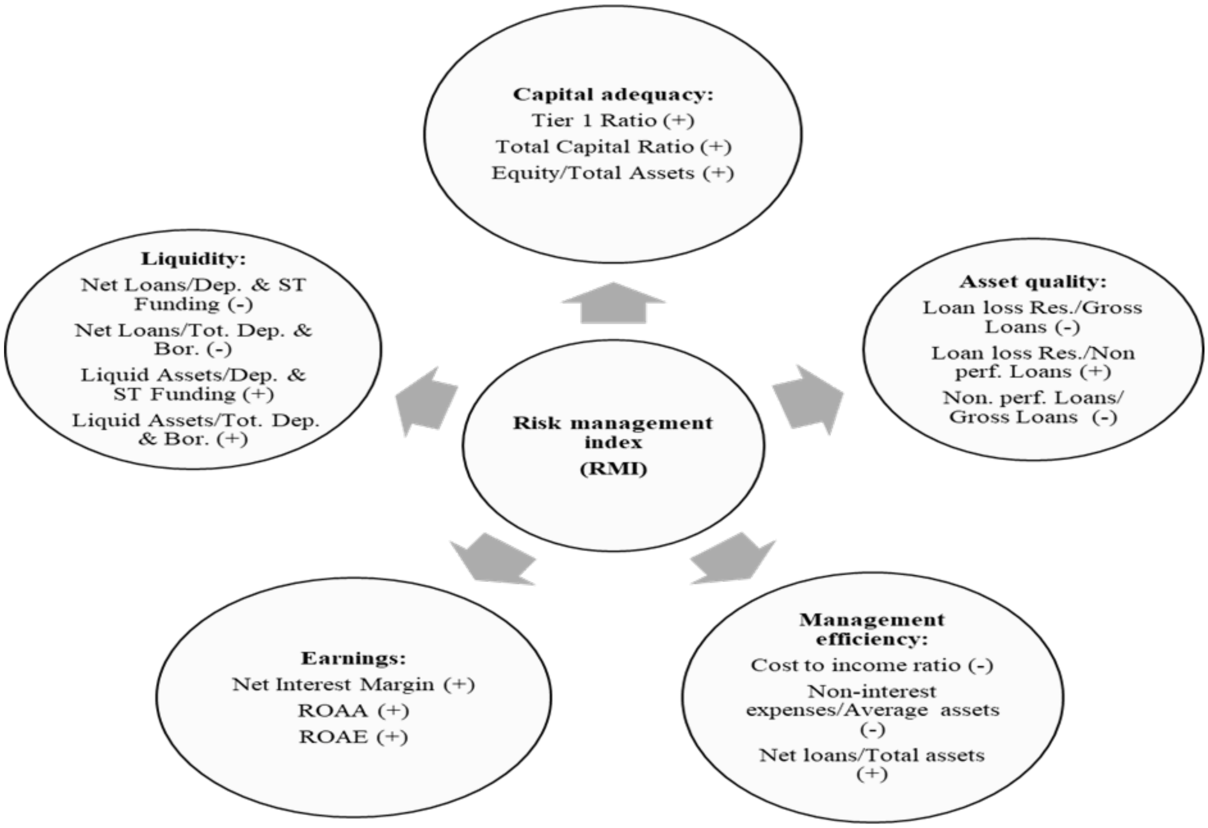
This research design provides a robust and systematic approach to exploring the relationship between risk management and the efficiency of financial institutions, thereby laying the groundwork for the quantitative analysis presented in the subsequent chapters.

The proposed RMI for banks is based on the CAMEL framework, which is widely recognized in the banking industry and extensively utilized in empirical literature (Alzayed et al., 2023; Bhatti et al., 2022; de Abreu & de Camargos, 2022; Handorf, 2016; Pekkaya & Demir, 2018; Qureshi & Siddiqui, 2023; Risal & Panta, 2019; Shaddady & Moore, 2019; Sloan Swindle, 1995). The rationale for the inclusion of specific variables and their corresponding polarities is explained in the second scientific paper (Petrović et al., 2025a).

The RMI for banks consists of 16 variables categorized into five sub-indicators within the CAMEL framework: Capital Adequacy, Asset Quality, Management Efficiency, Earnings, and Liquidity:

- Capital adequacy is evaluated through various indicators that reflect a bank's capitalization, with higher capital levels generally assumed to enhance risk efficiency. This framework ensures that banks are better positioned to absorb losses and manage financial risks effectively.

Figure 2 Risk Management Index for banks



Source: Appended scientific paper 2: Petrović D., Dasilas A., Karanović G. (2025a), "Bank risk-adjusted efficiency using a composite risk management index". Journal of Risk Finance, Vol. 26 No. 3 pp. 485–515, doi: https://doi.org/10.1108/JRF-11-2024-0362 (493)

- Asset quality is assessed using three key variables:
  - Loan Loss Reserves (LLRs) as a percentage of Gross Loans: A higher ratio suggests an expectation of defaults, subpar credit scoring, or insufficient prior risk management.
  - Non-Performing Loans (NPLs) as a percentage of Gross Loans: A lower ratio indicates effective credit risk management, which reduces the likelihood of loan defaults.
  - LLRs in relation to NPLs: A higher ratio indicates that there are adequate reserves to cover current defaults, demonstrating effective credit risk management.
- Management efficiency is measured by variables such as:
  - The cost-to-income ratio: Lower ratios indicate more effective cost management.

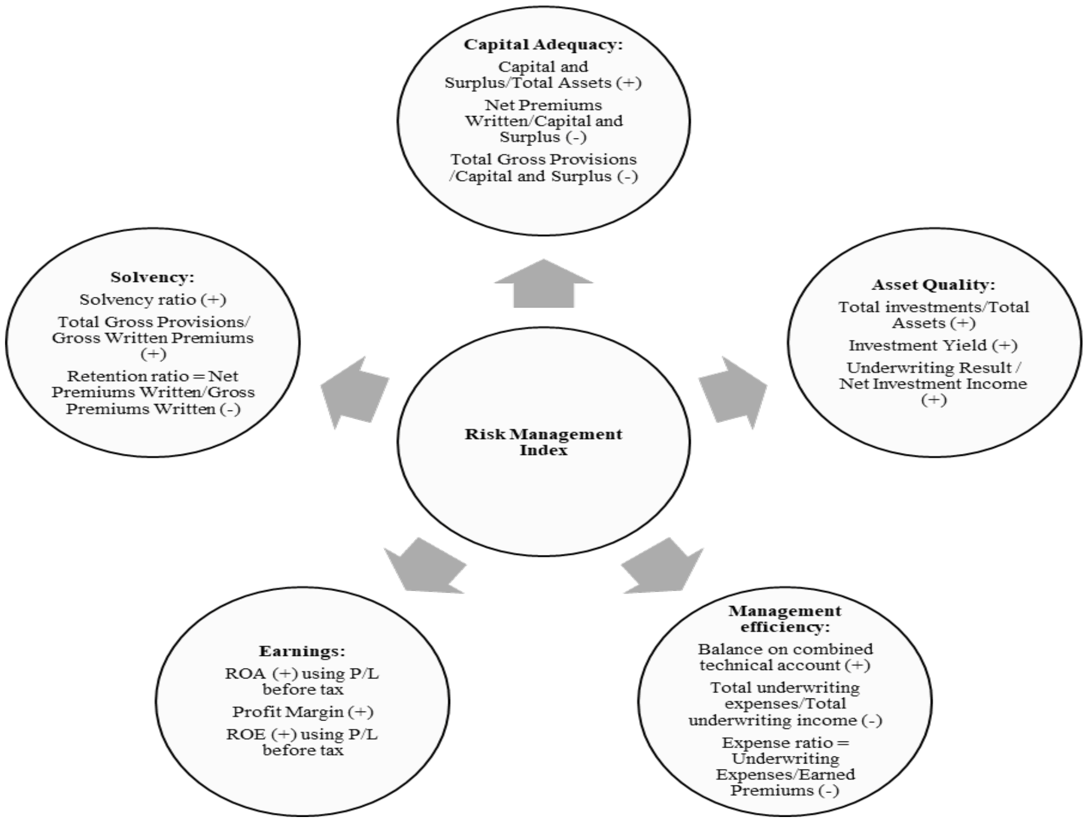
  - Non-Interest Expenses as a percentage of Average Assets: This metric indicates operational efficiency.
  - Net Loans as a percentage of Total Assets: This metric highlights the extent to which a bank's assets are allocated to loans. Deviations from this focus may indicate a shift towards activities more akin to investment banking or real estate.
- Earnings are assessed using three widely recognized profitability metrics whose increased values indicate increased profitability:
  - Net Interest Margin
  - Return on Average Assets (ROAA)
  - Return on Average Equity (ROAE)
- The liquidity sub-indicator consists of four ratios that highlight the significance of maintaining a robust deposit base while facilitating loan issuance. Sufficient liquidity guarantees operational stability and enhances resilience against external shocks.

For insurance companies, the list of variables of the proposed RMI are presented in Figure 3. The RMI for insurance companies reflects the structure of the CAMEL framework while adapting it to the unique characteristics of the insurance industry, resulting in the CAMES framework: Capital Adequacy, Asset Quality, Management Efficiency, Earnings, and Solvency. This index comprises 15 variables, which are evenly distributed among the sub-indicators, as detailed below:

- Capital adequacy employs three ratios to assess insurer's capitalization:
  - Capital and Surplus relative to Total Assets: A higher ratio reflects insurance company's increasing capitalisation, ensuring that insurers are able to absorb losses and fulfil claims.
  - Net Premiums Written relative to Capital and Surplus: Higher values indicate an increased risk of insolvency.
  - Total Gross Provisions relative to Capital and Surplus: This metric reflects the insurer's capacity to absorb shocks from increasing claims.
- Asset Quality Asset quality is defined as:
  - Total Investments over Total Assets: This metric reflects the retention of premiums and their conversion into profitable investments.
  - Investment Yield: This metric assesses the profitability of investments.
  - Underwriting Result over Net Investment Income: Higher ratios indicate greater profitability from core insurance activities as opposed to investment income.
- Management Efficiency is evaluated using metrics such as:
  - Balance on the Combined Technical Account: higher positive balances exhibit effective risk and cost management of insurance companies' core operations.

  - Total Underwriting Expenses over Total Underwriting Income: expresses overall insurer’s efficiency favouring lower values.
  - Expense Ratio: Lower ratios indicate effective cost management.

Figure 3 Risk Management Index for insurance companies



Source: Appended scientific paper 3: Petrović D., Dasilas A., Karanović G. (2025b), “Insurance companies risk-adjusted efficiency using a composite risk management index”. Review of Accounting and Finance, pp. 1-23, doi: https://doi.org/10.1108/RAF-11-2024-0492 (6)

- The earnings sub-indicator includes the following variables, whose higher values indicate higher profitability:
  - Return on Assets (ROA): Calculated using pre-tax profits.
  - Return on Equity (ROE): Calculated using pre-tax profits.
  - Profit Margin: Reflects the insurer's efficiency in generating profitability.
- Solvency is assessed using three key ratios:
  - The solvency ratio ensures sufficient capital coverage for potential risks.
  - Gross Provisions relative to Gross Written Premiums: This metric indicates the level of preparedness for potential claims.

- The retention ratio indicates that lower values reflect effective management of risk transfer.

In the following chapter, the strategies for data collection and the methods for analysing these variables are explained in detail.

3.2 DATA COLLECTION

The data for the SLR (Petrović & Karanović, 2024) was collected from the Web of Science (WoS) database between September and December 2023. This process yielded a total of 173 papers focusing on the topics of risk management and the efficiency of financial institutions. The financial data used to develop the proposed RMI for banks and insurance companies was sourced from the Orbis database.

A comprehensive dataset containing information on over 11,000 banks spanning more than 20 years was initially retrieved from the Orbis database. However, to meet the requirements of the DEA BoD model, which necessitates a balanced dataset, the dataset was refined to exclude banks with missing data. Additionally, banks that exited the industry due to bankruptcy, mergers, acquisitions, or new market entries were also excluded. This refinement resulted in a longitudinal dataset comprising 589 banks from 34 countries, covering the period from 2015 to 2021.

Similarly, the Orbis database provided a substantial dataset of over 5,000 insurance companies spanning more than 20 years. By applying the same criteria used for banks—addressing missing data and excluding companies that exited or entered the market—this dataset was refined into a longitudinal dataset comprising 744 insurance companies from 31 countries, covering the period from 2012 to 2021.

Before constructing the proposed Risk Management Indices, a series of preprocessing and data preparation steps were undertaken to ensure the dataset's suitability for analysis. These procedures, which include data cleaning, variable selection, and model-specific adjustments, are described in detail in the following section.

3.3 DATA ANALYSIS

The results of the SLR (Petrović & Karanović, 2024) entitled "Financial Institutions Efficiency: Systematic Literature Review", were discussed in detail in earlier sections. This sub-chapter focuses on the data analysis conducted in the second and third papers: "Bank Risk-Adjusted Efficiency Using a Composite Risk Management Index" (Petrović et al., 2025a) and "Insurance Companies Risk-Adjusted Efficiency Using a Composite Risk Management Index" (Petrović et al., 2025b). Both papers employ a consistent methodology, differing only in the variables and datasets used for banks and insurance companies, respectively.

The datasets extracted from the Orbis database underwent standardization and normalization procedures in accordance with the guidelines outlined in the OECD (2008) handbook on constructing composite indicators. The methodology proposed by Gulati (2023) was closely followed in both papers. The longitudinal study design addressed issues related to missing data by excluding institutions with incomplete records, thereby eliminating the need for imputation stated by OECD (2008). Banks and insurance companies with assets under USD 1 billion were excluded to minimize the influence of outliers, a common practice in empirical studies on financial institutions. To further mitigate the impact of extreme values, all variables were winsorized at the 90% level. This process ensured that values between the 5th and 95th percentiles remained unchanged, while values outside this range were replaced with the respective bounds.

Following winsorization, normalization was conducted to ensure the comparability of the variables used in the creation of the composite RMI. As suggested in Gulati (2023), the Min–Max normalisation method was based on the perception of the indicators with risk management and efficiency of banks and insurance companies respectively. A positive polarity of variables is defined with (+), and a negative with (-), as presented in Figures 2 and 3. A more detailed description and argumentation of polarities is available in the second (Petrović et al., 2025a) and third (Petrović et al., 2025b) scientific paper appended to this doctoral dissertation. For variables which can be interpreted to positively affect risk management and efficiency of financial institutions (banks and insurance companies) the following normalisation formula is applied (Gulati, 2023, p. 5):

$$I_{rj} = \frac{(y_{rj} - min_j(y_r))}{(max_j(y_r) - min_j(y_r))} \tag{1}$$

where I_{rj} denotes the normalised value of the variable in the r^{th} sub-indicator for the j^{th} bank and insurance company respectively. The actual value of each variable is denoted y_{rj} of the the r^{th} sub-indicator for the j^{th} bank and insurance company respectively. The variable minimum value in the r^{th} sub-indicator for the j^{th} bank and insurance company respectively is denoted $min_j(y_r)$ and the maximum value of a variable in the r^{th} sub-indicator for the j^{th} bank and insurance company respectively is denoted $max_j(y_r)$.

However, for variables used to construct the proposed RMIs that are interpreted as negatively affecting the risk management and efficiency of banks and insurance companies, the following Max–Min normalisation formula is applied (Gulati, 2023, p. 5):

$$I_{rj} = \frac{\left(max(y_r) - y_{rj}\right)}{(max_j(y_r) - \ min_j(y_r))} \tag{2}$$

Variables transformed with Min–Max and Max–Min normalisation assume values between 0 and 1, eliminating negative values and allowing for comparability between variables used in the construction of composite indices. Nonetheless, before the use of the normalised datasets in the creation of the composite RMIs, it is necessary to rescale the variables as some variables assumed the zero value during the normalisation process. These variables would be dropped during the construction of the composite index as the constrained DEA BoD requires non-zero variables. To ensure all variables are implemented in the first stage of the composite RMI construction, the normalised variables are rescaled using Z-score standardization with mean 100 and standard deviation at 10 using the following formulas:

$$Z_{rj} = \frac{(I_{rj} - \bar{I}_{rj})}{\sigma_{rj}} \tag{3}$$

where Z_{rj} is the standardised value of the normalised value I_{rj} for each variable in the r^{th} sub-indicator for the j^{th} bank and insurance company respectively. The average value of the normalised variable in the r^{th} sub-indicator for the j^{th} bank and insurance company respectively is denoted with $\bar{I}_{rj}$ while the standard deviation of the normalised value I_{rj} for each variable in the r^{th} sub-indicator for the j^{th} bank and insurance company respectively is defined as σ_{rj}.

Moreover, to achieve nonnegative and nonzero values for all variables in the sampled datasets it is necessary for the Z-scores to have a mean of 100 and a standard deviation of 10, which is achieved using the following formula:

$$Z'_{rj} = 100 + 10 * \ Z_{rj} \tag{4}$$

where Z'_{rj} is the standardised value with mean 100 and the standard deviation of 10 for each variable in the r^{th} sub-indicator for the j^{th} bank and insurance company respectively.

After the required data transformations, the samples are ready for constructing the composite RMIs following the two-step constrained DEA BoD procedure proposed by Gulati (2023). As outlined in the previous sections the DEA methodology is widely used in estimating frontier efficiency of financial institutions as a linear programming model that was first introduced by Charnes et al. (1978) and Banker et al. (1984). The BoD model is the application of DEA methodology adapted for composite indicators, as originally proposed by Melyn & Moesen (1991) to evaluate macroeconomic performance. The BoD was later refined by Cherchye et al. (2004) and Cherchye et al. (2007) and presented as a viable alternative to equal weight allocation by the OECD (2008). The benefit of the DEA BoD model in composite indices construction is that it eliminates subjectivity from weight distribution of sub-indicators and indicators since weighting is solely data-driven and focuses on the optimal allocation of weights in order to maximise the benchmark score. Consequently, the weights of the sub-indicators can assume values from 0 to 1, and the resulting composite indices will range from 0 which is the worst possible performance, in our case poor risk management efficiency, and 1 which is the best possible performance or the efficient risk management.

The second (Petrović et al., 2025a) and third (Petrović et al., 2025b) scientific paper appended as an integral part of this doctoral dissertation apply this methodology to construct the RMI for banks and insurance companies, respectively. To achieve this goal, the methodology presented in Gulati (2023) greatly influenced the construction of the proposed composite RMIs, which were computed using the Compind package in R (Vidoli & Fusco, 2018).

The two-stage process for constructing the RMIs implemented a constrained DEA BoD model ensuring that all variables used in sub-indicators are represented in the composite RMI for banks and insurance companies respectively. The first step in constructing the proposed RMI using the constrained DEA BoD model for banks set the lower limit at 10% in each sub-indicator, meaning that for the CAMEL sub-indicators, starting with Capital Adequacy the variables had a lower limit of 10%, and consequently an upper limit of 80% since there are three variables constructing the Capital Adequacy sub-indicator. The process is identical for the following three sub-indicators, Asset Quality, Management Efficiency, and Earnings, all calculated with a lower bound at 10% and upper bound at 80%. Liquidity, the final sub-indicator for the bank's RMI is constructed using four variables, with a lower limit of 10% and upper limit at 70%. This means that the variables weights in the CAMEL sub-indicator could not be lower than 10% and higher than 80%, or 70% in the case of liquidity. This ensured that each variable was represented in the sub-indicator, thus reducing overfocusing on highly effective and excluding less effective, though still important variables. This procedure resulted in five sub-indicators with values between 0 and 1 for each bank in each year. The second stage of the constrained DEA BoD model is used to aggregate the CAMEL sub-indicators results. As they are non-negative and non-zero, there was no requirements for additional normalisation and standardization procedures. For the creation of the RMI for banks, the same lower limit of 10% was applied, setting the upper limit at 60% since there were five sub-indicators. The procedure was repeated for all 589 banks over the period from 2015 to 2021. The resulting composite RMI for banks ranges between 0 and 1 and presents a benchmark for ranking and comparing the quality of bank risk management efficiency. Their yearly averages and additional insights are provided in the following section, with a more detailed analysis available in the second scientific paper (Petrović et al., 2025a) appended to this dissertation.

The two-step constrained DEA BoD procedure proposed by Gulati (2023) and outlined above was also implemented in the third appended scientific paper (Petrović et al., 2025b), focusing on the construction of a composite RMI for insurance companies. As outlined in previous sections, the proposed RMI for insurance companies was constructed using five sub-indicators establishing the CAMES framework (Capital Adequacy, Asset Quality, Management Efficiency, Earning, and Solvency), with 15 variables equally divided between five sub-indicators.

As in the construction of the RMI for banks, in the first step of the constrained DEA BoD model for the construction of the RMI for insurance companies also used a lower limit of 10% and an upper limit of 80% for all sub-indicator variables, as each sub-indicator was constructed out of three specific variables of each insurance company. The resulting sub-indicators composite indices ranging from 0 to 1 were then aggregated in the second stage of the constrained DEA BoD model identically as for banks. The lower limit was set to 10% and the upper limit was set to 60% as the composite CAMES RMI for insurance companies was composed of five sub-indicators. This process was repeated for each of the 744 insurance companies in the sample over the period from 2012 to 2021. The insurance company RMIs ranges between zero and one, providing a benchmark for ranking and comparing the quality of their risk management efficiency. Yearly averages and additional insights on the insurance companies' RMIs are provided in the following section, with a more detailed analysis available in the third scientific paper (Petrović et al., 2025b) appended to this dissertation.

Finally, after developing and calculating the RMIs for banks and insurance companies respectively, a fixed effects panel data analysis with robust standard errors was employed to evaluate the hypotheses (H1 – H4) presented in the introduction of this dissertation. As noted earlier, the hypotheses asses the validity of the constructed RMIs, and the effect of risk management activities on the efficiency of the included financial institutions (banks and insurance companies). More nuanced details on the methodology presented and briefly discussed in this dissertation are available in the second (Petrović et al., 2025a) and third (Petrović et al., 2025b) scientific paper appended herein. The following section presents summarized results from the three scientific papers included in this doctoral dissertation. It focuses on the developed composite RMIs for banks and insurance companies, evaluating the effect of risk management on the efficiency of these financial institutions using econometric models.

4. RESULTS

This section provides a summary of the research findings from the three scientific papers included in this doctoral dissertation. The results of the first paper (Petrović & Karanović, 2024), which involved a systematic literature review, addressed research questions RQ1–RQ3 and offered critical insights into the existing literature on the risk management and efficiency of financial institutions. The conclusions drawn from this review were previously discussed in the literature review section. For reference, a brief overview of the key findings from the first paper is presented in Table 4.

Table 4 Systematic literature review – results

Research question	Findings
RQ1: What are the most used methods employed in studies on the efficiency of financial institutions?	Parametric models, primarily SFA, and non-parametric models, mainly DEA, are both utilized alongside additional econometric models such as Ordinary Least Squares (OLS) and Generalized Method of Moments (GMM) for robustness testing.
RQ2: What are the most used variables for measuring the efficiency of financial institutions?	The SLR concluded that the variables are defined by the approach, with the intermediation approach being the most widely used, followed by the operating approach. In the intermediation approach, the balance sheet components of banks and insurance companies are utilized, including capital, total assets (to define size), investments, loans, and deposits. Conversely, the operating approach places greater emphasis on the operations of banks and insurance companies, employing financial data from their profit and loss statements. This includes interest and non-interest income and expenses, operating expenses, revenue, and profitability ratios such as return on assets (ROA) and return on equity (ROE), as well as profit margins. For insurance companies, relevant metrics include net premiums, investment income, investment yield, incurred claims, and administrative costs (including labour costs). A general consensus on the most appropriate input and output variables has yet to be achieved, particularly regarding the categorization of variables such as deposits for banks and incurred claims for insurance companies.
RQ3: What are the most used measures of risk and efficiency for evaluating the impact of risk management on operational efficiency? Are composite indices utilized in the efficiency assessment of financial institutions?	The most commonly used measures of risk and efficiency include internal risk metrics such as Non-Performing Loans (NPLs), Loan Loss Provisions (LLPs), and Loan Loss Reserves (LLRs), along with risk premiums, beta, and other market risk indicators for banks. An efficiency measure for banks is the efficiency ratio, which is defined as the ratio of overhead costs (including non-interest and administrative expenses) to net income (comprising interest income and net fees). For insurance companies, the risk variables considered are capital and surplus (risk capital) and total gross provisions, while the efficiency ratio can be defined as the ratio of total underwriting expenses to total underwriting income. Recent studies have developed composite indices to estimate bank stability (Gulati, 2023; Gulati et al., 2023), bank risk-adjusted efficiency (Gulati, 2022), and bank governance (Gulati et al., 2020), as well as to measure systemic risk (Acharya et al., 2016), and develop early warning indicators (Babecký et al.,

	2014). Furthermore, the nature and the determinants of disclosure practices in the insurance industry were explored by Malafronte et al. (2016), which led to the creation of a risk disclosure index for insurance companies by Malafronte et al. (2018). The ease of use and the data-driven allocation of weights in the frequently employed DEA BoD model used in constructing composite indices, prompted the adoption of this methodology to develop the proposed RMI for banks and insurance companies respectively. The objective of the RMI is to estimate their risk-adjusted efficiency and evaluate the effect of risk management on the efficiency of financial institutions.

Source: PhD candidate's compilation based on the results from the appended scientific paper 1: Petrović, D., & Karanović, G. (2024). Financial institutions efficiency: a systematic literature review. Zbornik Radova Ekonomskog Fakulteta u Rijeci / Proceedings of Rijeka Faculty of Economics, 42(2), 411–446. https://doi.org/10.18045/zbefri.2024.2.11

The results of the conducted SRL in the first appended scientific paper guided the development and methodology for constructing the RMIs for banks and insurance companies respectively. The average DEA BoD results for the proposed banks' RMIs are presented in Table 5. From Table 5, it is evident that, banks achieve an average high risk-adjusted efficiency of over 90%, with the highest recorded in 2016 (0.9508) and the lowest in 2017 (0.9371). The average risk-adjusted efficiency over the period amounts to 94.53%, indicating that, on average, banks could enhance their risk management efficiency by 5.47%. Analysing the five CAMEL sub-indicator scores reveals that asset quality has the highest average score of 0.9270, followed by management efficiency at 0.8889. Liquidity (0.8342) and capital adequacy (0.8410) recorded the lowest average scores, while earnings fell in the middle with a score of 0.8528. A more in-depth analysis of the banks' RMI sub-indicators and their weights is provided in the second scientific paper (Petrović et al., 2025a) appended to this dissertation.

The results of the composite RMI weight analysis available in the second scientific paper (Petrović et al., 2025a) indicate that asset quality, with a period average weight of 0.3632, and management efficiency, with a period average weight of 0.2305, achieve the highest average weights among the five CAMEL RMI sub-indicators. This is followed by liquidity, which has an average weight of 0.1524, while capital adequacy and earnings have the lowest weights, at 0.1253 and 0.1285, respectively. These findings align with the efficiency scores presented in Table 5, as the most efficient sub-indicators received the highest weights.

Table 5 Bank Risk Management Index and sub-indicators results

Year	Capital Adequacy	Asset Quality	Management Efficiency	Earnings	Liquidity	RMI
2015	0.8342	0.9241	0.8924	0.8528	0.8228	0.9430
2016	0.8308	0.9208	0.8948	0.8490	0.8207	0.9508
2017	0.8410	0.9225	0.8948	0.8516	0.8229	0.9371
2018	0.8418	0.9243	0.8938	0.8645	0.8315	0.9463
2019	0.8488	0.9299	0.8926	0.8605	0.8299	0.9480
2020	0.8458	0.9311	0.8810	0.8351	0.8480	0.9450
2021	0.8443	0.9360	0.8727	0.8562	0.8637	0.9468
Average	0.8410	0.9270	0.8889	0.8528	0.8342	0.9453

Source: Appended scientific paper 2: Petrović D., Dasilas A., Karanović G. (2025a), "Bank risk-adjusted efficiency using a composite risk management index". Journal of Risk Finance, Vol. 26 No. 3 pp. 485–515, doi: https://doi.org/10.1108/JRF-11-2024-0362 (497)

Furthermore, the weight analysis of each individual RMI CAMEL sub-indicators revealed the most significant variables contributing to the construction of the RMI. For the capital adequacy sub-indicator, the equity to total assets ratio is the most significant driver of risk-adjusted efficiency stressing the importance of adequate capitalisation in banking. Moreover, for the asset quality sub-indicator, the most significant variables are the loan loss reserves to gross loans ratio and the non-performing loans to gross loans ratio, thus showing the significance of credit risk management in reducing non-performing loans and accumulating adequate reserves for defaults (Petrović et al., 2025a).

Regarding the management efficiency sub-indicator, the net loans to total assets ratio and the cost-to-income ratio are the most significant variables, underscoring the importance of loan origination and cost minimization in banking. Earnings is the only sub-indicator that achieves nearly equal weighting, with only ROAA assuming a slightly lower weight. Furthermore, liquidity is primarily influenced by the net loans to deposits ratio and the short-term funding ratio (for more information, see Petrović et al., 2025a).

To evaluate the proposed RMI for banks using the CAMEL framework, a fixed effects model with robust standard errors is employed to mitigate potential autocorrelation and heteroskedasticity. The dependent variable is the constructed RMI for banks, while the independent variables are the CAMEL sub-indicators. This analysis tests the first hypothesis (H1): There is a significant relationship between bank specific risks (CAMEL) and the composite risk management index, as proposed in the introduction of this doctoral dissertation. The results are presented in Table 6.

Table 6 Fixed effects panel data analysis with robust (HAC) standard errors (testing H1)

Variables	**Results**
Capital Adequacy (CA)	0.1062*** (0.0063)
Asset Quality (AQ)	0.1796*** (0.0084)
Management Efficiency (ME)	0.2296*** (0.0112)
Earnings (E)	0.1342*** (0.0046)
Liquidity (L)	0.1493*** (0.0073)
Constant	0.2464*** (0.0172)
Observations	4123
R-squared	0.9109
R-squared within	0.5819

Note: The table reports the results from the panel fixed effect with robust (HAC) standard errors regression on the relationship between bank-specific risks denoted by the CAMEL sub-indicators and the composite RMI. The dependent variable is the composite RMI as defined in previous sections using the constrained DEA BoD model. Standard errors are reported in parenthesis. *, **, *** indicates significance levels at the 10%, 5%, and 1%, respectively.

Source: Appended scientific paper 2: Petrović D., Dasilas A., Karanović G. (2025a), "Bank risk-adjusted efficiency using a composite risk management index". Journal of Risk Finance, Vol. 26 No. 3 pp. 485–515, doi: https://doi.org/10.1108/JRF-11-2024-0362 (500)

Focusing on the results presented in Table 6, we reject the null hypothesis in favour of H1: There is a significant relationship between bank specific risks (CAMEL) and the composite risk management index. All components of the CAMEL framework demonstrate a positive and statistically significant relationship with the proposed RMI for banks. Therefore, we can conclude that there is a significant positive relationship between bank-specific risks, as expressed through the CAMEL framework, and the computed RMI for banks. The highest coefficients are associated with management efficiency and asset quality, underscoring the importance of minimizing costs and credit risk. Furthermore, the model accounts for over 91% of the variance in the RMI, with 58% of the variation attributable to changes within individual banks and their CAMEL components. Autocorrelation was addressed using robust standard errors, as indicated by the Durbin-Watson statistics (additional robustness tests have been provided in the Appendix of the second scientific paper, see Petrović et al., 2025a). The same fixed effects model with robust standard errors is applied to evaluate H2: There is a significant relationship between risk management index and bank efficiency, with the results presented in Table 7.

Table 7 Fixed effects panel data analysis with robust (HAC) standard errors (testing H2)

Variables	Results
Risk Management Index (RMI)	0.2676* (0.1399)
Capital Adequacy (CA)	−0.0497 (0.0778)
Asset Quality (AQ)	0.0814 (0.0637)
Management Efficiency (ME)	0.0360680 (0.1404)
Earnings (E)	−0.3634*** (0.0673)
Liquidity (L)	0.0609 (0.0849)
Constant	0.5623*** (0.1494)
Observations	4,123
R-squared	0.9423
R-squared within	0.0359

Note: The table reports the results from the panel fixed effect with robust (HAC) standard errors regression on the relationship between the RMI with its components and operational efficiency. The dependent variable is the Efficiency ratio (ER) defined as the ratio of bank overheads to the sum of interest income and net fees. Standard errors are reported in parenthesis. *, **, *** indicates significance levels at the 10%, 5%, and 1%, respectively.

Source: Appended scientific paper 2: Petrović D., Dasilas A., Karanović G. (2025a), "Bank risk-adjusted efficiency using a composite risk management index". Journal of Risk Finance, Vol. 26 No. 3 pp. 485–515, doi: https://doi.org/10.1108/JRF-11-2024-0362 (501)

In this study (see Petrović et al., 2025a), the efficiency ratio, defined as the ratio of bank overheads (operating expenses) to the sum of interest income and net fees, serves as the dependent variable. The proposed RMI and the CAMEL sub-indicators are treated as independent variables. The results presented in Table 7 indicate that the constructed RMI, with a coefficient of 0.2676, has a positive but marginally significant effect on the efficiency ratio, with a p-value of 0.0563. This suggests a relationship between the efficiency ratio and the RMI. In contrast, the earnings sub-indicator exhibits a negative and significant relationship (-0.3634; $p < 0.0001$). This finding implies that higher earnings are associated with a lower efficiency ratio, likely due to an excessive focus on profit maximization at the expense of cost minimization. The model accounts for 94% of the variation in the efficiency ratio. However, the low R^2 within (0.0359) indicates that the explanatory power primarily stems from differences among banks rather than time-based changes within individual banks (additional robustness tests are provided in the appendix of the second scientific paper, see Petrović et al., 2025a). In conclusion, the null hypothesis is rejected in favour of H2, supporting the existence of a marginally positive relationship between the proposed RMI for banks and efficiency, as well as a strong inverse effect of earnings on efficiency (Petrović et al., 2025a).

Focusing on the RMI developed for insurance companies, the average period results of the computed RMI are presented in Table 8. The RMI was calculated for 744 insurance companies over the period from 2012 to 2021. As shown in Table 8, the average RMI for insurance companies is 0.9295, indicating an average risk management inefficiency of just 0.0705. The calculated average RMI was highest in 2015 (0.9536) and lowest in 2019 (0.9221).

Focusing on the RMI for insurance company sub-indicators, Capital Adequacy achieved the highest average score of 0.9248, closely followed by Asset Quality at 0.9174 and Solvency at 0.9140. Earnings were the lowest-performing sub-indicator, with an average score of 0.8313. Further analysis of the RMI sub-indicators and their weights for insurance companies is provided in the third scientific paper appended to this dissertation (Petrović et al., 2025b). The key findings indicate that Capital Adequacy attained the highest average weight of 0.3152, followed by Solvency at 0.2046 and Asset Quality at 0.1951. Earnings had the lowest average weight at 0.1401, followed closely by Management Efficiency at 0.1451. These findings underscore the importance of adequate capitalization and solvency reserves for effective risk management in insurance companies (Petrović et al., 2025b).

Moreover, the weight analysis available in the third scientific paper (see Petrović et al., 2025b) of each individual RMI for the insurance company sub-indicators revealed the most significant variables contributing to the construction of the RMI. For Capital Adequacy, the ratio of total gross provisions to capital and surplus, with a period average weight of 0.6102, is the most significant variable, highlighting the role of reserves in ensuring stability and effective risk management. The ratio of total investments to total assets, with a period average weight of 0.5088, is the most important variable concerning the Asset Quality of insurance companies.

Table 8 Insurance company Risk Management Indices and sub-indicators results

Year	Capital Adequacy	Asset Quality	Management Efficiency	Earnings	Solvency	RMI
2012	0.9270	0.9228	0.8802	0.8346	0.9156	0.9325
2013	0.9260	0.9289	0.8569	0.8359	0.9109	0.9293
2014	0.9266	0.9125	0.8665	0.8329	0.9042	0.9269
2015	0.9272	0.9191	0.9390	0.8339	0.9631	0.9536
2016	0.9263	0.9166	0.8546	0.8275	0.9070	0.9260
2017	0.9237	0.9167	0.8771	0.8342	0.9149	0.9302
2018	0.9212	0.9130	0.8490	0.8387	0.9072	0.9233
2019	0.9231	0.9131	0.8637	0.8246	0.9037	0.9221
2020	0.9217	0.9170	0.8672	0.8260	0.9050	0.9254
2021	0.9250	0.9147	0.8651	0.8245	0.9085	0.9257
Average	0.9248	0.9174	0.8719	0.8313	0.9140	0.9295

Source: Appended scientific paper 3: Petrović D., Dasilas A., Karanović G. (2025b), "Insurance companies risk-adjusted efficiency using a composite risk management index". Review of Accounting and Finance, pp. 1-23, doi: https://doi.org/10.1108/RAF-11-2024-0492 (9)

For the Management Efficiency sub-indicator, the variable with the highest average weight is expense ratio (0.5861). Conversely, the Earnings sub-indicator is primarily explained by ROA using P/L before tax, which has an average weight of 0.4796. Finally, the Solvency sub-indicator exhibits a distribution that is closest to equal weighting, with the highest average weight assigned to the solvency ratio (0.3719). In contrast, the retention ratio and total gross provisions over gross written premiums each achieve approximately equal weights of 0.314. A more detailed analysis of the insurance company RMIs and sub-indicator weights is available in the third appended scientific paper (Petrović et al. 2025b).

Following the same process used for constructing and testing the RMI for banks, a fixed effects model with robust standard errors is employed to evaluate whether the proposed RMI for insurance companies accurately reflects the specific risks associated with these companies. The constructed RMI for insurance companies serves as the dependent variable, while its sub-indicators act as independent variables. This test is conducted to assess the third hypothesis (H3): There is a significant relationship between insurance company specific risks (capital, assets, operational, liquidity, and solvency) and the composite risk management index, as proposed in the introduction of this doctoral dissertation.

The results of the proposed RMI for insurance companies are presented in Table 9. The results indicate that all sub-indicators of the proposed RMI for insurance companies demonstrate a positive and statistically significant relationship with the overall RMI. Among these sub-indicators, Solvency has the highest coefficient (0.2471), indicating it has the most substantial impact on the risk-adjusted efficiency of insurance companies. The model explains 97.48% of the variance in the RMI, with 93.25% of the variation within individual insurance companies attributable to the RMI sub-indicators and their changes over time.

Table 9 Fixed effects panel data analysis with robust (HAC) standard errors (testing H3)

Variables	Results
Capital Adequacy (CA)	0.1605*** (0.0053)
Asset Quality (AQ)	0.1779*** (0.0057)
Management Efficiency (ME)	0.1446*** (0.0022)
Earnings (E)	0.1445*** (0.0023)
Solvency (S)	0.2471*** (0.0046)
Constant	0.1458*** (0.0079)
Observations	7,440
R-squared	0.9748
R-squared within	0.9325

Note: The table reports the results from the panel fixed effect with robust (HAC) standard errors regression on the relationship between insurer-specific risks denoted by Capital Adequacy (CA), Asset Quality (AQ), Management Efficiency (ME), Earnings (E), and Solvency (S) sub-indicators and the composite RMI. The dependent variable is the composite RMI as constructed in previous sections using the constrained DEA BoD model. Standard errors are reported in parenthesis. *, **, *** indicates significance levels at the 10%, 5%, and 1% respectively.

Source: Appended scientific paper 3: Petrović D., Dasilas A., Karanović G. (2025b), “Insurance companies risk-adjusted efficiency using a composite risk management index”. Review of Accounting and Finance, pp. 1-23, doi: https://doi.org/10.1108/RAF-11-2024-0492 (13)

The Durbin-Watson statistic of 1.683 indicates that autocorrelation is not a major concern, which is further supported by the Wooldridge test for autocorrelation (p = 0.1305) that fails to reject the null hypothesis, suggesting the absence of first-order autocorrelation. However, the Pearson CD test revealed significant cross-sectional dependence (z = 82.54, p = 0), implying that some unobserved factors influence all units within the panel, a phenomenon commonly observed in large datasets. To address this issue, the (HAC) standard errors are employed in the fixed effects model (additional robustness tests are reported in the appendix of the third scientific paper, see Petrović et al. 2025b).

Considering all factors, the null hypothesis is rejected in favour of H3, confirming a significant positive relationship between the specific risks of insurance companies, represented as CAMES components, and the RMI, with solvency significantly impacting the RMI of insurance companies. Following the same methodology used to assess the RMI for banks, a fixed effects model with robust standard errors is applied to evaluate H4: There is a significant relationship between risk management index and insurance company efficiency whose results are presented in Table 10.

In this case, the dependent variable is the ratio of total underwriting expenses to total underwriting income, which reflects the efficiency of insurance companies' core operations. The independent variables include the proposed RMI and its sub-indicators. As shown in Table 10, the RMI demonstrates a positive and statistically significant effect on the efficiency of insurance companies. Furthermore, all RMI sub-indicators, except for Solvency, are negative and statistically significant, indicating an inverse relationship between Capital Adequacy, Asset Quality, Management Efficiency, Earnings, and the Efficiency of insurance companies.

In the case of Solvency, the relationship is positive (0.6612) and statistically significant, indicating that an increase in Solvency leads to an increase in the efficiency of insurance companies. The model accounts for 71.99% of the variation in the efficiency of insurance companies, utilizing the constructed RMI and its sub-components. Furthermore, 55.95% of the variance is attributed to differences within individual insurance companies (additional robustness tests are reported in the appendix of the third scientific paper, see Petrović et al. 2025b). A more detailed explanation of the inverse relationships between the RMI sub-indicators and efficiency is provided in the third appended scientific paper (Petrović et al., 2025b). In conclusion, the null hypothesis is rejected in favour of H4, supporting the assertion that a positive relationship exists between the proposed RMI for insurance companies and their efficiency (Petrović et al., 2025b).

The results presented in this section support the main hypothesis that risk management activities have a positive and statistically significant effect on financial institutions, specifically banks and insurance companies. It is important to note that this section summarizes findings from the appended scientific papers, which are an integral component of this doctoral dissertation. The first paper (Petrović & Karanović, 2024) addressed key research questions and laid the foundation for the methodology used in the second (Petrović et al. 2025a) and third (Petrović et al. 2025b) papers. These subsequent papers developed, constructed, and empirically tested the RMIs for banks and insurance companies, thereby providing insights into the effect of risk management on the efficiency of financial institutions.

Table 10 Fixed effects panel data analysis with robust (HAC) standard errors (testing H4)

Variables	Results
Risk Management Index (RMI)	1.1375*** (0.1606)
Capital Adequacy (CA)	−0.5001*** (0.0666)
Asset Quality (AQ)	−0.3687*** (0.0497)
Management Efficiency (ME)	−1.1170*** (0.0354)
Earnings (E)	−0.3776*** (0.0290)
Solvency (S)	0.6612*** (0.0554)
Constant	1.4063*** (0.0612)
Observations	7,440
R-squared	0.7199
R-squared within	0.5595

Note: The table reports the results from the panel fixed effect with robust (HAC) standard errors regression on the relationship between the RMI with its components and operational efficiency. The dependent variable is the Efficiency ratio (ER) defined as the ratio of total underwriting expenses to total underwriting income. Standard errors are reported in parenthesis. *, **, *** indicates significance levels at the 10%, 5%, and 1% respectively.

Source: Appended scientific paper 3: Petrović D., Dasilas A., Karanović G. (2025b), "Insurance companies risk-adjusted efficiency using a composite risk management index". Review of Accounting and Finance, pp. 1-23, doi: https://doi.org/10.1108/RAF-11-2024-0492 (14)

The following section discusses the results obtained, outlines the methodology employed, and compares these results with those of previous studies. Furthermore, this section clearly articulates the scientific and applied contributions of this doctoral dissertation, concluding with recommendations for future research on the topic of risk-adjusted efficiency in financial institutions.

5. CONCLUSION

Despite decades of empirical research on financial institution efficiency, the effect of risk management on the efficiency of banks and insurance companies remains inadequately defined. Neglecting the influence of risk management on financial institutions could lead to inaccurate efficiency estimation and misleading decision-making. A comprehensive understanding of how risk management impacts the efficiency of financial institutions (particularly banks and insurance companies) is essential for producing more precise efficiency measures and fostering better-informed decisions. The main challenge lies in defining the determinants of financial institution efficiency and risk management to adequately assess risk-adjusted efficiency.

Through the systematic literature review conducted as part of the appended scientific papers, this research proposed a novel framework for estimating financial institutions' risk-adjusted efficiency. Central to this framework is the development of composite risk management indices, which offer a robust means of assessing the interplay between risk management and efficiency.

5.1 DISCUSSION

To evaluate the effect of risk management on the efficiency of financial institutions, this doctoral dissertation proposed the development of composite RMIs. This novel methodology was applied to longitudinal international datasets of banks and insurance companies. The outcomes of this doctoral dissertation, derived from the empirical results and conclusions of the three appended scientific papers, are presented in Figure 4.

Figure 4 Thesis outcome based on published scientific papers results

Appended scientific paper 1: Financial institutions efficiency: a systematic literature review	**Appended scientific paper 2:** Bank Risk-Adjusted Efficiency Using a Composite Risk Management Index	**Appended scientific paper 3:** Insurance Companies Risk-Adjusted Efficiency Using a Composite Risk Management Index
•Research objectives: 1 - 5 •RQ1: Conceptual findings •RQ2: Conceptual findings •RQ3: Conceptual findings	•Research objectives: 1,2,5 •H1: positive statistically significat •H2: positive weakly statistically significat	•Research objectives: 3,4,5 •H3: positive statistically significat •H4: positive statistically significat

Source: PhD candidate's compilation based on the results from the appended scientific papers

From Figure 4, it can be concluded that all the research objectives and hypotheses proposed in this doctoral dissertation have been successfully met in the appended scientific papers.

The first scientific paper (Petrović & Karanović, 2024) achieved the conceptual research objectives (1–5) outlined in the introduction. The systematic literature review conducted in this paper provided answers to the established research questions (RQ1–RQ3). The conceptual findings addressed the need for a robust theoretical framework for assessing financial institution efficiency and its determinants. This theoretical framework facilitated the development of a novel methodology for risk-adjusted efficiency estimation, enabling the construction of composite RMIs tailored to banks and insurance companies.

The empirical research objectives stated in the introduction were addressed in the second (Petrović et al. 2025a) and third (Petrović et al. 2025b) scientific articles appended to this doctoral dissertation. The second scientific paper (Petrović et al. 2025a) fulfilled research objectives 1 and 2 by constructing the RMI for banks using the CAMEL framework and validating its relevance for assessing the effect of risk management on efficiency. Objective 5 was met by comparing relevant studies on this topic. The third scientific paper (Petrović et al. 2025b) addressed research objectives 3 and 4 by developing the RMI for insurance companies using the proposed CAMES framework and validating its effectiveness in assessing the impact of risk management on efficiency. Research objective 5 was again achieved through a critical assessment of relevant empirical studies.

The fulfilment of the research objectives led to the evaluation of the main hypothesis of this doctoral dissertation as stated H: There is significant relationship between risk management and financial institution efficiency, which was divided in four hypotheses empirically assessed in the second and third appended scientific papers. The main hypothesis is supported from the empirical results attained in the second and third appended scientific papers.

The first hypothesis focuses on the relationship between the constructed RMI for banks and the CAMEL framework defined sub-indicators, which is positive and statistically significant. However, the second hypothesis evaluating the relationship between risk management represented by the constructed RMI for banks is positive but only weakly significant with bank operational efficiency, while there is a strongly inverse, statistically significant relationship between the Earnings sub-indicator and bank operational efficiency.

The third hypothesis concentrates on the relationship between the constructed RMI for insurance companies through the proposed CAMES sub-indicator and was found to be positive and statistically significant. Furthermore, the fourth and last hypothesis evaluates the positive and statistically significant relationship between insurance companies' risk management through the proposed RMI with insurance companies' operational efficiency. Solvency is the only sub-indicator to positively affect the insurance companies' operational efficiency.

In conclusion, based on the empirical results and evidence presented in this doctoral dissertation, it can be suggested that risk management activities exhibit a positive effect on financial institution efficiency. Additionally, a deeper analysis of the proposed RMI for banks reveals that the major drivers of the banks' risk-adjusted efficiency are good asset quality as a proxy for adequate credit risk management, and management efficiency focusing on operational risk management and cost minimisation. On a similar note, a subsequent analysis of the proposed RMI for insurance companies reveals that the major drivers of the insurance companies' risk-adjusted efficiency are solvency, capital adequacy (capitalisation) and asset quality. The following section provides additional reflections on the proposed methodology.

5.2 METHODOLOGICAL CONSIDERATIONS

This doctoral dissertation proposes a novel methodology for estimating the risk-adjusted efficiency of financial institutions. As summarized through the SLR in the first scientific paper (Petrović & Karanović, 2024) appended herein, the field of financial institution efficiency estimation is vast and heterogeneous. However, two major methodologies dominate the empirical research in this topic, parametric (SFA) and nonparametric (DEA). However, integrating the effect of risk management on financial institutions' efficiency is a new area of interest with new challenges.

The field of risk-adjusted efficiency estimation is still small and developing with no comprehensive methodology established in the mainstream. The SLR, based on the PRISMA framework, provided insight into the most widely used variables, approaches and methods in efficiency estimation, while also outlining the main areas of interest. The effect of risk management on financial institution efficiency is a new field of interest as the relationship between financial institution risk management activities and efficiency has not yet been clearly defined.

This was the main motivation for this doctoral dissertation. Empirical studies on the topic yielded mixed results regarding the effect of risk management on efficiency while the theoretical arguments for considering the effect of risk management on efficiency were first voiced by Mester (1996). Furthermore, the SLR systematized the extensive body of work on financial institution efficiency, consequently outlining a novel approach to risk-adjusted efficiency estimation through the development of risk management indices. To achieve the goal of establishing the relationship between risk management activities and financial institution efficiency, this dissertation first defined the specific risk variables for banks (non-performing loans, loan loss reserves), and insurance companies (total gross provisions) as a part of the CAMEL framework and the proposed CAMES framework. Furthermore, to construct the proposed RMIs, a constrained DEA BoD model was employed since it allows for a data-driven weight allocation.

The proposed methodology is advantageous for its simplicity and applicability to small samples since DEA as a nonparametric linear programming method allows for efficiency estimation of a smaller sample. As reported by Gulati (2023), the constraint of 10% applied for the constrained DEA BoD model is appropriate for financial institutions. The proposed and implemented methodology provides a novel approach to estimating risk-adjusted efficiency of financial institutions by developing and constructing composite risk management indices specifically for banks and insurance companies.

Future studies are prompted to employ and evolve this methodology, by reevaluating the list of variables and expanding it. Furthermore, recent work by Maricic & Jeremic (2023) proposed the imposition of unsupervised constraints to the BoD model,ß thus improving the constrained model proposed herein, although its use is well established in previous studies. Finally, the employment of machine learning (ML) and artificial intelligence (AI) to parametric and non-parametric models will surely improve and advance this methodology in future empirical studies. The following section focuses on the comparison of results between this doctoral dissertation and other studies.

5.3 COMPARISON WITH OTHER STUDIES

The empirical results in this dissertation contribute to the existing knowledge on financial institution risk-adjusted efficiency. Previous research focused on a specific geographical area or on external risk management, while the topic on internal risk management is still being developed. Mester (1996) was of the earliest to advocate for the inclusion of the effect of risk management on financial institutions, while Berger & DeYoung (1997) were the first to decompose risk management to internal and external factors. Moreover, they coined the term “bad luck” for losses due to external factors (market shocks, wars, political instability, pandemics, etc.) which risk management cannot be fully mitigated, and “bad management” for losses due to internal factors that could have been avoided by implementing adequate risk management practices.

Since then, there have been several studies focusing on internal risk management activities as does this doctoral dissertation. Chang (1999) studies the risk-adjusted efficiency of Taiwan’s rural financial intermediaries and concludes that non-performing loans and loan loss reserves are appropriate measures of credit risk that should be controlled by regulators. This is in line with the research conducted in the second appended research paper (Petrović et al., 2025a), as it employed NPLs and LLRs as credit risk variables in the asset quality sub-indicator while developing the composite RMI for banks. On the other hand, Huang & Paradi (2011) focus on the risk-adjusted efficiency of the Chinese insurance industry, confirming that efficiency estimates tend to be underestimated. They implement insurance reserves as a risk measure, which is in line with the third scientific paper appended to this dissertation (Petrović et al. 2025b), since it implements total gross provisions to the solvency and capital adequacy sub-indicators in the proposed RMI for insurance companies. The results show a positive relationship between risk management and insurance company efficiency, which is in line with the results attained in the third appended scientific paper to this dissertation (Petrović et al. 2025b). Safiullah & Shamsuddin (2019) studied the differences between Islamic and conventional banks by examining risk-adjusted efficiency and corporate governance. Their results show that Islamic banks achieve higher risk-adjusted cost efficiency at the cost of risk-adjusted profit efficiency. Cost efficiency scores are lower when adjusted for risk, which is not the same for risk-adjusted profit efficiency that showed slightly increased levels, thus implying that risk-taking negatively effects cost performance but has a positive effect on profit (revenue) efficiency. Risk-adjusted efficiency of Indian banks was studied by Gulati (2022) by employing a non-oriented directional distance function (DDF) model with quasi-fixed inputs (Gulati, 2022, p. 23). This study uses two standard risk control variables, equity and NPLs to estimate risk-adjusted efficiency defined as a measure of efficiency obtained by incorporating these risk control variables directly into the efficiency measurement model. The choice of risk control variables is comparable to the variables used in the construction of the RMI for banks, where equity was used as a sub-indicator for capital adequacy and NPLs were used in asset quality as a sub-indicator. Their econometric results indicate that banking crises seem to exert an idiosyncratic and differential impact on the efficiency of banks (Gulati, 2022, p. 36).

By comparing relevant studies with the results attained in this dissertation, it is important to note that the studies above implemented econometric, parametric and non-parametric models for risk-adjusted efficiency estimation. This differs from the approach applied in this dissertation that focused on developing and constructing composite RMI for banks and insurance companies, as motivated by the following studies. Asmild & Zhu (2016) employ a weight constrained DEA methodology to control for the use of extreme weights in bank efficiency assessments during financial crisis they employ NPLs and LLPs as (credit) risk parameters and proxies for loan (asset) quality. Their results confirm a bias occurring when unrestricted DEA models are calculated by neglecting the effect of risk, as such models score potentially risky banks with lower asset quality as having higher efficiency, as Mester (1996) argued. Gang et al. (2018) proposed the "M&A Index" using the SFA approach to facilitate the evaluation of mergers and acquisitions. Their results indicate that "M&A Index" as a proxy for the takeover efficiency is positively related to abnormal returns for acquirers in the short run. In the long run, a higher M&A Index indicates better acquirers' post-merger operating performance. On a similar note, Gaganis et al. (2021) propose a composite index of social, environmental and financial performance (CISEF) by employing the multiple-criteria analysis approach. Since the constrained DEA BoD methodology is employed in this doctoral dissertation, the most relevant studies in composite indice development and construction are by Rogge (2018) and Verbunt & Rogge (2018). Regarding the composite indices development for insurance companies, relevant work is provided by Malafronte et al. (2016) in studying the determinants of disclosure practices. Moreover, Malafronte et al. (2018) further develop a composite risk disclosure index (RDII) for insurers for the evaluation of the effectiveness of risk disclosure practices in the insurance industry. The results indicate that higher RDII contributes to higher volatility, thus less disclosure is better during the good times, while the opposite is true during the bad times. This study differs from the third appended scientific paper (Petrović et al., 2025b) as it focuses on risk disclosure, while the appended study focuses exclusively on the effect of risk management on efficiency. The most relevant work in the development of banks composite indices development is provided by Gulati et al. (2020), who construct a corporate governance index for Indian banks by employing the constrained DEA BoD methodology. Furthermore, Gulati et al. (2023) develop a bank stability index (BSI) using the BoD framework integrated with the meta-frontier approach (meta-BoD framework). The BSI is developed and tested on 76 Indian banks that on average operate below the stability frontier, providing an opportunity for improvements in stability. Finally, the study by Gulati (2023) proposes a novel measure of bank stability for effective policymaking on Indian public sector banks by employing the constrained DEA BoD model. The methodology proposed by Gulati (2023) heavily influenced the development and construction of the proposed RMIs for both banks and insurance companies in this dissertation.

However, from the comparison of relevant studies, it is important to point out the uniqueness of the research conducted in this dissertation. Firstly, on a conceptual basis, the first study appended to this doctoral dissertation (Petrović & Karanović, 2024) conducts a SLR to provide an overview of relevant studies in the field of financial institutions efficiency. Furthermore, the SLR proposes a sound theoretical framework for efficiency estimation while incorporating the effect of risk management that yields a novel methodological approach in assessing the risk-adjusted efficiency for both banks and insurance companies, based on the construction of composite risk management indices. Moreover, on a methodological basis, the second scientific paper (Petrović et al., 2025a) appended herein differs from previously compared studies in the list of variables employed in the construction of the RMIs. The CAMEL framework is extensively used (Bhatti et al., 2022; Danlami et al., 2022; de Abreu & de Camargos, 2022; Handorf, 2016; Kaur, 2010; Muhmad & Hashim, 2015; Nguyen & Dang, 2020; Nugroho et al., 2020; Pekkaya & Demir, 2018; Qureshi & Siddiqui, 2023; Risal & Panta, 2019; Shaddady & Moore, 2019; Shukla, 2015; Sloan Swindle, 1995), however the second scientific paper (Petrović et al. 2025a) appended to this dissertation employs 16 variables in the five CAMEL sub-indicators for the development of a bank-specific RMI. On a similar note, the third scientific paper appended to this dissertation (Petrović et al. 2025b) proposes the CAMES framework, stressing the importance of solvency in insurance companies. The CAMES framework equally divides 15 specific insurance company variables in five sub-indicators to construct the composite RMI for insurance companies.

Finally, the research conducted herein differs from the previously compared studies on an empirical basis, as the proposed RMIs for banks and insurance companies are computed using the constrained DEA BoD model and empirically tested on large longitudinal, international datasets of banks and insurance companies. The DEA BoD model not only reports on bank and insurance company risk-adjusted efficiency, making ranking and comparison possible among financial institutions, but it also allows for the identification of the most important sub-indicators and drivers of efficiency. Consequently, the empirical analysis conducted in the second and third appended scientific papers reveal a positive and statistically significant effect of risk management on financial institutions efficiency.

5.4 SCIENTIFIC AND APPLIED CONTRIBUTION

This doctoral dissertation yielded several scientific and applicative contributions through the appended scientific papers. Regarding the scientific contribution, the first appended scientific paper (Petrović & Karanović, 2024) provided an overview of the current state of the field of knowledge on financial institutions efficiency, identifying the most widely used models, approaches, and variables, as well as the most popular topics of research. The conceptual part of the contribution is achieved through the proposition of a theoretical framework for financial institutions risk-adjusted efficiency estimation. These scientific contributions influenced the development of a novel approach to financial institutions risk-adjusted efficiency estimation based on the construction of composite RMIs.

The methodological contribution can be observed through the specific methodologies implemented in the second (Petrović et al., 2025a) and third (Petrović et al., 2025b) appended scientific papers, as a unique variable mix is used in the construction of composite RMIs for banks and insurance companies. More specifically, though the application of the CAMEL framework in the second appended paper is not a novelty in the literature, its application to the development of a bank-specific RMI brings new insights. The use of LLRs as a proxy for adequate credit risk management in the asset quality sub-indicator differs from previous studies that focused solely on NPLs and LLPs. Moreover, the third appended scientific paper makes a methodological leap by proposing a CAMES framework, as solvency is a more important sub-indicator for insurance companies than liquidity. The proposed methodology also proposes the use of Total Gross Provisions as measure of solvency risk – the expectation of incurred claims, and the retention ratio as a measure of the risk-taking affinity of insurance companies. Furthermore, this methodology implements the Total Gross Provisions over Capital and Surplus as a risk-capital measure.

Finally, the empirical contribution of the research conducted in the second (Petrović et al., 2025a) and third (Petrović et al., 2025b) appended to this doctoral thesis is evident through the calculation of the composite RMIs using the constrained DEA BoD model on longitudinal and international datasets of 589 banks over the period 2015-2021, and 744 insurance companies over the period 2012-2021. The proposed RMIs not only provide information on bank and insurance company risk management quality over time, but also enables ranking and comparison of the risk-adjusted efficiency across banks and insurance companies. Due to the constrained DEA

BoD methodology employed, the research conducted contributed to the body of knowledge by identifying the most important sub-indicators, areas of risk management and drivers of risk-adjusted efficiency. The empirical findings in the second appended scientific paper (Petrović et al., 2025a) contributed by identifying asset quality and management efficiency as the most important sub-indicators of the RMI, while NPLs over gross loans and LLRs over gross loans, cost to income ratio, and net loans over total assets are the main drivers of the banks' risk-adjusted efficiency. The empirical findings in the third appended scientific paper (Petrović et al., 2025b) contributed by identifying solvency and capital adequacy as the most important sub-indicators of the RMI for insurance companies. The main drivers of insurance company risk-adjusted efficiency are total gross provisions over capital and surplus, solvency ratio, total gross provisions over gross written premium, and the retention ratio.

In conclusion, a significant empirical contribution is made through the empirical testing of the proposed RMIs by confirming a positive and statistically significant relationship between risk management and financial institutions efficiency.

Regarding the research applicative contribution of this doctoral dissertation, the empirical results provide new insights on the effect of risk management activities on financial institution efficiency. Based on the findings from this research, especially the positive effect of risk management activities on bank and insurance company efficiency, could motivate upper management to increase efforts to improve risk management practices. The proposed RMIs could be used as a tool by financial institution management in identifying weak and inefficient areas of risk management, thus improving efficiency and stability of individual banks and insurance companies, and consequently improving the financial system as whole.

Furthermore, the theoretical, methodological and empirical contributions of the research conducted in this doctoral dissertation could influence policymakers when improving future regulations for financial institutions. The proposed RMIs for banks and insurance companies could become an additional tool for evaluating financial institution risk management quality. The empirical results show that policymakers already focus on key areas of risk management such as asset quality for banks, and solvency for insurance companies. The results also suggest that policymakers should allocate more attention to management efficiency for banks, and capital adequacy and asset quality for insurance companies. The ability of direct comparison and ranking of RMI across banks and insurance companies could provide additional information for the public on identifying financial institutions with adequate and efficient risk management, indicating a more stable bank or insurance company. This effect could be significantly amplified by policymakers in the future by mandating RMI reporting in financial institution annual reports.

5.5 IMPLICATIONS FOR FURTHER RESEARCH

Despite the extensive conceptual, methodological, and empirical research provided in this doctoral dissertation, there are areas for future study. The systematic literature review conducted in the first appended scientific paper provided insights on financial institution efficiency. However, more research is needed in mapping all possible variables and models employed in the efficiency estimations for financial institutions. Due to the vastness and heterogeneity of the field of study, the SLR of this doctoral dissertation focused exclusively on risk-adjusted efficiency and the use of composite indices (Petrović & Karanović, 2024). Consequently, the demanding task of providing a definitive verdict on the most appropriate models, approaches and variables in financial institutions efficiency estimation is left for future research.

Furthermore, although the proposed RMIs for banks and insurance companies developed and empirically tested in the second (Petrović et al., 2025a) and third (Petrović et al., 2025b) appended scientific paper offer a novel combination of variables using the widely employed CAMEL and the proposed CAMES framework, future research could expand and improve the variables used by incorporating a sub-indicator for external-market risk, as the CAMEL framework has recently been expanded to CAMELS, where the S stands for (market) sensitivity. The same approach could be applied to the CAMES framework for insurance companies, becoming CAMESS. Moreover, the RMI for banks was constructed and evaluated on an international longitudinal sample of 589 banks with total assets exceeding USD 1 billion over the period 2015–2021 (Petrović et al., 2025a). Future research could address the large differences discovered between banks in this sample, by focusing on a limited geographical area that would guarantee identical or similar reporting standards and financial characteristics. Future studies could also focus on banks with total assets under USD 1 billion to examine for potential differences due to scale efficiency. Similarly, the RMI for insurance companies was empirically tested on an international longitudinal sample of 744 insurance companies with total assets exceeding USD 1 billion over the period 2012–2021 (Petrović et al., 2025b). As discussed in the case of banks, future research could focus on a smaller geographical area or a single country, and on smaller insurance companies with assets under USD 1 billion to control for efficiencies of scale. In addition, future studies could check for structural breaks such as the COVID-19 pandemic.

Based on the methodology used in this research, the constrained DEA BoD model reduces subjectivity in weight redistribution during the construction of composite indices, as this model allows for data-driven weighting. However, the constrained model requires supervision over the minimal weights allowed, and thus future research could improve the constrained DEA BoD model by implementing the unsupervised constraints DEA BoD model as suggested by Maricic & Jeremic (2023). Future studies are also expected to improve the proposed methodology by implementing machine learning (ML) and artificial intelligence (AI) algorithms in weighting and efficiency estimation models.

While the research conducted in this doctoral dissertation describes the positive effect between risk management activities and financial institution efficiency, the research could be enriched in future studies by introducing qualitative data considering managerial risk-taking behaviour. This would add a new qualitative dimension, as research conducted in the three appended scientific papers was solely based on quantitative data. In conclusion, despite endless possibilities for future research, this doctoral thesis fulfilled all its research objectives and provided insights on the effect of risk management on the efficiency of financial institutions.

6. REFERENCES

ABS. (2021). *ABS - Academic Journal Guide, Technical Report*. Chartered Association of Business Schools. https://charteredabs.org/

Acharya, V. V, Pedersen, L. H., Philippon, T., & Richardson, M. (2016). Measuring Systemic Risk. *The Review of Financial Studies*, *30*(1), 2–47. https://doi.org/10.1093/rfs/hhw088

Agliardi, E., Agliardi, R., Pinar, M., Stengos, T., & Topaloglou, N. (2012). A new country risk index for emerging markets: A stochastic dominance approach. *Journal of Empirical Finance*, *19*(5), 741–761. https://doi.org/10.1016/j.jempfin.2012.08.003

Ahmad, N., Naveed, A., Ahmad, S., & Butt, I. (2020). Banking Sector Performance, Profitability, and Efficiency: A Citation-Based Systematic Literature Review. *Journal of Economic Surveys*, *34*(1), 185–218. https://doi.org/10.1111/JOES.12346

Aiello, F., & Bonanno, G. (2018). On the Sources of Heterogeneity in Banking Efficiency Literature. *Journal of Economic Surveys*, *32*(1), 194–225. https://doi.org/10.1111/JOES.12193

Aigner, D., Lovell, C. A. K., & Schmidt, P. (1977). Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics*, *6*(1), 21–37. https://doi.org/10.1016/0304-4076(77)90052-5

Akin, T., Iqbal, Z., & Mirakhor, A. (2016). The composite risk-sharing finance index: Implications for Islamic finance. *Review of Financial Economics*, *31*(C), 18–25. https://ideas.repec.org//a/eee/revfin/v31y2016icp18-25.html

Ali, W., Bekiros, S., Hussain, N., Khan, S. A., & Nguyen, D. K. (2023). Determinants and consequences of corporate social responsibility disclosure: A survey of extant literature. *Journal of Economic Surveys*. https://doi.org/10.1111/JOES.12556

Ali, W., & Wilson, J. (2023). Multi-level analysis on determinants of sustainability disclosure: a survey of academic literature. *Managerial Finance*, *50*(1), 228–265. https://doi.org/10.1108/MF-03-2023-0189/FULL/XML

Allen, F., & Santomero, A. (1997). The theory of financial intermediation. *Journal of Banking & Finance*, *21*(11–12), 1461–1485. https://doi.org/10.1016/S0378-4266(97)00032-0

Altunbas, Y., Carbo, S., Gardener, E. P. M., & Molyneux, P. (2007). Examining the Relationships between Capital, Risk and Efficiency in European Banking. *European Financial Management*, *13*(1), 49–70. https://doi.org/10.1111/J.1468-036X.2006.00285.X

Alzayed, N., Eskandari, R., & Yazdifar, H. (2023). Bank failure prediction: corporate governance and financial indicators. *Review of Quantitative Finance and Accounting*, *61*(2), 601–631. https://doi.org/10.1007/s11156-023-01158-z

Aouini, A., & Abdennadher, C. (2022). Performance in the Insurance Industry (Islamic versus Conventional) and Risk Management. *Journal of Financial Risk Management*, *11*(3), 601–620. https://doi.org/10.4236/JFRM.2022.113028

Ardia, D., Bluteau, K., & Meghani, M. A. (2023). Thirty years of academic finance. *Journal of Economic Surveys*. https://doi.org/10.1111/JOES.12571

Asmild, M., & Zhu, M. (2016). Controlling for the use of extreme weights in bank efficiency assessments during the financial crisis. *European Journal of Operational Research*, *251*(3), 999–1015. https://doi.org/10.1016/j.ejor.2015.12.021

Assaf, A. G., Berger, A. N., Roman, R. A., & Tsionas, M. G. (2019). Does efficiency help banks survive and thrive during financial crises? *Journal of Banking & Finance*, *106*, 445–470. https://doi.org/10.1016/j.jbankfin.2019.07.013

Ayadi, R., Naceur, S. Ben, Casu, B., & Quinn, B. (2016). Does Basel compliance matter for bank performance? *Journal of Financial Stability*, *23*, 15–32. https://doi.org/10.1016/j.jfs.2015.12.007

Babecký, J., Havránek, T., Matějů, J., Rusnák, M., Šmídková, K., & Vašíček, B. (2014). Banking, debt, and currency crises in developed countries: Stylized facts and early warning indicators. *Journal of Financial Stability*, *15*, 1–17. https://doi.org/10.1016/J.JFS.2014.07.001

Banker, R. D., Charnes, A., & Cooper, W. W. (1984). Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis. *Management Science*, *30*(9), 1078–1092. https://econpapers.repec.org/article/inmormnsc/v_3a30_3ay_3a1984_3ai_3a9_3ap_3a1078-1092.htm

Barra, C., Papaccio, A., & Ruggiero, N. (2022). Basel accords and banking inefficiency: Evidence from the Italian local market. *International Journal of Finance & Economics*, *28*(4), 4079–4119. https://doi.org/10.1002/ijfe.2637

Barth, J. R., Lin, C., Ma, Y., Seade, J., & Song, F. M. (2013). Do bank regulation, supervision and monitoring enhance or impede bank efficiency? *Journal of Banking & Finance*, *37*(8), 2879–2892. https://doi.org/10.1016/j.jbankfin.2013.04.030

Battese, G. E., & Corra, G. S. (1977). Estimation of a Production Frontier Model: With Application to the Pastoral Zone of Eastern Australia. *Australian Journal of Agricultural Economics*, *21*(3), 169–179. https://doi.org/10.22004/AG.ECON.22266

Berger, A. N., & DeYoung, R. (1997). Problem loans and cost efficiency in commercial banks. *Journal of Banking & Finance*, *21*(6), 849–870. https://doi.org/10.1016/S0378-4266(97)00003-4

Berger, A. N., Hasan, I., & Zhou, M. (2009). Bank ownership and efficiency in China: What will happen in the world's largest nation? *Journal of Banking & Finance*, *33*(1), 113–130. https://doi.org/10.1016/j.jbankfin.2007.05.016

Berger, A. N., & Humphrey, D. B. (1997). Efficiency of financial institutions: International survey and directions for future research. *European Journal of Operational Research*, *98*(2), 175–212. https://doi.org/10.1016/S0377-2217(96)00342-6

Berger, A. N., & Mester, L. J. (1997). Inside the black box: What explains differences in the efficiencies of financial institutions? *Journal of Banking and Finance*, *21*(7), 895–947. https://doi.org/10.1016/S0378-4266(97)00010-1

Bhatia, V., Basu, S., Mitra, S. K., & Dash, P. (2018). A review of bank efficiency and productivity. *OPSEARCH 2018 55:3*, *55*(3), 557–600. https://doi.org/10.1007/S12597-018-0332-2

Bhatti, M. A., Sadiq, M., Albarq, A. N., & Juhari, A. S. (2022). Risk Management and Financial Performance of Banks: An Application of CAMEL Framework. *Cuadernos de Economia - Spain*, *45*(128), 113–123. https://doi.org/10.32826/cude.v1i128.713

Bolt, W., & Humphrey, D. (2010). Bank competition efficiency in Europe: A frontier approach. *Journal of Banking & Finance*, *34*(8), 1808–1817. https://doi.org/10.1016/J.JBANKFIN.2009.09.019

Bomhard, N. von. (2005). Risk and Capital Management in Insurance Companies. *The Geneva Papers on Risk and Insurance - Issues and Practice*, *30*(1), 52–59. https://ideas.repec.org/a/pal/gpprii/v30y2005i1p52-59.html

Bonin, J. P., Hasan, I., & Wachtel, P. (2005). Bank performance, efficiency and ownership in transition countries. *Journal of Banking and Finance*, *29*(1), 31–53. https://doi.org/10.1016/j.jbankfin.2004.06.015

Bos, J. W. B., & Kool, C. J. M. (2006). Bank efficiency: The role of bank strategy and local market conditions. *Journal of Banking and Finance* , *30*(7), 1953–1974. https://doi.org/10.1016/j.jbankfin.2005.07.008

Boussemart, J. P., Leleu, H., Shen, Z., Vardanyan, M., & Zhu, N. (2019). Decomposing banking performance into economic and credit risk efficiencies. *European Journal of Operational Research*, *277*(2), 719–726. https://doi.org/10.1016/J.EJOR.2019.03.006

Canhoto, A., & Dermine, J. (2003). A note on banking efficiency in Portugal, New vs. Old banks. *Journal of Banking and Finance*, *27*(11), 2087–2098. https://doi.org/10.1016/S0378-4266(02)00316-3

Chan, S. G., Karim, M. Z. A., Burton, B., & Aktan, B. (2013). Efficiency and risk in commercial banking: empirical evidence from East Asian countries. *The European Journal of Finance*, *20*(12), 1114–1132. https://doi.org/10.1080/1351847X.2012.745008

Chang, C.-C. (1999). The Nonparametric Risk-Adjusted Efficiency Measurement: An Application to Taiwan's Major Rural Financial Intermediaries. *American Journal of Agricultural Economics*, *81*(4), 902–913. https://doi.org/10.2307/1244333

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research*, *2*(6), 429–444. https://doi.org/10.1016/0377-2217(78)90138-8

Cherchye, L., Knox Lovell, C. A., Moesen, W., & Van Puyenbroeck, T. (2007). One market, one number? A composite indicator assessment of EU internal market dynamics. *European Economic Review*, *51*(3), 749–779. https://doi.org/10.1016/j.euroecorev.2006.03.011

Cherchye, L., Moesen, W., & Van Puyenbroeck, T. (2004). Legitimately Diverse, yet Comparable: On Synthesizing Social Inclusion Performance in the EU*. *JCMS: Journal of Common Market Studies*, *42*(5), 919–955. https://doi.org/10.1111/J.0021-9886.2004.00535.X

Choi, B. P., & Weiss, M. A. (2005). An empirical investigation of market structure, efficiency, and performance in property-liability insurance. *Journal of Risk and Insurance*, *72*(4), 635–673. https://doi.org/10.1111/j.1539-6975.2005.00142.x

Chortareas, G. E., Girardone, C., & Ventouri, A. (2012). Bank supervision, regulation, and efficiency: Evidence from the European Union. *Journal of Financial Stability*, *8*(4), 292–302. https://doi.org/10.1016/j.jfs.2011.12.001

Chortareas, G. E., Kapetanios, G., & Ventouri, A. (2016). Credit market freedom and cost efficiency in US state banking. *Journal of Empirical Finance*, *37*, 173–185. https://doi.org/10.1016/j.jempfin.2016.03.002

Coase, R. H. (1937). The Nature of the Firm. *Economica*, *4*(16), 386–405. https://doi.org/10.1111/j.1468-0335.1937.tb00002.x

Cummins, J. D., Tennyson, S., & Weiss, M. A. (1999). Consolidation and efficiency in the US life insurance industry. *Journal of Banking & Finance*, *23*(2–4), 325–357. https://doi.org/10.1016/S0378-4266(98)00089-2

Danlami, M. R., Abduh, M., & Razak, L. A. (2022). CAMELS, risk-sharing financing, institutional quality and stability of Islamic banks: evidence from 6 OIC countries. *Journal of Islamic Accounting and Business Research*, *13*(8), 1155–1175. https://doi.org/10.1108/JIABR-08-2021-0227

de Abreu, D., & de Camargos, M. A. (2022). Applying the CAMELS Model to Evaluate the Profitability of the Brazilian Banking Sector. *Revista Evidenciacao Contabil & Financias*, *10*(3), 100–117. https://doi.org/10.22478/ufpb.2318-1001.2022v10n3.61571 de Abreu, E. S., Kimura, H., & Sobreiro, V. A. (2019). What is going on with studies on banking efficiency? *Research in International Business and Finance*, *47*, 195–219. https://doi.org/10.1016/j.ribaf.2018.07.010

de Castries, H. (2005). Capital Adequacy and Risk Management in Insurance. *The Geneva Papers on Risk and Insurance - Issues and Practice*, *30*(1), 47–51. https://doi.org/10.1057/palgrave.gpp.2510017

Demsetz, H. (1973). Industry Structure, Market Rivalry, and Public Policy. *Https://Doi.Org/10.1086/466752*, *16*(1), 1–9. https://doi.org/10.1086/466752

Dong, Y., Girardone, C., & Kuo, J.-M. (2017). Governance, efficiency and risk taking in Chinese banking. *The British Accounting Review*, *49*(2), 211–229. https://doi.org/10.1016/j.bar.2016.08.001

Eling, M., & Jia, R. (2018). Business failure, efficiency, and volatility: Evidence from the European insurance industry. *International Review of Financial Analysis*, *59*, 58–76. https://doi.org/10.1016/j.irfa.2018.07.007

Emrouznejad, A., & Yang, G. liang. (2018). A survey and analysis of the first 40 years of scholarly literature in DEA: 1978–2016. *Socio-Economic Planning Sciences*, *61*, 4–8. https://doi.org/10.1016/J.SEPS.2017.01.008

Erel, I., Myers, S. C., & Read, J. A. (2015). A theory of risk capital. *Journal of Financial Economics*, *118*(3), 620–635. https://doi.org/10.1016/j.jfineco.2014.10.006

Fries, S., & Taci, A. (2005). Cost efficiency of banks in transition: Evidence from 289 banks in 15 post-communist countries. *Journal of Banking and Finance*, *29*(1), 55–81. https://doi.org/10.1016/j.jbankfin.2004.06.016

Fukuyama, H., & Tan, Y. (2022). Deconstructing three-stage overall efficiency into input, output and stability efficiency components with consideration of market power and loan loss provision: An application to Chinese banks. *International Journal of Finance & Economics*, *27*(1), 953–974. https://doi.org/10.1002/IJFE.2185

Gaganis, C., Pasiouras, F., Tasiou, M., & Zopounidis, C. (2021). CISEF: A composite index of social, environmental and financial performance. *European Journal of Operational Research*, *291*(1), 394–409. https://doi.org/10.1016/j.ejor.2020.09.035

Gang, J., Guo, J. (Michael), Hu, N., & Li, X. (2018). Indexing mergers and acquisitions. *Quantitative Finance*, *18*(6), 1033–1048. https://doi.org/10.1080/14697688.2017.1369145

Gonzalez, F. (2009). Determinants of Bank-Market Structure: Efficiency and Political Economy Variables. *Journal of Money, Credit, and Banking*, *41*(4), 735–754. https://doi.org/10.1111/j.1538-4616.2009.00229.x

Gulati, R. (2022). Global and local banking crises and risk-adjusted efficiency of Indian banks: Are the impacts really perspective-dependent? *The Quarterly Review of Economics and Finance*, *84*, 23–39. https://doi.org/10.1016/J.QREF.2022.01.004

Gulati, R. (2023). Beyond the Z-score: A novel measure of bank stability for effective policymaking. *Journal of Public Affairs*, *23*(4), e2866. https://doi.org/10.1002/PA.2866

Gulati, R., Hassan, M. K., & Charles, V. (2023). Developing a New Multidimensional Index of Bank Stability and Its Usage in the Design of Optimal Policy Interventions. *Computational Economics*. https://doi.org/10.1007/s10614-023-10401-7

Gulati, R., Kattumuri, R., & Kumar, S. (2020). A non-parametric index of corporate governance in the banking industry: An application to Indian data. *Socio-Economic Planning Sciences*, *70*, 100702. https://doi.org/10.1016/J.SEPS.2019.03.008

Hadad, M. D., Hall, M. J., B, Kenjegalieva, K. A., Santoso, W., & Simper, R. (2011). Banking efficiency and stock market performance: an analysis of listed Indonesian banks. *Review of Quantitative Finance and Accounting*, *37*(1), 1–20. https://doi.org/10.1007/s11156-010-0192-1

Handorf, W. C. (2016). CAMEL to CAMELS: The risk of sensitivity. *Journal of Banking Regulation*, *17*(4), 273–287. https://doi.org/10.1057/jbr.2015.24

Henriques, I. C., Sobreiro, V. A., Kimura, H., & Mariano, E. B. (2020). Two-stage DEA in banks: Terminological controversies and future directions. *Expert Systems with Applications*, *161*, 113632. https://doi.org/10.1016/j.eswa.2020.113632

Herring, R., & Santomero, A. (1995). The Role of the Financial Sector in Economic Performance. *Center for Financial Institutions Working Papers 95-08, Wharton School Center for Financial Institutions, University of Pennsylvania.* https://ssrn.com/abstract=7647

Huang, L.-Y., Lai, G. C., McNamara, M., & Wang, J. (2011). Corporate Governance and Efficiency: Evidence From U.S. Property-Liability Insurance Industry. *The Journal of Risk and Insurance*, *78*(3), 519–550. https://doi.org/10.1111/j.1539-6975.2011.01410.x

Huang, W., & Paradi, J. C. (2011). Risk-adjusted efficiency of the insurance industry: Evidence from China. *Service Industries Journal*, *31*(11), 1871–1885. https://doi.org/10.1080/02642069.2010.503875

Hughes, J. P., & Mester, L. J. (2008). Efficiency in banking: theory, practice, and evidence. *Oxford Handbook of Banking*. https://doi.org/https://dx.doi.org/10.2139/ssrn.1092220

Jensen, M. C., & Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics*, *3*(4), 305–360. https://doi.org/10.1016/0304-405X(76)90026-X

Kalyvas, A. N., & Mamatzakis, E. (2014). Does business regulation matter for banks in the European Union? *Journal of International Financial Markets, Institutions and Money*, *32*, 278–324. https://doi.org/10.1016/j.intfin.2014.06.007

Kaur, H. V. (2010). Analysis of Banks in India-A CAMEL Approach. *Global Business Review*, *11*(2), 257–280. https://doi.org/10.1177/097215091001100209

Kim, D., & Santomero, A. (1988). Risk in Banking and Capital Regulation. *The Journal of Finance*, *43*(5), 1219–1233. https://doi.org/10.1111/j.1540-6261.1988.tb03966.x

Knight, F. H. (1921). *Risk, Uncertainty and Profit*. University of Illinois at Urbana-Champaign's Academy for Entrepreneurial Leadership Historical Research Reference in Entrepreneurship. https://papers.ssrn.com/abstract=1496192

Kumar, A., Ahmed, K., Bhayo, M.-R., & Kalhoro, M. R. (2022). Banking performance and institutional quality: Evidence from dynamic panel data analysis. *International Journal of Finance & Economics*, *28*(4), 4717–4737. https://doi.org/10.1002/ijfe.2673

Lartey, T., James, G. A., & Danso, A. (2021). Interbank funding, bank risk exposure and performance in the UK: A three-stage network DEA approach. *International Review of Financial Analysis*, *75*, 101753. https://doi.org/10.1016/J.IRFA.2021.101753

Lozano-Vivas, A., Pastor, J. T., & Pastor, J. M. (2002). An efficiency comparison of European banking systems operating under different environmental conditions. *Journal of Productivity Analysis*, *18*(1), 59–77. https://doi.org/https://doi.org/10.1023/A:1015704510270

Malafronte, I., Porzio, C., & Starita, M. G. (2016). The nature and determinants of disclosure practices in the insurance industry: Evidence from European insurers. *International Review of Financial Analysis*, *45*, 367–382. https://doi.org/10.1016/J.IRFA.2015.02.003

Malafronte, I., Starita, M. G., & Pereira, J. (2018). The effectiveness of risk disclosure practices in the European insurance industry. *Review of Accounting and Finance*, *17*(1), 130–147. https://doi.org/10.1108/RAF-09-2016-0150

Mamatzakis, E. (2015). Risk and efficiency in the Central and Eastern European banking industry under quantile analysis. *Quantitative Finance*, *15*(3), 553–567. https://doi.org/10.1080/14697688.2012.715245

Mamatzakis, E., & Bermpei, T. (2014). What drives investment bank performance? The role of risk, liquidity and fees prior to and during the crisis. *International Review of Financial Analysis*, *35*, 102–117. https://doi.org/10.1016/j.irfa.2014.07.012

Mamatzakis, E., Staikouras, C., Triantopoulos, C., & Wang, Z. C. (2023). Measuring the efficiency and productivity of U.K. insurance market. *International Journal of Finance & Economics*. https://doi.org/10.1002/ijfe.2723

Maricic, M., & Jeremic, V. (2023). Imposing unsupervised constraints to the Benefit-of-the-Doubt (BoD) model. *Metron*, *81*(3), 259–296. https://doi.org/10.1007/S40300-023-00254-3/METRICS

Markowitz, H. (1952). Portfolio Selection. *The Journal of Finance*, *7*(1), 77–91. https://doi.org/10.2307/2975974

Maudos, J., Pastor, J. M., Pérez, F., & Quesada, J. (2002). Cost and profit efficiency in European banks. *Journal of International Financial Markets, Institutions and Money*, *12*(1), 33–58. https://doi.org/https://doi.org/10.1016/S1042-4431(01)00051-8

McKee, G., & Kagan, A. (2018). Community bank structure an x-efficiency approach. *Review of Quantitative Finance and Accounting*, *51*(1), 19–41. https://doi.org/10.1007/s11156-017-0662-9

Meeusen, W., & van Den Broeck, J. (1977). Efficiency Estimation from Cobb-Douglas Production Functions with Composed Error. *International Economic Review*, *18*(2), 435. https://doi.org/10.2307/2525757

Melyn, W., & Moesen, W. (1991). Towards a synthetic indicator of macroeconomic performance : unequal weighting when limited information is available. *Public Economic Research Paper 17, CES, KU Leuven*. https://www.econbiz.de/Record/towards-a-synthetic-indicator-of-macroeconomic-performance-unequal-weighting-when-limited-information-is-available-melyn-wim/10000836584

Merton, R. C. (1995). A Functional Perspective of Financial Intermediation. *Financial Management*, *24*(2), 23–41. https://doi.org/10.2307/3665532

Mester, L. J. (1996). A study of bank efficiency taking into account risk-preferences. *Journal of Banking & Finance*, *20*(6), 1025–1045. https://doi.org/https://doi.org/10.1016/0378-4266(95)00047-X

Mohsin, M., Nurunnabi, M., Zhang, J., Sun, H., Iqbal, N., Iram, R., & Abbas, Q. (2021). The evaluation of efficiency and value addition of IFRS endorsement towards earnings timeliness disclosure. *International Journal of Finance & Economics*, *26*(2), 1793–1807. https://doi.org/10.1002/ijfe.1878

Mühlnickel, J., & Weiss, G. N. F. (2015). Consolidation and systemic risk in the international insurance industry. *Journal of Financial Stability*, *18*, 187–202. https://doi.org/10.1016/J.JFS.2015.04.005

Muhmad, S. N., & Hashim, H. A. (2015). Using the CAMEL Framework in Assessing Bank Performance in Malaysia. *International Journal of Economics Management and Accounting*, *23*(1), 109–127. https://doi.org/https://doi.org/10.31436/ijema.v23i1.292

Murillo-Zamorano, L. R. (2004). Economic Efficiency and Frontier Techniques. *Journal of Economic Surveys*, *18*(1), 33–77. https://doi.org/10.1111/J.1467-6419.2004.00215.X

Nguyen, H. D. H., & Dang, V. D. (2020). Bank-Specific Determinants of Loan Growth in Vietnam: Evidence from the CAMELS Approach. *JOURNAL OF ASIAN FINANCE ECONOMICS AND BUSINESS*, *7*(9), 179–189. https://doi.org/10.13106/jafeb.2020.vol7.no9.179

Nippani, S., & Ling, R. (2021). Bank size and performance: An analysis of the industry in the United States in the post-financial-crisis era. *Journal of Financial Research*, *44*(3), 587–606. https://doi.org/10.1111/jfir.12255

Nugroho, M., Halik, A., & Arif, D. (2020). Effect of CAMELS Ratio on Indonesia Banking Share Prices. *Journal of Asian Finance Economics and Business*, *7*(11), 101–105. https://doi.org/10.13106/jafeb.2020.vol7.no11.101

OECD. (2008). *Handbook on Constructing Composite Indicators: Methodology and User Guide*. OECD. https://doi.org/10.1787/9789264043466-en

Oldfield, G., & Santomero, A. (1970). The Place of Risk Management in Financial Institutions. *Sloan Management Review*, *39*. https://www.researchgate.net/publication/2598120_The_Place_of_Risk_Management_in_Financial_Institutions

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., … Moher, D. (2021). The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. *BMJ*, *372*. https://doi.org/10.1136/BMJ.N71

Pastor, J. M. (1999). Efficiency and risk management in Spanish banking: a method to decompose risk. *Applied Financial Economics*, *9*(4), 371–384. https://doi.org/10.1080/096031099332267

Pastor, J. T., Lozano, A., & Pastor, J. M. (1997). Efficiency of European banking systems: A correction by environment variables. *Working Papers. Serie EC*. https://ideas.repec.org//p/ivi/wpasec/1997-12.html

Pekkaya, M., & Demir, F. E. (2018). Determining the Priorities of CAMELS Dimensions Based on Bank Performance. In H. Dincer, U. Hacioglu, & S. Yuksel (Eds.), *Global Approaches in Financial Economics, Banking, and Finance* (pp. 445–463). https://doi.org/10.1007/978-3-319-78494-6_21

Pessarossi, P., & Weill, L. (2015). Do capital requirements affect cost efficiency? Evidence from China. *Journal of Financial Stability*, *19*, 119–127. https://doi.org/10.1016/j.jfs.2014.11.002

Petrović D., Dasilas A., Karanović G. (2025a), "Bank risk-adjusted efficiency using a composite risk management index". *Journal of Risk Finance* , Vol. 26 No. 3 pp. 485–515, doi: https://doi.org/10.1108/JRF-11-2024-0362

Petrović D., Dasilas A., Karanović G. (2025b), "Insurance companies risk-adjusted efficiency using a composite risk management index". Review of Accounting and Finance, doi: https://doi.org/10.1108/RAF-11-2024-0492

Petrović, D., & Karanović, G. (2024). Financial institutions efficiency: a systematic literature review. *Zbornik Radova Ekonomskog Fakulteta u Rijeci / Proceedings of Rijeka Faculty of Economics*, *42*(2), 411–446. https://doi.org/10.18045/zbefri.2024.2.11

Proaño-Rivera, B., & Feria-Dominguez, J. M. (2023). Are Ecuadorian banks enough technically efficient for growth? A clinical study. *International Journal of Finance & Economics*. https://doi.org/10.1002/IJFE.2775

Qureshi, A. S., & Siddiqui, D. A. (2023). The Impact of the CAMEL Model on Banks' Profitability. *SSRN Electronic Journal*. https://doi.org/10.2139/SSRN.4432257

Radojicic, M., Savic, G., & Jeremic, V. (2018). Measuring the efficiency of banks: the bootstrapped I-distance GAR DEA approach. *Technological and Economic Development of Economy*, *24*(4), 1581–1605. https://doi.org/10.3846/TEDE.2018.3699

Rayeni, M. M., & Saljooghi, F. H. (2016). Examining the effect of risk on bank performance by using data envelopment analysis. *International Journal of Services and Operations Management*, *24*(1), 18–32. https://doi.org/10.1504/IJSOM.2016.075762

Risal, H. G., & Panta, S. B. (2019). CAMELS-Based Supervision and Risk Management: What Works and What Does Not. *Fortune Institute of International Business (FIIB) Business Review*, *8*(3), 194–204. https://doi.org/10.1177/2319714519873747

Rogge, N. (2018). On aggregating Benefit of the Doubt composite indicators. *European Journal of Operational Research*, *264*(1), 364–369. https://doi.org/10.1016/j.ejor.2017.06.035

Ruinan, L. (2019). Comparison of Bank Efficiencies Between the U.S. and Canada: Evidence Based on SFA and DEA. *SSRN Electronic Journal*. https://doi.org/10.2139/SSRN.3317196

Safiullah, M., & Shamsuddin, A. (2019). Risk-adjusted efficiency and corporate governance: Evidence from Islamic and conventional banks. *Journal of Corporate Finance*, *55*, 105–140. https://doi.org/10.1016/j.jcorpfin.2018.08.009

Santomero, A. (1984). Modeling the Banking Firm: A Survey. *Journal of Money, Credit and Banking*, *16*(4), 576–602. https://doi.org/10.2307/1992092

Santomero, A. (1997). Commercial Bank Risk Management: An Analysis of the Process. *Journal of Financial Services Research*, *2/3*. https://doi.org/10.1023/A:1007971801810

Santomero, A., & Babbel, D. F. (1997). Financial Risk Management by Insurers: An Analysis of the Process. *The Journal of Risk and Insurance*, *64*(2), 231–270. https://doi.org/10.2307/253730

Scholtens, B., & van Wensveen, D. (2000). A critique on the theory of financial intermediation. *Journal of Banking & Finance*, *24*(8), 1243–1251. https://doi.org/10.1016/S0378-4266(99)00085-0

Seward, J. K. (1990). Corporate Financial Policy and the Theory of Financial Intermediation. *The Journal of Finance*, *45*(2), 351–377. https://doi.org/10.1111/j.1540-6261.1990.tb03694.x

Shaddady, A., & Moore, T. (2019). Investigation of the effects of financial regulation and supervision on bank stability: The application of CAMELS-DEA to quantile regressions. *Journal of International Financial Markets Institutions and Money*, *58*, 96–116. https://doi.org/10.1016/j.intfin.2018.09.006

Shamshur, A., & Weill, L. (2019). Does bank efficiency influence the cost of credit? *Journal of Banking and Finance*, *105*, 62–73. https://doi.org/10.1016/j.jbankfin.2019.05.002

Shukla, S. S. (2015). Analysing Financial Strength of Public and Private Sector Banks: A CAMEL Approach. *Pacific Business Review International*, *7*(8), 44–50. https://doi.org/http://www.pbr.co.in/2015/2015_month/February/6.pdf

Sloan Swindle, C. (1995). Using CAMEL ratings to evaluate regulator effectiveness at commercial banks. *Journal of Financial Services Research*, *9*(2), 123–141. https://doi.org/10.1007/BF01068074

Spokeviciute, L., Keasey, K., & Vallascas, F. (2019). Do financial crises cleanse the banking industry? Evidence from US commercial bank exits. *Journal of Banking and Finance* , *99*, 222–236. https://doi.org/10.1016/j.jbankfin.2018.12.010

Srairi, S. A. (2010). Cost and profit efficiency of conventional and Islamic banks in GCC countries. *Journal of Productivity Analysis*, *34*(1), 45–62. https://doi.org/10.1007/s11123-009-0161-7

Stulz, R. M. (1984). Optimal Hedging Policies. *The Journal of Financial and Quantitative Analysis*, *19*(2), 127–140. https://doi.org/10.2307/2330894

Stulz, R. M. (2023). *Crisis Risk and Risk Management*. National Bureau of Economic Research. https://doi.org/http://dx.doi.org/10.2139/ssrn.4439633

Sun, L., & Chang, T.-P. (2011). A comprehensive analysis of the effects of risk measures on bank efficiency: Evidence from emerging Asian countries. *Journal of Banking and Finance*, *35*(7), 1727–1735. https://doi.org/10.1016/j.jbankfin.2010.11.017

Učkar, D., & Petrović, D. (2021). Financial Institutions Efficiency: Theory, Methods and Empirical Evidence. *Economic and Social Development (Book of Proceedings), 64th International Scientific Conference on Economic and Social Development*, 63. https://www.bib.irb.hr/1106438

Verbunt, P., & Rogge, N. (2018). Geometric composite indicators with compromise Benefit-of-the-Doubt weights. *European Journal of Operational Research*, *264*(1), 388–401. https://doi.org/10.1016/j.ejor.2017.06.061

Vidoli, F., & Fusco, E. (2018). *Compind: Composite indicators functions based on frontiers in R (Compind package version 2.0)*. http://composite-indicators.jrc.ec.europa.eu/S6_weighting.htm

Walker, J. T., Fenton, E., Salter, A., & Salandra, R. (2019). What Influences Business Academics' Use of the Association of Business Schools (ABS) List? Evidence From a Survey of UK Academics. *British Journal of Management*, *30*(3), 730–747. https://doi.org/10.1111/1467-8551.12294

Williams, J. (2004). Determining management behaviour in European banking. *Journal of Banking & Finance*, *28*(10), 2427–2460. https://doi.org/10.1016/j.jbankfin.2003.09.010

Williams, J., & Gardener, E. (2003). The Efficiency of European Regional Banking. *Regional Studies*, *37*(4), 321–330. https://doi.org/10.1080/0034340032000074361

Zamore, S., Beisland, L. A., & Mersland, R. (2023). Excessive focus on risk? Non-performing loans and efficiency of microfinance institutions. *International Journal of Finance & Economics*, *28*(2), 1290–1307. https://doi.org/10.1002/ijfe.2477

7. LIST OF TABLES

8. LIST OF FIGURES

9. APPENDIX

9.1 THE LIST OF APPENDED SCIENTIFIC PAPERS AND DOCTORAL CANDIDATE'S CONTRIBUTION

Scientific paper 1	Appendix 1
Author(s)	*Petrović, D., & Karanović, G.*
Title of the paper	Financial Institutions Efficiency: A Systematic Literature Review
Year of publication	2024
Journal	Zbornik radova Ekonomskog fakulteta u Rijeci: časopis za ekonomsku teoriju i praksu /Proceedings of Rijeka Faculty of Economics: Journal of Economics and Business
ISSN/ISBN number (e-ISSN)	1331-8004 / 1846-7520 (Online)
Publisher	University of Rijeka Faculty of Economics and Business
Volume and Issue number	Volume 42, No. 2, 2024
Pages (from-to)	411-446
Language	English
Indexation	*Web of Science* Q3; Scopus Q4
Scientific contribution of the paper	The study synthesizes the body of knowledge on financial institutions efficiency with a specific focus on risk management and the utilisation of composite indices by employing a systematic literature review. It contributes to the existing body of knowledge by providing a sound theoretical framework for financial institutions efficiency estimation and identified the predominant areas of research outlining the critical gap in defining the effect of risk management on financial institutions efficiency.
Scientific contribution of the doctoral candidate	The identification of a theoretical framework for financial institutions efficiency estimation. Through the results of a systematic literature review, identified and outlined a comprehensive financial institutions' frontier efficiency estimation framework. The proposed efficiency estimation framework provides insights on the most widely used

	methods, approaches and variables used in financial institutions efficiency study.
Applied contribution of the paper	The results of the systematic literature review contribute to the existing literature in the field of financial institution's risk-adjusted efficiency estimation by proposing a novel methodological approach. This approach outlines the use of non-parametric methodology in constructing composite risk management indices with the goal of estimating financial institutions risk-adjusted efficiency.

Scientific paper 2	Appendix 2
Author(s)	*Petrović, D., Dasilas, A., & Karanović, G.*
Title of the paper	Bank Risk-Adjusted Efficiency Using a Composite Risk Management Index
Year of publication	2025
Journal	Journal of Risk Finance
ISSN/ISBN number (e-ISSN)	1526-5943 / 2331-2947 (Online)
Publisher	Emerald Group Publishing Ltd
Volume and Issue number	Vol. 26 No. 3
Pages (from-to)	485-515
Language	English
Indexation	Web of Science Q1; Scopus Q2
Scientific contribution of the paper	The scientific contribution of this article is outlined in the development and computation of a composite risk management index on an international, longitudinal sample of banks using a constrained Data Envelopment Analysis Benefit-of-the-Doubt model. The main contribution is the empirical analysis of the proposed RMI and the identification of a weak but positive relationship between risk management and bank efficiency.
Scientific contribution of the doctoral candidate	Within the development of the proposed RMI for banks, based on the insights attained from the SLR, the main contribution of is a unique dataset of 16 bank variables into five sub-indicators defined by the widely employed CAMEL framework.

Applied contribution of the paper	Research results empirically test the proposed methodology for bank risk-adjusted efficiency estimation. The hypotheses tested show a statistically significant and positive relationship between the proposed RMI and its sub-indicators, while a positive but statistically weak relationship between the RMI and bank's efficiency. The results also contribute on identifying key sub-indicators of the RMI such as management efficiency and asset quality, but also the most important drivers of bank's risk-adjusted efficiency.

Scientific paper 3	Appendix 3
Author(s)	*Petrović, D., Dasilas, A., & Karanović, G.*
Title of the paper	Insurance Companies Risk-Adjusted Efficiency Using a Composite Risk Management Index
Year of publication	2025
Journal	Review of Accounting and Finance
ISSN/ISBN number (e-ISSN)	1475-7702 / 1758-7700 (Online)
Publisher	Emerald Group Publishing Ltd
Volume and Issue number	
Pages (from-to)	1-23
Language	English
Indexation	Web of Science Q2; Scopus Q2
Scientific contribution of the paper	The scientific contribution of this article is outlined in the development and computation of a composite risk management index on an international, longitudinal sample of insurance companies using a constrained Data Envelopment Analysis Benefit-of-the-Doubt model. The main contribution is the empirical analysis of the proposed RMI and the identification of a statistically positive relationship between risk management and insurance companies' efficiency.
Scientific contribution of the doctoral candidate	Within the development of the proposed RMI for insurance companies, based on the insights attained from the SLR, the main contribution of is a unique dataset of 15 insurance companies' variables equally divided into five sub-indicators in

	the proposed CAMES framework thus stressing the importance of solvency in insurance companies' operations.
Applied contribution of the paper	Research results empirically test the proposed methodology for insurance companies' risk-adjusted efficiency estimation. The hypotheses tested show a statistically significant and positive relationship between the proposed RMI and its sub-indicators, with a positive and statistically significant relationship between the RMI and insurance companies' efficiency, with solvency being the most important, statistically significant and positive sub-indicator. The results also contribute on identifying key sub-indicators of the RMI such as solvency, capital adequacy and asset quality, but also the most important drivers of insurance companies' risk-adjusted efficiency.

9.2 COPYRIGHT

Scientific Paper 1 **Financial Institutions Efficiency: A Systematic Literature Review** is published as Open Access Paper courtesy of Zbornik radova Ekonomskog fakulteta u Rijeci: časopis za ekonomsku teoriju i praksu /Proceedings of Rijeka Faculty of Economics: Journal of Economics and Business.

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9.3 APPENDED SCIENTIFIC PAPER 1: FINANCIAL INSTITUTIONS EFFICIENCY: A SYSTEMATIC LITERATURE REVIEW

Financial Institutions Efficiency: A Systematic Literature Review

Petrović, D. & Karanović, G. (2024)

Zbornik radova Ekonomskog fakulteta u Rijeci: časopis za ekonomsku teoriju i praksu/Proceedings of Rijeka Faculty of Economics: Journal of Economics and Business, 42(2), 411-446. https://doi.org/10.18045/zbefri.2024.2.11

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Financial institutions efficiency: a systematic literature review*

Danijel Petrović[1], *Goran Karanović*[2]

Abstract

This study conducts a systematic literature review on the effect of risk management on financial institutions' efficiency. Using the PRISMA method, we analysed 173 studies published between 1990 and 2023 in journals ranked by Academic Journal Guide, issued by the Chartered Association of Business Schools in 2021. The results reveal that both parametric (Stochastic Frontier Approach) and non-parametric (Data Envelopment Analysis) models are equally utilized in estimating the efficiency of financial institutions. The limitations of these methodologies are discussed, while also indicating a lack of consensus on the classification of variables. Furthermore, the results show that recent studies mainly focus on the effects of mergers and acquisitions activities, regulation, and risk management on the efficiency of banks and insurance companies. Finally, a current trend towards developing composite indices in efficiency estimation is emphasized. Findings from this study will be useful to academics, researchers, financial institution managers, policymakers, and regulators interested in financial institutions' efficiency.

Keywords: *efficiency, risk management, financial institutions, composite indices*

JEL classifications: *C61, G21, G22*

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1. Introduction

Financial institutions are essential in providing financial services to the private and public sectors. They serve as financial intermediaries that enhance capital allocation, thereby fostering economic growth and development. Furthermore, these institutions enable effective risk management, hedging, and pricing. Efficient financial institutions reduce the costs and risks associated with goods and services, contributing to economic growth and development (Herring and Santomero, 1995), while simultaneously improving the competitiveness of the financial system for optimal resource allocation.

Financial institutions can fail due to internal mismanagement or external factors such as market shocks, regulatory changes, pandemics, wars, political crises, and democratic instability (Mousavi et al., 2015). Research indicates that robust risk management and effective corporate governance enhance institutional resilience, although this may come at the expense of performance (Stulz, 2023). Identifying institutions with strong risk management practices is essential for investors seeking to increase their wealth. The survival of banks is crucial for economic developments, as it ensures the efficient transfer of financial resources (Kocenda and Iwasaki, 2021). For managers, a thorough understanding of risk management is vital for maintaining institutional resilience.

Berger and DeYoung (1997) identified that risk management influences efficiency through internal factors, such as managerial skills or *bad management* as well as external factors like market uncertainty, often referred to as *bad luck*. Increased cost (and profit) efficiency can result in mixed performance during market shocks (Assaf et al., 2019). Regulators emphasize stability and fairness underscoring the importance of information sharing among institutions with varying risk management capabilities to enhance macroprudential policies (Kim and Santomero, 1988; Herring and Santomero, 1995; Assaf et al., 2019). The public values efficiency for its role in reducing transaction costs and risks, while relying on institutional stability to prevent financial losses and crises. Trust and reputation are crucial for maintaining a stable financial system (Adeabah et al., 2022; van der Cruijsen et al., 2023). Accurate bankruptcy prediction is essential for mitigating the impacts of crises, with survival analysis models demonstrating the most effective results, followed by linear probability and multivariate discriminant analysis models (Mousavi et al., 2015).

Since the survey conducted by Berger and Humphrey (1997), empirical studies on the efficiency of financial institutions have grown significantly, as noted in a recent review by Ardia et al. (2023). Bhatia et al. (2018) highlighted a growing focus on risk and uncertainty in bank efficiency, noting the most frequently employed methods as the Stochastic Frontier Approach (SFA) and the Data Envelopment Analysis (DEA). Recent studies by Elshandidy and Acheampong (2021), Bhatia

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et al. (2018), and Ahmad et al. (2020) identified and examined various variables influencing efficiency and bank performance like risk and uncertainty, ownership, financial crisis, economics of scale, and failure to disclose risk information. The latest studies utilized composite indices as a tool for early warnings of systemic risks (Ellis et al., 2022; Gulati, 2022; Malafronte et al., 2018).

The main objective of this study is defined through the following research questions:

RQ1: What are the most used methods employed in studies on the efficiency of financial institutions?

RQ2: What are the most used variables for measuring the efficiency of financial institutions?

RQ3: What are the most used measures of risk and efficiency for evaluating the impact of risk management on operational efficiency? Are composite indices utilized in the efficiency assessment of financial institutions?

Our systematic literature review (SLR) is based on the Web of Science (WoS) database and adheres to the journal quality criteria implemented by de Abreu et al. (2018) focusing on the Chartered Association of Business Schools ABS (2021) journal list categories of 3, 4, and 4*. This SLR focuses on works that examine risk management and its impact on efficiency in banks and insurance companies. To our knowledge, this is the first review that explores risk management and composite indices within financial institutions efficiency. Additionally, we evaluate the strengths and weaknesses of parametric and non-parametric methods for estimating the efficiency of banks and insurance companies. Our findings aim to help improve decisions made by financial institutions, based on the interplay between risk management, efficiency, and stability.

This paper is structured as follows: Section 2 outlines the methodology and the search procedure. Section 3 presents the bibliometric analysis. Section 4 discusses the main findings, while Section 5 provides the conclusion.

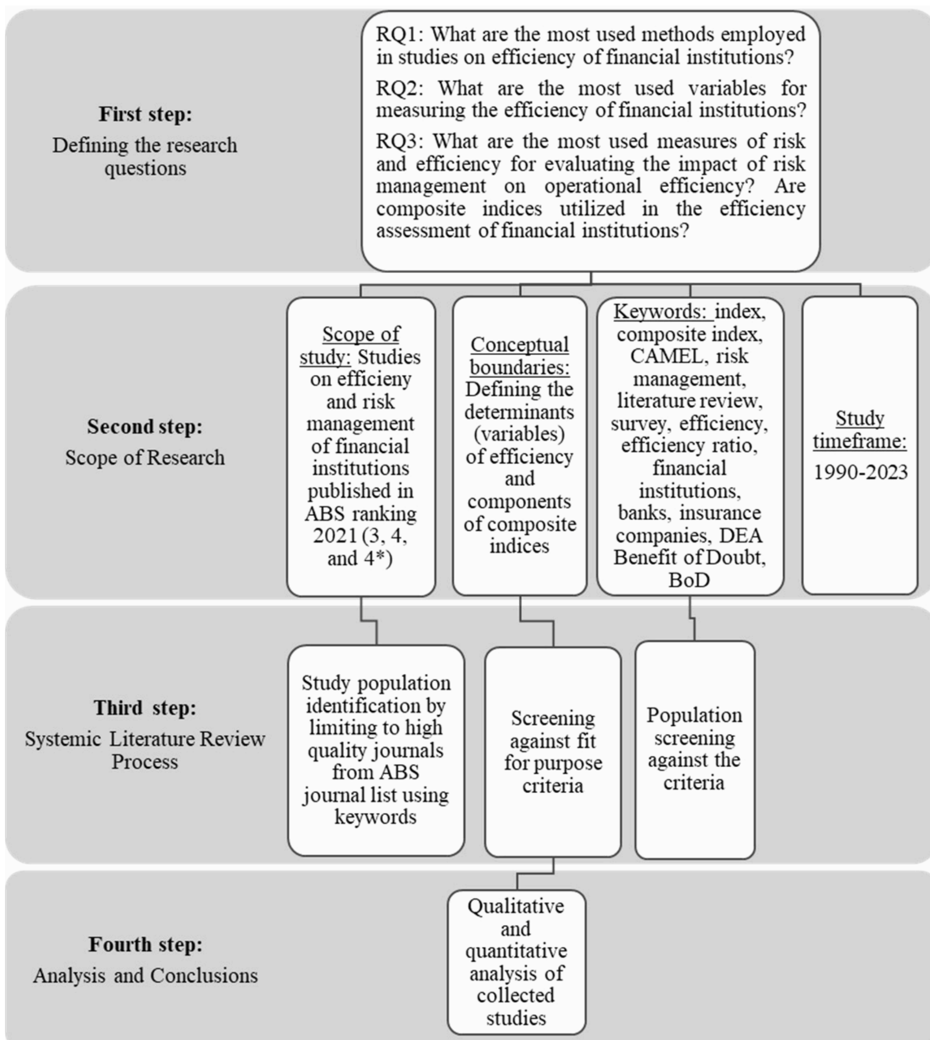
2. Methodology

In retrospect to traditional literature reviews, SLRs are superior due to their structured and objective methodology (Figure 1).

Page et al. (2021) claim that SLRs mitigate subjectivity, bias, and personal judgment through clearly defined search methods, research questions, and data extraction techniques. SLRs not only synthesize existing knowledge but also help identify research gaps and guide future studies. This paper adopts the

Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework. Following the work of Kuizinienė et al. (2022), Nazareth and Ramana Reddy (2023), and Shakeel et al. (2023), the authors apply the PRISMA stages: Identification, Screening, Eligibility, and Inclusion. This structured methodology enhances the review's transparency and replicability, ensuring a rigorous and high-quality analysis.

Figure 1: Stepwise process of a SLR



Source: Authors' construction according to the PRISMA framework by (Page et al., 2021)

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2.1. Identification

To define a representative sample, authors in this study included published articles, reviews, and empirical studies in English from 1990 to 2023, while excluding conference proceedings, books, book chapters, working papers, early open-access publications, and unpublished studies. The focus on investigating only the WoS (Web of Science) database is based on studies by Martín-Martín et al. (2021), Visser et al. (2021), and Mongeon and Paul-Hus (2016) who reported a significant overlap of 80% to over 90% with the Scopus database. WoS is considered a gold standard for bibliometric studies (Birkle et al., 2020; Zhu and Liu, 2020). Following the guidelines established by Ali et al. (2023), Almeida and Gonçalves (2023), and de Abreu et al. (2019) our SLR focused on journals ranked 3, 4, and 4* in the ABS (2021) list, a common quality criterion among UK academics (Walker et al., 2019). This categorization allows for an objective measure of study quality by focusing on highly rated journals (Ali et al., 2023; Ali and Wilson, 2023; Almeida and Gonçalves, 2023; de Abreu et al., 2019).

In this SLR, we selected 454 journals rated 3, 4, and 4* from the ABS (2021) list. Followed by a manual search of the WoS database using a specific combination of keywords such as *index* OR *composite index* AND *CAMEL* (Capital Adequacy, Asset Quality, Management Efficiency, Earnings, Liquidity) AND *risk management literature review* OR *survey* AND *efficiency* OR *efficiency ratio* AND *financial institutions* OR *banks* OR *insurance companies*, as well as methodological terms *DEA* AND/OR *Benefit of Doubt* OR *BoD*. This search strategy yielded 19,383 results as of December 31st, 2023, with searches conducted between September and December 2023.

2.2. Screening

From the initial pool of 19,383 results, we used Excel's duplicate detection tool to eliminate 13,783 duplicate papers, which left us with 5,600 papers for the screening phase. The screening process, conducted alongside the identification phase, involved excluding papers beyond the scope of the study. By reviewing the titles and abstracts, 5,427 non-relevant studies were eliminated, resulting in a final sample of 173 studies, of which 120 (69%) are from rank 3 journals, 40 (23%) from rank 4, and 13 (8%) from rank 4* journals.

2.3. Eligibility

To evaluate the eligibility of the full-text articles sample we have applied specific inclusion and exclusion criteria:

Inclusion Criteria:

- Studies that focus on the risk-adjusted efficiency of financial institutions.
- Studies that incorporate composite indices to measure the efficiency of financial institutions.
- Studies that outline and compare various methods for estimating efficiency.

Exclusion Criteria:

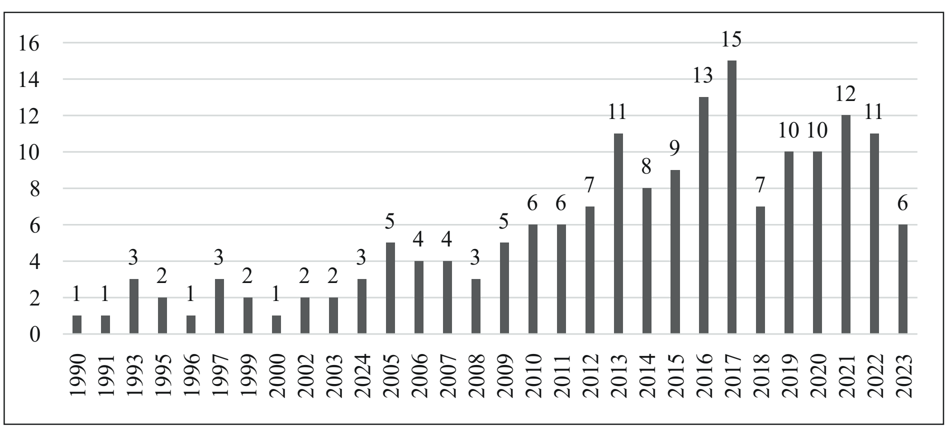
- Studies that have exclusively focused on the financial market from a macroeconomic perspective and deal with trading efficiency and stock price movements.
- Studies that do not focus on the efficiency of financial institutions, risk management, and composite indices in finance.
- Studies with unclear methodologies.

Among the 173 articles evaluated, 35 were identified as theoretical or conceptual, while 138 were classified as empirical studies and included in the bibliometric analysis (Figure A in the Appendix).

2.4. Inclusion

Bibliometric analysis involved the collection of author details, year of publication, journal, keywords, methods, variables, and results. Figure 2 illustrates the distribution of 173 published articles from 1990 to 2023. The highest number of articles was published in 2017 (15), followed by 2016 (13), 2021 (12), and both 2013 and 2022 with 11 alongside 2019 and 2020 with 10 articles.

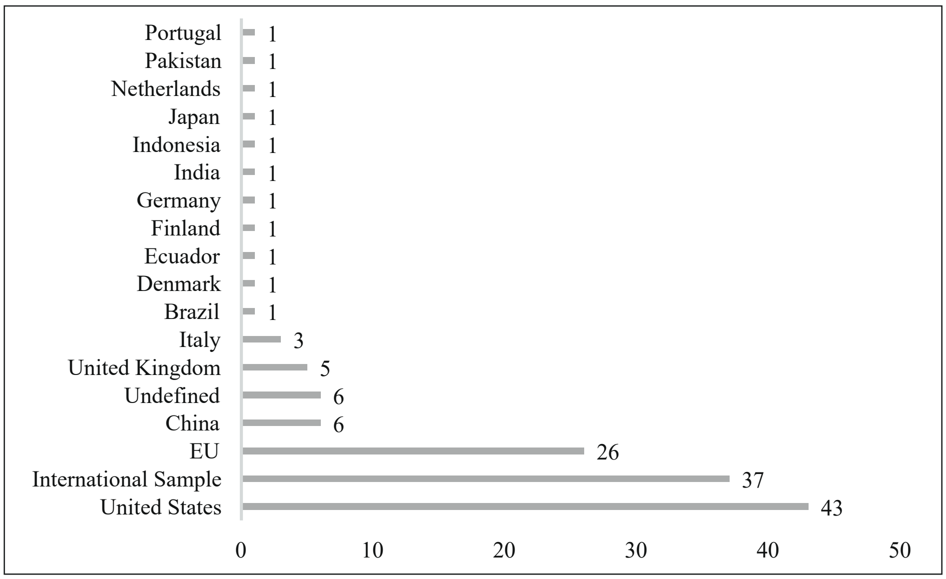
Figure 2: Temporal distribution of published articles



Source: Author’s construction

Total of 541 authors contributed to these studies, with most papers co-authored by two authors (67 papers; 39%) or three authors (43 papers; 25%). Single-author studies accounted for 17% (30 papers), while 15% (26 papers) had four authors, and 3% (5 papers) had five authors. Only one study involved six (Babecký et al., 2014) and another seven authors (Mohsin et al., 2021). Figure 3 illustrates the geographical distribution of the 138 empirical studies reviewed. Among these, 43 studies (31%) focused on U.S. financial institutions, 37 studies (27%) utilized international samples, and 26 studies (19%) analysed data from European Union countries. Additionally, six studies (4%) concentrated on Chinese financial institutions, and five studies (4%) examined UK institutions, while the geographical area remained unidentified in six studies (4%).

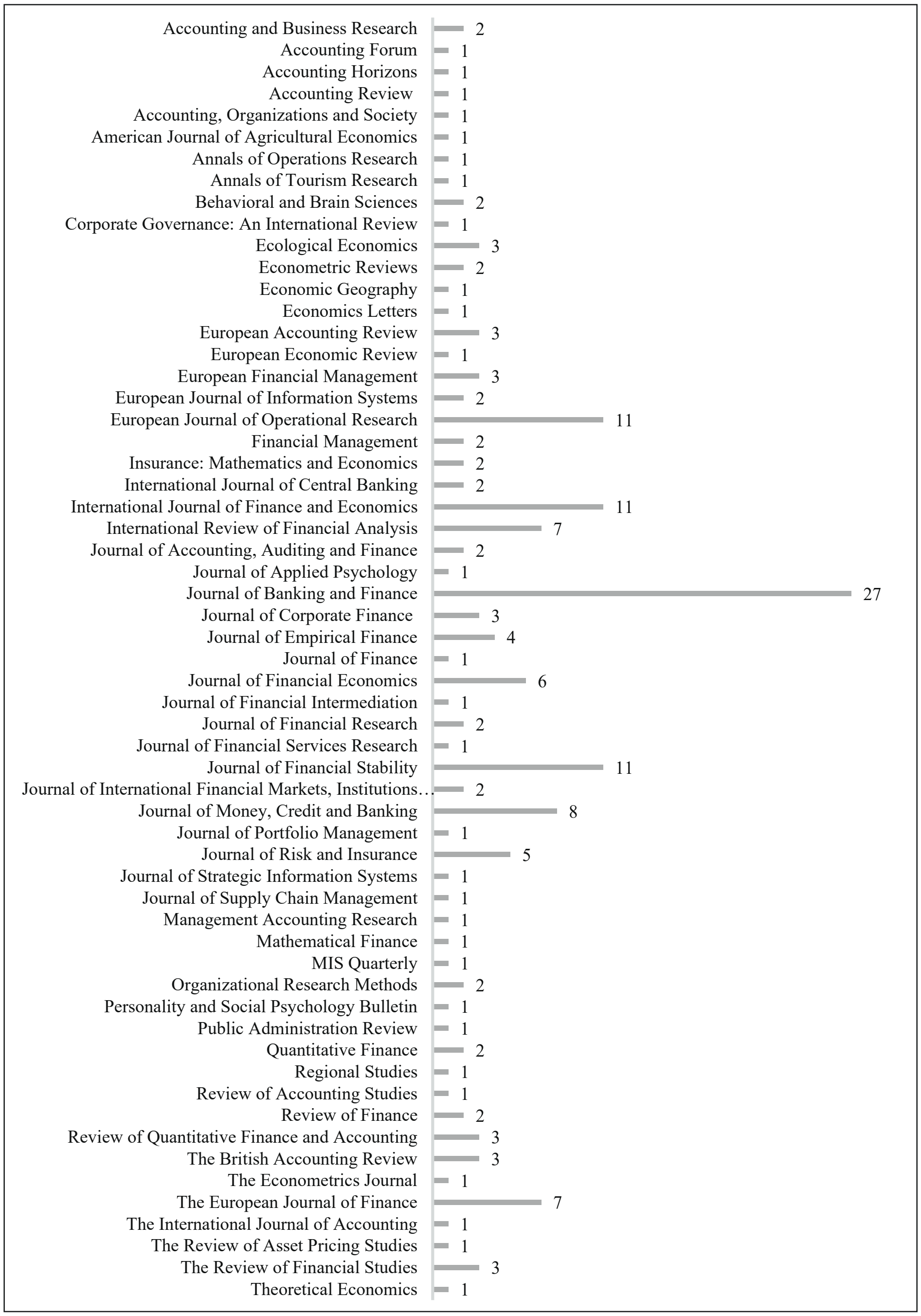
Figure 3: Geographical distribution of 138 empirical studies



Source: Author's construction

Out of the 173 studies, 59 were published at the top ranked journals according to the ABS (2021) list (Figure 4). *Journal of Banking and Finance* leads with 27 papers and boasts the highest citation count, followed by the *Journal of Financial Stability* (11 papers), the *International Journal of Finance and Economics* (11 papers), and the *European Journal of Operational Research* (11 papers). The *Journal of Money, Credit and Banking* published 8 papers, while both the *International Review of Financial Analysis* and the *European Journal of Finance* published 7 papers each.

Figure 4: Distribution of sampled empirical studies by publications in journals



Source: Author's construction

Most cited studies are Landis et al. (2000) on composite measures (849 citations), Berger and DeYoung (1997) on problem loans and cost efficiency (828 citations), and Acharya et al. (2017) on systemic risk (741 citations). Followed by Berger et al. (2009) with 529, beside Bonin et al. (2005) with 514, and Abedifar et al. (2013) with 356 citations. Recently, studies on risk and financial stability such as Benoit et al. (2017), Schaeck and Cihák (2014), Altunbas et al. (2007) and Crook et al. (2007) each amassed over 200 citations.

Recent topics in literature concentrate on determinants of risk and its effects on financial institutions' efficiency and stability. Furthermore, the development and comparison of composite indices yield equal or greater insights than individual financial indicators, as noted by the OECD (2008). Composite indices are invaluable for policymakers and stakeholders, as they distil complex, multidimensional concepts into more comprehensible formats. Ghosh (2015) and Gambacorta and Shin (2018) examined the determinants of non-performing loans (NPLs) and the role of capital in monetary policy. Based on findings from this SLR, the most frequently cited authors are Allen Berger (Berger et al., 2009; Berger and Bonaccorsi di Patti, 2006; Berger and DeYoung, 1997; Berger and Humphrey, 1997 Berger et al., 1993) and Mamatzakis (Mamatzakis et al., 2023; Mamatzakis, 2015; Kalyvas and Mamatzakis, 2014; Mamatzakis and Bermpei, 2014), followed by Rogge (Rogge, 2018; Van Puyenbroeck and Rogge, 2018; Verbunt and Rogge, 2018).

3. Review of the sampled literature

The primary advantage of employing PRISMA framework in a SLR is its focus on quality and transparency (Page et al., 2021). This framework guarantees a comprehensive presentation of commonly utilized methods, variables, and performance or efficiency metrics within the field, thereby enhancing the reliability and replicability of the research findings.

3.1. Overview of the methods in financial institutions' efficiency estimation

Financial institutions' efficiency is traditionally assessed using financial data from balance sheet and profit/loss statements, with a focus on profitability ratios such as return on assets (ROA) and return on equity (ROE). However, the efficiency ratio, which compares non-interest costs (overhead) to gross income, is a more suitable measure of efficiency (Fukuyama and Tan, 2022; Hays et al., 2009; Forster and Shaffer, 2005). Although financial indicators are widely accessible and relatively straightforward to interpret, they can sometimes be misleading. To mitigate this issue, parametric (SFA) and non-parametric (DEA) models are frequently employed (Murillo-Zamorano, 2004; Berger and Humphrey, 1997). Recent discussions by Učkar and Petrović (2021b) highlight that the efficiency of financial institutions is influenced by various economic theories, including microeconomic theory, agency theory, and financial intermediation theory. Demsetz's (1973) efficient structure hypothesis suggests that institutions that operate more efficiently are likely to be more profitable and capture a larger market share. Both parametric and non-parametric methods are employed almost equally in efficiency estimation (Učkar and Petrović, 2021b; Berger and Humphrey, 1997).

The 138 empirical studies can be categorized into two groups (Table 1) based on frontier analysis: parametric studies (SFA) with 22 (15.94%) articles and 32 (23.19%) non-parametric studies (DEA). Additionally, econometric methods, such as OLS and panel regression were employed in most studies 84 (60,87%). Many studies, regardless of the model, conducted robustness tests on efficiency results through both static (OLS) and dynamic (GMM) panel data analyses. Studies using SFA and econometric models focus on the effects of regulation on bank performance (Barra et al., 2022; Ayadi et al., 2016; Kalyvas and Mamatzakis, 2014; Dimitras et al., 2018), on the effect of regulatory capital and bank failure (Abou-El-Sood, 2015), and the implementation of International Financial Reporting Standards (IFRS) by Kyiu and Tawiah (2023). SFA is also used to evaluate the impact of corporate governance on efficiency (Chen et al., 2021; Abedifar et al., 2013; Leventis et al., 2013), transparency and competition (Andrievskaya and Semenova, 2016). A major topic of SFA studies is the effect of mergers and acquisitions (M&A) on efficiency (Mamatzakis et al., 2023; Gang et al., 2018; Altunbas et al., 2007; Choi and Weiss, 2005: Williams and Gardener, 2003; Shaffer; 1993) that support Demsetz's (1973) efficient structure hypothesis. Nonetheless, studies by Mühlnickel and Weiss (2015), Amel et al. (2004), Cummins et al. (1999), and Fixler and Zieschang (1993) report contradictory results. Similar studies on M&A employ DEA methodology (Proaño-Rivera et al., 2023; Nippani and Ling, 2021; Učkar and Petrović, 2021a; McKee and Kagan, 2018; Pessarossi and Weill, 2015; Hadad et al., 2011). Followed by studies on regulation (Mohsin et al., 2021; Chortareas et al., 2016) and on the impact of risk on efficiency. Positive effects from adequate risk management on efficiency are reported by Stulz (2023), Lartey et al. (2021), Eling and Jia (2018), Mamatzakis and Bermpei (2014), and Chan et al. (2013) while Boussemart et al. (2019) reports negative effects.

Table 1: Parametric and non-parametric models

Model	Number of studies	Definition	Banks	Insurance Companies	Context
SFA	22/138 (15.94%)	SFA is the most widely used parametric method for estimating efficiency. Described by Berger and Humphrey (1997) as an econometric frontier approach it was introduced by Aigner et al. (1977), Battese and Corra (1977), and Meeusen and van Den Broeck (1977). This method is frequently modelled using a Cobb-Douglas production function (Williams and Gardener, 2003)	Agliardi et al. (2012) Altunbas et al. (2007), Barra et al. (2022), Berger et al. (2009), Bolt and Humphrey (2010), Bonin et al. (2005), Bos and Kool (2006), Dong et al. (2017), Fries and Taci (2005) Gang et al. (2018) Kalyvas and Mamatzakis (2014), Mamatzakis (2015), Mamatzakis and Bermpei (2014), Maudos et al. (2002), Mester (1996), Safiullah and Shamsuddin (2019), Shamshur and Weill, (2019), Sun and Chang (2011), Williams, (2004), Williams and Gardener (2003), Zamore et al. (2023).	Mamatzakis et al. (2023)	The primary limitation of SFA is the necessity of a functional form and the relationships involving costs, profits, or production in relation to inputs, outputs, and environmental factors (Berger and Humphrey, 1997). Defining these relationships is relatively straightforward for goods producers, it becomes more complex for service providers, particularly in the financial sector. Depending on the model employed, variables such as deposits in banking or incurred claims in insurance may be classified as inputs, outputs, or both (Učkar and Petrović, 2021b). SFA necessitates compliance with sample size and distribution axioms due to its stochastic nature.
DEA	32/138 (23.19%)	DEA is a linear programming approach designed to optimize input-output efficiency. First introduced by Charnes et al. (1978) under the assumption of constant returns to scale (CRS), known as the CCR model. Banker et al. (1984) extended the model to account for variable returns to scale (VRS), also known as the BCC model.	Asmild and Zhu, (2016), Ayadi et al. (2016), Barth et al. (2013), Boussemart et al. (2019), Canhoto and Dermine (2003), Chan et al. (2013), Chang (1999), Chortareas et al. (2016), Chortareas et al. (2012), Eling and Jia (2018), Fukuyama and Tan (2022), Gaganis et al. (2021), González(2009), Hadad et al. (2011), Lartey et al. (2021) Maudos et al. (2002), McKee and Kagan (2018), Mohsin et al. (2021), Nippani and Ling (2021) Pessarossi and Weill (2015), Proaño-Rivera et al. (2023), Spokeviciute et al. (2019).	Cummins et al. (1999), Eling and Jia, (2018), Huang et al. (2011)	DEA methodology is widely utilized across various disciplines, including finance, due to its simplicity, versatility, and minimal assumptions regarding the inputs and outputs of decision-making units (DMUs). It is particularly well-suited for smaller sample sizes (Emrouznejad and Yang, 2018). Its primary limitation is the absence of a random error term, making it highly sensitive to inaccurate data. Inaccuracies are classified as DMU inefficiency rather than statistical noise. Consequently, studies typically employ a two-stage procedure or an econometric approach to further validate their results.

Source: Author's construction

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Studies by Zamore et al. (2023), Tan and Tsionas (2022), Baule and Tallau (2021), Nippani and Ling (2021), Simper et al. (2019), and Marton and Runesson (2017) used NPLs, loan loss provisions (LLPs) and loan loss reserves (LLRs) as credit risk proxies and reported a positive relationship between risk management and efficiency. Furthermore, Alzayed et al. (2023) and Kumar et al. (2022) utilized the CAMEL framework to study the effect of corporate governance and risk management on efficiency. Abendschein and Grundke (2022) and Acharya et al. (2017) report that bank-specific variables are more relevant in less volatile markets. Bernard et al. (2019), Bohnert et al. (2018), and Lechner and Gatzert (2018) state that enterprise risk management is positively influenced by firm size and diversification (Lee and Li, 2012), therefore enhancing efficiency. Fredriksson and Moro (2014), Zhang et al. (2013), and Brewer and Jackson (2006) find that incorporating bank-specific risk variables diminishes the significance of the negative relationship between market concentration and performance, where lower-risk banks perform better.

3.2. Input and output data in efficiency estimation

The selection of methods and variables for efficiency estimation is critical, as it significantly influences the reliability of results. Due to the absence of a consensus on the most effective approaches, efficiency studies yield varied outcomes (Aiello and Bonanno, 2018). Učkar and Petrović (2021b) highlighted the importance of evaluating key variables, particularly in sectors such as banking and insurance, where inadequate variable selection (e.g., deposits or incurred losses) can adversely affect empirical findings. Consequently, choosing appropriate variables is essential to prevent misleading conclusions.

Although there is no consensus, studies indicate some overlap in variables used in efficiency estimation as shown in Table 2 (Ahmad et al., 2020; Bhatia et al., 2018; de Abreu et al., 2018; Berger and Humphrey, 1997).

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Table 2: Most common input and output variables

Model	Studies	Inputs	Outputs
SFA	Altunbas et al. (2007), Barra et al. (2022), Gang et al. (2018), Kalyvas and Mamatzakis (2014), Mamatzakis et al. (2023), Mamatzakis and Bermpei (2014), Pessarossi and Weill (2015), Williams and Gardener (2003), Zamore et al. (2023), Bolt and Humphrey (2010), Bos and Kool (2006), Mester (1996), Ruinan (2019), Safiullah and Shamsuddin (2019), Shamshur and Weill (2019), Srairi (2010), Williams (2004).	*Banks:* Loan-loss reserves; interest rate spread/3-year government bonds; operating expenses/total assets; number of employees; number of branches; loan loss reserves/ gross loans (as proxy for risk); nonperforming loans; labour expenses; administrative expenses; interest expenses; non-interest expenses; total cost; administration expenses/ total assets; net technical provisions/total assets; equity; assets; personnel expenses/total assets; total earning assets, total operating expenses/fixed assets; interest expenses/total assets; book value of equity/total assets; operating costs or overhead *Insurance companies:* Total equity, total investments, operating costs, investment costs, claims incurred	*Banks:* ROA; ROE; current assets/ current liabilities; loans (differentiated by type); services; securities; net claims paid; total investments; customer deposits; non-interest income; ordinary profits/sum of equity and reserves; net loans/total assets; ln (total assets); *Insurance companies:* ROA; ROE; Earned premiums, investment income
DEA	Boussemart et al. (2019), Chan et al. (2013), Chortareas et al. (2016), Chortareas et al. (2012), Eling and Jia (2018), Hadad et al. (2011), Lartey et al. (2021), McKee and Kagan (2018), Mohsin et al. (2021), Nippani and Ling (2021), Pessarossi and Weill (2015), Proaño-Rivera et al. (2023), Barth et al. (2013), Canhoto and Dermine (2003), Chang (1999), Cummins et al. (1999), González (2009), Huang et al. (2011), Ruinan (2019), Spokeviciute et al. (2019)		

Source: Author's construction

The main approaches are the *intermediation approach*, which emphasizes the transfer of funds through deposits and premiums, and the *operating approach*, which focuses on financial operations. Inputs and outputs typically encompass balance sheet components such as total assets, loans, equity, and deposits, with income and expenses categorized by type (e.g., interest, non-interest, or incurred claims for insurance). Recent studies also use environmental factors (Breitenstein et al., 2021; Lozano-Vivas et al., 2002; Pastor et al., 1997), control variables for GDP, inflation, ownership and bank size (Barth et al., 2013; Sun and Chang, 2011; Srairi, 2010), and financial indicators such as ROA, ROE, and NPLs, LLRs and LLPs to account for credit risk (Bischof et al., 2022; Bhat et al., 2021; Chen et al., 2021; Afzal et al., 2020; Dong et al., 2017; Ghosh, 2015; Matousek et al., 2015; Leventis et al., 2013). For instance, Safiullah and Shamsuddin (2019) utilized common inputs and outputs and introduced risk proxies for operational risk (standard deviation of ROA), insolvency risk (Altman's Z-score), credit risk (LLRs), and liquidity risk (liquidity ratios). Ferro and León (2018) report on a consensus on inputs (labour and capital) for insurance companies but note a lack of agreement on methodologies and variable combinations across studies (Aiello and Bonanno, 2018). Consequently, the results between studies vary significantly (de Abreu et al., 2019; Bhatia et al., 2018), thus complicating cross-study comparisons (Henriques et al., 2020).

3.3. Measures of risk and efficiency

From our study, we may conclude that the effect of risk management on financial institutions has become a central focus of numerous studies. Mester (1996) noted that neglecting the influence of risk on efficiency could lead to misleading conclusions. Building on the work of Hughes and Mester (2008), Berger and DeYoung (1997), and Berger and Mester (1997), many studies have investigated risk-adjusted efficiency. Brewer and Jackson (2006) discovered that banks with lower NPLs tend to offer lower deposit rates. Sun and Chang (2011) and Chang (1999) demonstrated that risk measures (such as NPLs) significantly influence bank efficiency. Berger and DeYoung (1997) argued that cost efficiency during stable periods mitigates the risk of failure during crises, a viewpoint supported by Assaf et al. (2019), who emphasized the importance of cost efficiency over profit efficiency due to riskier investments.

The results from our SLR show an uptake in the use of composite indices in efficiency estimation. When constructed properly, composite indices can effectively inform government policy. Unlike financial ratios, composite indices incorporate multiple components to summarize multidimensional concepts without sacrificing essential information (Purvis and Genovese, 2023). The PRISMA framework used in this SLR has identified several studies that utilized composite indices (Pinto et al., 2020; Rogge, 2018; Verbunt and Rogge, 2018; Acharya et al., 2017; Babecký et al., 2014; Schaeck and Cihák, 2014; Foster et al., 2013; Leventis et al, 2013; Groh et al., 2010; Sahoo and Acharya, 2010). Composite indices must be constructed with care, following the 10-step framework outlined in the OECD (2008) Handbook. A common challenge in constructing composite indices is determining the weight of each component (Foster et al., 2013). Some studies assign equal weights, while others base the weights on professional opinion, employing questionnaires to rank the importance of each component (Hatefi and Torabi, 2018). Paruolo et al. (2013) recommended utilizing Pearson's correlation coefficient to address issues related to weighting and aggregation while Choi (2023) proposed projected principal component analysis. To mitigate the limitations of equal weighting, more sophisticated methods have been employed, such as the ASW algorithm used by Elshandidy et al. (2024). The Benefit of Doubt (BoD) DEA model, introduced by Melyn and Moesen (1991), is frequently applied to minimize bias in the allocation of component weights (Gulati, 2023; Gulati et al., 2023; Maricic and Jeremic, 2023; Gulati et al., 2020; Färe et al., 2019; Rogge,

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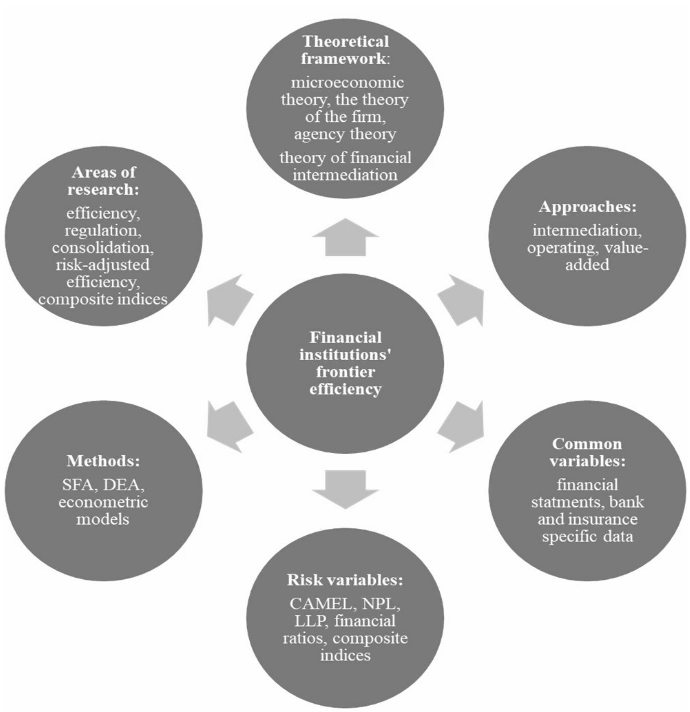
2018; Verbunt and Rogge, 2018; Van Puyenbroeck and Rogge, 2018; Cherchye et al., 2008). CAMEL framework has been adopted as a risk proxy in various studies (Alzayed et al., 2023; Kumar et al., 2022; Chen et al., 2021; Nippani and Ling, 2021; Afzal et al., 2020; Hwa et al., 2018; Beltratti and Paladino, 2016). Williams and O'Boyle (2011) and Landis et al. (2000) found that composite indices generally enhance model fit in structural equation models.

4. Discussion

Utilizing the PRISMA framework, this study's results indicate that DEA and SFA are the most frequently used methods for assessing efficiency in financial institutions, providing valuable insights for academics, investors, policymakers, managers, regulators, and the general public. The study focuses on identifying key input and output variables and explores the use of composite indices in constructing risk management indices and estimating risk-adjusted efficiency. Our findings, summarized in Figure 5, identify six key determinants of financial institutions' efficiency.

Figure 5: Financial institutions' frontier efficiency estimation framework

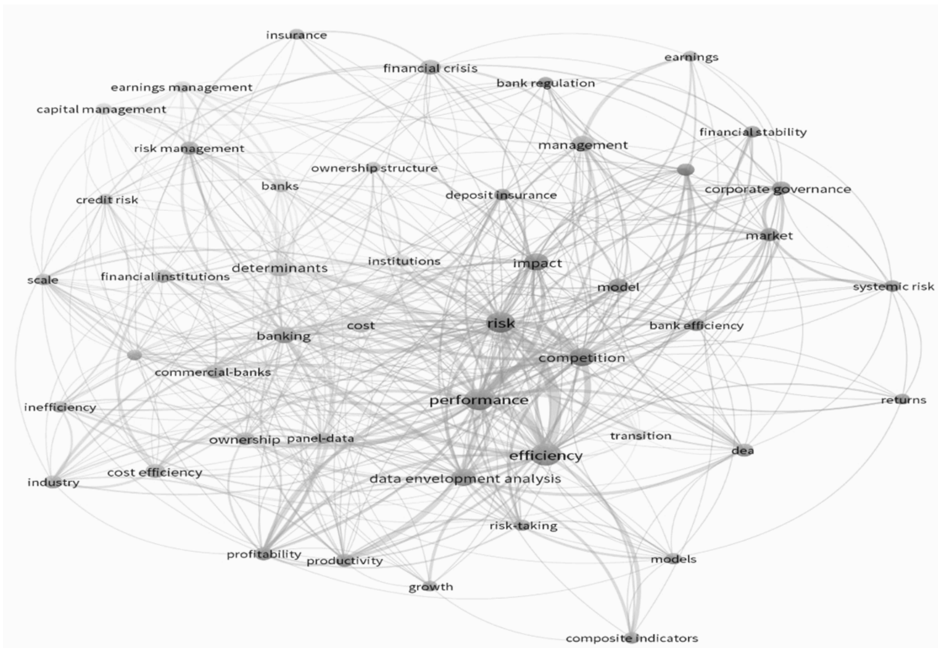


Source: Authors' construction

Depending on whether the intermediation or operating approach is employed, data is sourced from either the balance sheet or the income statement. Studies also incorporate bank and insurance company's specific data (such as ownership, employee count, and risk measures), macroeconomic indicators (including inflation and GDP), and environmental variables. The choice between a parametric and nonparametric model is contextual, as both have distinct advantages and limitations (Ahmad et al., 2020; Aiello and Bonanno, 2018; Bhatia et al., 2018; de Abreu et al., 2018; Murillo-Zamorano, 2004; Berger and Humphrey, 1997). Our SLR categorizes studies focusing on *efficiency* (Proaño-Rivera et al., 2023; Kumar et al., 2022; Nippani and Ling, 2021; Shamshur and Weill, 2019; Eling and Jia, 2018), the impact of *regulation* on efficiency (Kyiu and Tawiah, 2023; Mohsin et al., 2021; Gambacorta and Shin, 2018; Pessarossi and Weill, 2015; Kalyvas and Mamatzakis, 2014; Barth et al., 2013), the effects of *consolidation* (Andrievskaya and Semenova, 2016; Mühlnickel and Weiss, 2015; Bolt and Humphrey, 2010; Amel et al., 2004; Cummins et al., 1999; Fixler and Zieschang, 1993), the role of *risk management* (Mies 2024, Sen, 2023; Zamore et al., 2023; Bhat et al., 2021; Boussemart et al., 2019; Lechner and Gatzert, 2018; Lee and Li, 2012), and the application of *composite indices* (Choi, 2023; Abendschein and Grundke, 2022; Gaganis et al., 2021; Gang et al., 2018; Mohanram et al., 2018; Acharya et al., 2017; Babecký et al., 2014; Schaeck and Cihák, 2014; Islami and Kurz-Kim, 2013; Hu et al., 2012). The diversity of financial institutions' efficiency is evident in the thematic map shown in Figure 6, which shows multiple connections between the 773 keywords used in 138 empirical studies.

Figure 6 not only provides a snapshot of the thematic diversity in financial institutions' studies but also highlights critical areas requiring further exploration. The largest cluster (red) is on risk and its impact on bank efficiency, competition, returns and financial stability which indicates the rising interest in risk-adjusted efficiency of financial institutions. The green cluster specifically focuses on technical efficiency, scale, cost efficiency and the effect of ownership on bank efficiency and other financial institutions. The blue cluster focuses on efficiency and performance of financial institutions including risk-taking, identifying DEA as one of the most important methods for efficiency estimation and composite indicators as a new avenue for efficiency studies. Methodological advancements in these areas could support the development of standardised metrics in efficiency estimation, allowing for direct ranking and comparability between financial institutions. The fourth cluster is denoted as yellow and outlines keywords such as determinants of bank efficiency, financial institutions, capital, earnings and cost management as the main topics of several empirical studies. The last cluster is purple and focuses on risk management, insurance, financial crisis and earnings which encompasses the consequences of inadequate risk management during the great financial crisis and more recently the collapse of Silicon Valley Bank.

Figure 6: Thematic map based on the keywords co-occurrence between 138 empirical studies



Source: Keyword co-occurrence network of 138 empirical studies using the VOSviewer software 1.6.20 (2024)

By analysing these clusters, researchers can identify leading trends such as the effect of risk management, and emerging methodologies such as DEA BoD model for composite indices construction, paving the way for more comprehensive and comparative research. This thematic map underscores the need for cross-regional studies especially in underrepresented regions (Africa and Latin America) to bridge gaps and achieve a more comprehensive understanding of financial institutions' efficiency.

We emphasize the necessity for further research to refine risk measures and their influence on efficiency. While there is no consensus on approaches for estimating efficiency, most common are the intermediation and operating approach. In our SLR, we have identified frequently used variables in accordance with Radojicic et al. (2018). However, debates persist regarding the classification of deposits in banking and claims in insurance. Our final insight is the increasing application of DEA BoD models in developing composite indices for risk management, aimed at evaluating risk-adjusted efficiency. These indices have the potential to yield more accurate results and improve internal assessments of risk management practices.

5. Conclusion

Although numerous studies have synthesized the extensive literature on the efficiency of financial institutions, significant gaps remain in understanding the most utilized theories, methodologies, variables, and research domains. This systematic review further investigates risk-adjusted efficiency and expands comprehension of composite risk management indices, simultaneously elucidating new evidence on precise efficiency estimations. Ongoing challenges, such as the lack of consensus on approaches, methods, and variables, contribute to the heterogeneity observed within the literature. This review determines that parametric (SFA) and non-parametric (DEA) methods are the predominant techniques utilized for efficiency estimation (RQ1). Furthermore, it is anticipated that future developments will increasingly incorporate machine learning (ML) and artificial intelligence (AI) to overcome existing methodological limitations. Although significant progress has been made in the field, numerous challenges remain unresolved, including inconsistencies in the classification of variables, along with insufficient practices and broader considerations such as macroeconomic, environmental, and governance factors. Proxies, including non-performing loans (NPLs), loan loss provisions (LLPs), loan loss reserves (LLRs), capital ratios, and profitability ratios, have gained prominence in financial institutions efficiency studies (RQ2). However, further research is required to explore the practical implementation of these proxies. The growing use of composite indices shows potential for synthesizing complex multidimensional data into accessible metrics that assess risk-adjusted efficiency (RQ3).

This study provides several innovative contributions. First, it identifies the most commonly employed theories, methodologies, and variables in efficiency estimation, providing valuable insights into the current state of the field. Moreover, the focus on risk-adjusted efficiency and composite indicators makes this SLR unique in its approach to synthesise the large body of knowledge provided by studies on financial institutions efficiency. Secondly, this SLR not only outlines the current state of financial institutions efficiency but also highlights areas for improvement, including the integration of risk-adjusted efficiency measures and the formulation of composite indicators to enhance risk management quality ranking and comparability among financial institutions. The importance of this area of study cannot be overstated. The efficiency of financial institutions is fundamental for maintaining financial stability, fostering economic growth and enhancing institutional resilience. In an era marked by rising risks and systemic shocks such as war conflicts, trade wars, biohazard threats and technological disruptions, a deeper understanding of the risk-adjusted efficiency of financial institutions is more important than ever. Additionally, the growing significance of cryptocurrencies and blockchain technology adds to this complexity. This study lays a foundation for addressing future challenges and provides valuable insights for both researchers and policyholders.

Future research should prioritize illuminating the existing lack of consensus concerning key variables, specifically deposits in the banking sector and incurred claims in the insurance industry. Additionally, further studies are encouraged to explore the influence of risk management practices in conjunction with environmental, social, and governance (ESG) factors on the efficiency of financial institutions. The methodological limitations of DEA and SFA outlined in this study can be improved by integrating ML and AI techniques to incorporate an error term in nonparametric models and specify an adequate production function specifically tailored to financial institutions. It is vital for future studies to prioritize the implementation of composite indices in efficiency estimation, particularly the development of Risk Management Indices (RMI). These indices could significantly enhance decision-making processes by providing standardized measures of risk management quality and facilitating comparability across institutions. The findings from this study are valuable to regulators as the advancements in risk-adjusted efficiency could refine regulatory frameworks, including Basel IV and Solvency II. These improvements could also strengthen early warning systems and support macroprudential objectives aimed at ensuring financial stability, thus supporting policyholders macroprudential goals. An understanding of risk-adjusted efficiency provides managers with valuable insights into best practices in risk management, thereby facilitating the identification of critical areas for improving operational performance. The RMI could provide a basis for practical insights in identifying institutions that possess a competitive advantage in cost management and financial stability. By addressing these priorities, future research has the potential to bridge the gaps identified in this review, stimulate the development of innovative methodologies, and provide guidance to stakeholders in their pursuit of more accurate and meaningful efficiency estimations within financial institutions.

The findings of this study provide several practical implications for policymakers and regulators by providing insights into the most important methodologies in efficiency estimation, as well as new trends in estimating risk-adjusted efficiency and the use of composite indices. The advancements in risk-adjusted efficiency indices, including the development of RMIs, can advise the refinement of regulatory frameworks such as Basel IV and Solvency II. The development of standardized measures of risk management quality, such as the proposed RMIs could be of support to policymakers in achieving their macroprudential objectives of an efficient and stable financial system by enhancing early warning systems and reducing the probability of financial institutions failures. On a similar note, financial institution managers could be motivated by the insights provided in this study to estimate risk-adjusted efficiency and leverage insights from studies to identify best practices in risk management and operational performance. Thus, the development of RMIs would serve as benchmarks for assessing and improving cost management and financial stability.

While this study provides valuable insights, it is not without limitations. By focusing exclusively on risk-adjusted efficiency of financial institutions, it excludes studies on the efficiency of entire financial systems and those examining ESG factors. Although this exclusion was intentional to maintain a clear scope, it highlights areas for improvement in future studies. Additionally, the reliance on studies published in high-quality journals, as identified by the ABS journal guide, and the sole focus on the WoS database may have excluded relevant studies from other sources, such as Scopus. Limitations of this study, also, could be identified in its geographical scope, as regions such as Africa and Latin America remain underrepresented. Despite the outlined limitations, we believe that this SLR contributes to the understanding of financial institutions efficiency while defining new research paths for future scholars.

Finally, this study contributes to a deeper understanding of financial institutions' efficiency and offers a novel area for future research. By addressing the identified gaps, researchers can develop more standardised and innovative approaches to efficiency estimation. Policymakers, in turn, can leverage these advancements to design more effective regulatory frameworks, ensuring the resilience and stability of financial systems. The integration of risk-adjusted efficiency metrics into decision-making processes represents a crucial step forward, fostering a more robust and sustainable financial system.

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References

Abedifar, P., Molyneux, P., Tarazi, A. (2013) "Risk in Islamic Banking", *Review of Finance*, Vol. 17, No. 6, pp. 2035–2096, https://doi.org/10.1093/rof/rfs041.

Abendschein, M., Grundke, P. (2022) "On the Ranking Consistency of Systemic Risk Measures: Empirical Evidence", *The European Journal of Finance*, Vol. 28, No. 3, pp. 261–290, https://doi.org/10.1080/1351847X.2021.1946413.

Abou-El-Sood, H. (2016) "Are Regulatory Capital Adequacy Ratios Good Indicators of Bank Failure? Evidence from US Banks", *International Review of Financial Analysis*, Vol. 48, pp. 292–302, https://doi.org/10.1016/J.IRFA.2015.11.011.

ABS (2021) *ABS – Academic Journal Guide, Technical Report*, Chartered Association of Business Schools. Available at: <https://charteredabs.org/> [Accessed: December 6, 2024]

Acharya, V. V. et al. (2016) "Measuring Systemic Risk", *The Review of Financial Studies*, Vol. 30, No. 1, pp. 2–47, https://doi.org/10.1093/rfs/hhw088.

Adeabah, D. et al. (2022) "Reputational Risks in Banks: A Review of Research Themes, Frameworks, Methods, and Future Research Directions", *Journal of Economic Surveys*, Vol. 37, No. 2, pp. 321–350, https://doi.org/10.1111/JOES.12506.

Afzal, A., Mirza, N., Arshad, F. (2020) "Market Discipline in South Asia: Evidence from Commercial Banking Sector", *International Journal of Finance & Economics*, Vol. 26, No. 2, pp. 2251–2262, https://doi.org/10.1002/ijfe.1904.

Agliardi, E. et al. (2012) "A New Country Risk Index for Emerging Markets: A Stochastic Dominance Approach", *Journal of Empirical Finance*, Vol. 19, No. 5, pp. 741–761, https://doi.org/10.1016/j.jempfin.2012.08.003.

Ahmad, N. et al. (2020) "Banking Sector Performance, Profitability, and Efficiency: A Citation-Based Systematic Literature Review", *Journal of Economic Surveys*, Vol. 34, No. 1, pp. 185–218, https://doi.org/10.1111/JOES.12346.

Aiello, F., Bonanno, G. (2017) "On the Sources of Heterogeneity in Banking Efficiency Literature", *Journal of Economic Surveys*, Vol. 32, No. 1, pp. 194–225, https://doi.org/10.1111/JOES.12193.

Aigner, D., Lovell, C.A.K., Schmidt, P. (1977) "Formulation and Estimation of Stochastic Frontier Production Function Models", *Journal of Econometrics*, Vol. 6, No. 1, pp. 21–37, https://doi.org/10.1016/0304-4076(77)90052-5.

Ali, W., Wilson, J. (2023) "Multi-Level Analysis on Determinants of Sustainability Disclosure: A Survey of Academic Literature", *Managerial Finance*, Vol. 50, No. 1, pp. 228–265, https://doi.org/10.1108/MF-03-2023-0189.

Ali, W. et al. (2023) "Determinants and Consequences of Corporate Social Responsibility Disclosure: A Survey of Extant Literature", *Journal of Economic Surveys*. https://doi.org/10.1111/JOES.12556.

Almeida, J., Gonçalves, T. C. (2023) "Portfolio Diversification, Hedge and Safe-Haven Properties in Cryptocurrency Investments and Financial Economics: A Systematic Literature Review", *Journal of Risk and Financial Management*, Vol. 16, No. 1, https://doi.org/10.3390/JRFM16010003.

Altman, E. I. (1968) "Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy", *The Journal of Finance*, Vol. 23, No. 4, pp. 589–609, https://doi.org/10.2307/2978933.

Altunbas, Y. et al. (2007) "Examining the Relationships Between Capital, Risk and Efficiency in European Banking", *European Financial Management*, Vol. 13, No. 1, pp. 49–70, https://doi.org/10.1111/J.1468-036X.2006.00285.X.

Alzayed, N., Eskandari, R., Yazdifar, H. (2023) "Bank Failure Prediction: Corporate Governance and Financial Indicators", *Review of Quantitative Finance and Accounting*, Vol. 61, No. 2, pp. 601–631, https://doi.org/10.1007/s11156-023-01158-z.

Amel, D. et al. (2004) “Consolidation and Efficiency in the Financial Sector: A Review of the International Evidence”, *Journal of Banking & Finance*, Vol. 28, No. 10, pp. 2493–2519, https://doi.org/10.1016/j.jbankfin.2003.10.013.

Andrievskaya, I., Semenova, M. (2016) “Does Banking System Transparency Enhance Bank Competition? Cross-Country Evidence”, *Journal of Financial Stability*, Vol. 23, pp. 33–50, https://doi.org/10.1016/J.JFS.2016.01.003.

Asmild, M., Zhu, M. (2016) “Controlling for the Use of Extreme Weights in Bank Efficiency Assessments During the Financial Crisis”, *European Journal of Operational Research*, Vol. 251, No. 3, pp. 999–1015, https://doi.org/10.1016/j.ejor.2015.12.021.

Assaf, A.G., Berger, A.N., Roman, R.A. and Tsionas, M.G. (2019) “Does Efficiency Help Banks Survive and Thrive During Financial Crises?”, *Journal of Banking & Finance* [Internet], Vol. 106, No. C, pp. 445–470. Available at: <https://ideas.repec.org/a/eee/jbfina/v106y2019icp445-470.html> [Accessed: October 3, 2024]

Ayadi, R. et al. (2016) “Does Basel Compliance Matter for Bank Performance?”, *Journal of Financial Stability*, Vol. 23, pp. 15–32, https://doi.org/10.1016/j.jfs.2015.12.007.

Babecký, J. et al. (2014) “Banking, Debt, and Currency Crises in Developed Countries: Stylized Facts and Early Warning Indicators”, *Journal of Financial Stability*, Vol. 15, pp. 1–17, https://doi.org/10.1016/J.JFS.2014.07.001.

Banker, R. D., Charnes, A., Cooper, W. W. (1984) “Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis”, *Management Science* [Internet], Vol. 30, No. 9, pp. 1078–1092. Available at: <https://econpapers.repec.org/article/inmormnsc/v_3a30_3ay_3a1984_3ai_3a9_3ap_3a1078-1092.htm> [Accessed: October 3, 2024]

Barra, C., Papaccio, A., Ruggiero, N. (2022) “Basel Accords and Banking Inefficiency: Evidence from the Italian Local Market”, *International Journal of Finance & Economics*, Vol. 28, No. 4, pp. 4079–4119, https://doi.org/10.1002/ijfe.2637.

Barth, J. R. (2013) “Do Bank Regulation, Supervision and Monitoring Enhance or Impede Bank Efficiency?”, *Journal of Banking & Finance*, Vol. 37, No. 8, pp. 2879–2892, https://doi.org/10.1016/j.jbankfin.2013.04.030.

Battese, G. E., Corra, G. S. (1977) “Estimation of a Production Frontier Model: With Application to the Pastoral Zone of Eastern Australia”, *Australian Journal of Agricultural Economics*, Vol. 21, No. 3, pp. 169–179, https://doi.org/10.22004/AG.ECON.22266.

Baule, R., Tallau, C. (2021) “The Risk Sensitivity of Basel Risk Weights and Loan Loss Provisions: Evidence from European Banks”, *The European Journal of Finance*, Vol. 27, No. 18, pp. 1855–1886, https://doi.org/10.1080/1351847X.2021.1918207.

Beltratti, A., Paladino, G. (2016) “Basel II and Regulatory Arbitrage: Evidence from Financial Crises”, *Journal of Empirical Finance*, Vol. 39, pp. 180–196, https://doi.org/10.1016/j.jempfin.2016.02.006.

Benoit, S. et al. (2017) “Where the Risks Lie: A Survey on Systemic Risk”, *Review of Finance*, Vol. 21, No. 1, pp. 109–152, https://doi.org/10.1093/rof/rfw026.

Berger, A. N., Bonaccorsi di Patti, E. (2006) “Capital Structure and Firm Performance: A New Approach to Testing Agency Theory and an Application to the Banking Industry”, *Journal of Banking & Finance*, Vol. 30, No. 4, pp. 1065–1102, https://doi.org/10.1016/j.jbankfin.2005.05.015.

Berger, A. N., DeYoung, R. (1997) “Problem Loans and Cost Efficiency in Commercial Banks”, *Journal of Banking & Finance*, Vol. 21, No. 6, pp. 849–870, https://doi.org/10.1016/S0378-4266(97)00003-4.

Berger, A. N., Humphrey, D. B. (1997) “Efficiency of Financial Institutions: International Survey and Directions for Future Research”, *European Journal of Operational Research*, Vol. 98, No. 2, pp. 175–212, https://doi.org/10.1016/S0377-2217(96)00342-6.

Berger, A. N., Mester, L. J. (1997) “Inside the Black Box: What Explains Differences in the Efficiencies of Financial Institutions?”, *Journal of Banking & Finance*, Vol. 21, No. 7, pp. 895–947, https://doi.org/10.1016/S0378-4266(97)00010-1.

Berger, A. N., Hancock, D., Humphrey, D. B. (1993) “Bank Efficiency Derived from the Profit Function”, *Journal of Banking & Finance*, Vol. 17, No. 2-3, pp. 317–347, https://doi.org/10.1016/0378-4266(93)90035-C.

Berger, A. N., Hasan, I., Zhou, M. (2009) “Bank Ownership and Efficiency in China: What Will Happen in the World’s Largest Nation?”, *Journal of Banking & Finance*, Vol. 33, No. 1, pp. 113–130, https://doi.org/10.1016/j.jbankfin.2007.05.016.

Bernard, C., Vanduffel, S., Ye, J. (2019) “A New Efficiency Test for Ranking Investments: Application to Hedge Fund Performance”, *Economics Letters*, Vol. 181, pp. 203–207, https://doi.org/10.1016/j.econlet.2019.05.023.

Bhat, G., Lee, J. A., Ryan, S. G. (2021) “Using Loan Loss Indicators by Loan Type to Sharpen the Evaluation of Banks’ Loan Loss Accruals”, *Accounting Horizons*, Vol. 35, No. 3, pp. 69–91, https://doi.org/10.2308/HORIZONS-18-014.

Bhatia, V. et al. (2018) “A Review of Bank Efficiency and Productivity”, *OPSEARCH*, Vol. 55, No. 3, pp. 557–600, https://doi.org/10.1007/S12597-018-0332-2.

Birkle, C. et al. (2020) “Web of Science as a Data Source for Research on Scientific and Scholarly Activity”, *Quantitative Science Studies*, https://doi.org/10.1162/qss_a_00018.

Bischof, J., Rudolf, N., Schmundt, W. (2022) “How Do Non-Performing Loans Evolve Along the Economic Cycle? The Role of Macroeconomic Conditions and Legal Efficiency”, *European Accounting Review*, Vol. 31, No. 5, pp. 1149–1174, https://doi.org/10.1080/09638180.2022.2071960.

Bohnert, A. et al. (2018) "The Drivers and Value of Enterprise Risk Management: Evidence from ERM Ratings", *The European Journal of Finance*, Vol. 25, No. 3, pp. 234–255, https://doi.org/10.1080/1351847X.2018.1514314.

Bolt, W., Humphrey, D. (2010) "Bank Competition Efficiency in Europe: A Frontier Approach", *Journal of Banking & Finance*, Vol. 34, No. 8, pp. 1808–1817, https://doi.org/10.1016/j.jbankfin.2009.09.019.

Bonin, J. P., Hasan, I., Wachtel, P. (2005) "Bank Performance, Efficiency and Ownership in Transition Countries", *Journal of Banking & Finance*, Vol. 29, No. 1, pp. 31–53, https://doi.org/10.1016/j.jbankfin.2004.06.015.

Bos, J. W. B., Kool, C. J. M. (2006) "Bank Efficiency: The Role of Bank Strategy and Local Market Conditions", *Journal of Banking & Finance*, Vol. 30, No. 7, pp. 1953–1974, https://doi.org/10.1016/j.jbankfin.2005.07.008.

Boussemart, J. P. et al. (2019) "Decomposing Banking Performance into Economic and Credit Risk Efficiencies", *European Journal of Operational Research*, Vol. 277, No. 2, pp. 719–726, https://doi.org/10.1016/J.EJOR.2019.03.006.

Breitenstein, M., Nguyen, D. K., Walther, T. (2021) "Environmental Hazards and Risk Management in the Financial Sector: A Systematic Literature Review", *Journal of Economic Surveys*, Vol. 35, No. 2, pp. 512–538, https://doi.org/10.1111/JOES.12411.

Brewer, E., Jackson, W. E. (2006) "A Note on the 'Risk-Adjusted' Price-Concentration Relationship in Banking", *Journal of Banking & Finance*, Vol. 30, No. 3, pp. 1041–1054, https://doi.org/10.1016/j.jbankfin.2005.06.006.

Canhoto, A., Dermine, J. (2003) "A Note on Banking Efficiency in Portugal, New vs. Old Banks", *Journal of Banking & Finance*, Vol. 27, No. 11, pp. 2087–2098, https://doi.org/10.1016/S0378-4266(02)00316-3.

Chan, S. G. et al. (2013) "Efficiency and Risk in Commercial Banking: Empirical Evidence from East Asian Countries", *The European Journal of Finance*, Vol. 20, No. 12, pp. 1114–1132, https://doi.org/10.1080/1351847X.2012.745008.

Chang, C. -C. (1999) "The Nonparametric Risk-Adjusted Efficiency Measurement: An Application to Taiwan's Major Rural Financial Intermediaries", *American Journal of Agricultural Economics*, Vol. 81, No. 4, pp. 902–913, https://doi.org/10.2307/1244333.

Charnes, A., Cooper, W. W., Rhodes, E. (1978) "Measuring the Efficiency of Decision Making Units", *European Journal of Operational Research*, Vol. 2, No. 6, pp. 429–444, https://doi.org/10.1016/0377-2217(78)90138-8.

Chen, J. et al. (2021) "Are Banks Improving Risk Governance After the Financial Crisis?", *Journal of Accounting, Auditing & Finance*, Vol. 36, No. 3, pp. 540–556, https://doi.org/10.1177/0148558X19870099.

Cherchye, L. et al. (2008) "Creating Composite Indicators with DEA and Robustness Analysis: The Case of the Technology Achievement Index", *Journal* *of the Operational Research Society*, Vol. 59, No. 2, pp. 239–251, https://doi.org/10.1057/PALGRAVE.JORS.2602445.

Choi, B. P., Weiss, M. A. (2005) "An Empirical Investigation of Market Structure, Efficiency, and Performance in Property-Liability Insurance", *Journal of Risk and Insurance*, Vol. 72, No. 4, pp. 635–673, https://doi.org/10.1111/j.1539-6975.2005.00142.x.

Choi, S. H. (2023) "Feasible Weighted Projected Principal Component Analysis for Semi-Parametric Factor Models", *The Econometrics Journal*, Vol. 26, No. 2, pp. 215–234, https://doi.org/10.1093/ectj/utac031.

Chortareas, G. E., Girardone, C., Ventouri, A. (2012) "Bank Supervision, Regulation, and Efficiency: Evidence from the European Union", *Journal of Financial Stability*, Vol. 8, No. 4, pp. 292–302, https://doi.org/10.1016/j.jfs.2011.12.001.

Chortareas, G., Kapetanios, G., Ventouri, A. (2016) "Credit Market Freedom and Cost Efficiency in US State Banking", *Journal of Empirical Finance*, Vol. 37, pp. 173–185, https://doi.org/10.1016/j.jempfin.2016.03.002.

Crook, J. N., Edelman, D. B., Thomas, L. C. (2007) "Recent Developments in Consumer Credit Risk Assessment", *European Journal of Operational Research*, Vol. 183, No. 3, pp. 1447–1465, https://doi.org/10.1016/j.ejor.2006.09.100.

Cummins, J. D., Tennyson, S., Weiss, M. A. (1999) "Consolidation and Efficiency in the US Life Insurance Industry", *Journal of Banking & Finance*, Vol. 23, No. 2-4, pp. 325–357, https://doi.org/10.1016/S0378-4266(98)00089-2.

de Abreu, E. S., Kimura, H., Sobreiro, V. A. (2019) "What Is Going on with Studies on Banking Efficiency?", *Research in International Business and Finance*, Vol. 47, pp. 195–219, https://doi.org/10.1016/j.ribaf.2018.07.010.

Demsetz, H. (1973) "Industry Structure, Market Rivalry, and Public Policy", *The Journal of Law and Economics*, Vol. 16, No. 1, pp. 1–9, https://doi.org/10.1086/466752.

Dimitras, A. I., Gaganis, C., Pasiouras, F. (2018) "Financial Reporting Standards' Change and the Efficiency Measures of EU Banks", *International Review of Financial Analysis*, Vol. 59, pp. 223–233, https://doi.org/10.1016/J.IRFA.2018.08.008.

Dong, Y., Girardone, C., Kuo, J.-M. (2017) "Governance, Efficiency and Risk Taking in Chinese Banking", *The British Accounting Review*, Vol. 49, No. 2, pp. 211–229, https://doi.org/10.1016/j.bar.2016.08.001.

Eling, M., Jia, R. (2018) "Business Failure, Efficiency, and Volatility: Evidence from the European Insurance Industry", *International Review of Financial Analysis*, Vol. 59, pp. 58–76, https://doi.org/10.1016/j.irfa.2018.07.007.

Ellis, S., Sharma, S., Brzeszczyński, J. (2022) "Systemic Risk Measures and Regulatory Challenges", *Journal of Financial Stability*, Vol. 61, 100960, https://doi.org/10.1016/j.jfs.2021.100960.

Elshandidy, T., Acheampong, A. (2021) "Does Hedge Disclosure Influence Cost of Capital for European Banks?", *International Review of Financial Analysis*, Vol. 78, https://doi.org/10.1016/J.IRFA.2021.101942.

Elshandidy, T., Bamber, M., Omara, H. (2024) "Across the Faultlines: A Multi-Dimensional Index to Measure and Assess Board Diversity", *International Review of Financial Analysis*, Vol. 93, https://doi.org/10.1016/J.IRFA.2024.103231.

Emrouznejad, A., Yang, G.L. (2018) "A Survey and Analysis of the First 40 Years of Scholarly Literature in DEA: 1978-2016", *Socio-Economic Planning Sciences*, Vol. 61, pp. 4–8, https://doi.org/10.1016/J.SEPS.2017.01.008.

Färe, R. et al. (2019) "A Benefit-of-the-Doubt Model with Reverse Indicators", *European Journal of Operational Research*, Vol. 278, No. 2, pp. 394–400, https://doi.org/10.1016/j.ejor.2019.02.009.

Ferro, G. and León, S. (2018) "A Stochastic Frontier Analysis of Efficiency in Argentina's Non-Life Insurance Market", *The Geneva Papers on Risk and Insurance – Issues and Practice* [Internet], Vol. 43, No. 1, pp. 158–174. Available at: <https://ideas.repec.org/a/pal/gpprii/v43y2018i1d10.1057_s41288-017-0058-z.html> [Accessed: October 3, 2024]

Fixler, D. J., Zieschang, K. D. (1993) "An Index Number Approach to Measuring Bank Efficiency: An Application to Mergers", *Journal of Banking & Finance*, Vol. 17, No. 2-3, pp. 437–450, https://doi.org/10.1016/0378-4266(93)90043-D.

Forster, J., Shaffer, S. (2005) "Bank Efficiency Ratios in Latin America", *Applied Economics Letters*, Vol. 12, No. 9, pp. 529–532, https://doi.org/10.1080/13504850500120623.

Foster, J. E., McGillivray, M., Seth, S. (2013) "Composite Indices: Rank Robustness, Statistical Association, and Redundancy", *Econometric Reviews*, Vol. 32, No. 1, pp. 35–56, https://doi.org/10.1080/07474938.2012.690647.

Fredriksson, A., Moro, A. (2014) "Bank-SMEs Relationships and Banks' Risk-Adjusted Profitability", *Journal of Banking & Finance*, Vol. 41, pp. 67–77, https://doi.org/10.1016/j.jbankfin.2013.12.026.

Fries, S., Taci, A. (2005) "Cost Efficiency of Banks in Transition: Evidence from 289 Banks in 15 Post-Communist Countries", *Journal of Banking & Finance*, Vol. 29, No. 1, pp. 55–81, https://doi.org/10.1016/j.jbankfin.2004.06.016.

Fukuyama, H., Tan, Y. (2022) "Deconstructing Three-Stage Overall Efficiency into Input, Output and Stability Efficiency Components with Consideration of Market Power and Loan Loss Provision: An Application to Chinese Banks", *International Journal of Finance & Economics*, Vol. 27, No. 1, pp. 953–974, https://doi.org/10.1002/IJFE.2185.

Gaganis, C. et al. (2021) "CISEF: A Composite Index of Social, Environmental and Financial Performance", *European Journal of Operational Research*, Vol. 291, No. 1, pp. 394–409, https://doi.org/10.1016/j.ejor.2020.09.035.

Gambacorta, L., Shin, H. S. (2018) "Why Bank Capital Matters for Monetary Policy", *Journal of Financial Intermediation*, Vol. 35, pp. 17–29, https://doi.org/10.1016/j.jfi.2016.09.005.

Gang, J. et al. (2018) "Indexing Mergers and Acquisitions", *Quantitative Finance*, Vol. 18, No. 6, pp. 1033–1048, https://doi.org/10.1080/14697688.2017.136914.

Ghosh, A. (2015) "Banking-Industry Specific and Regional Economic Determinants of Non-Performing Loans: Evidence from US States", *Journal of Financial Stability*, Vol. 20, pp. 93–104, https://doi.org/10.1016/j.jfs.2015.08.004.

González, F. (2009) "Determinants of Bank-Market Structure: Efficiency and Political Economy Variables", *Journal of Money, Credit, and Banking*, Vol. 41, No. 4, pp. 735–754, https://doi.org/10.1111/j.1538-4616.2009.00229.x.

Groh, A. P., von Liechtenstein, H., Lieser, K. (2010) "The European Venture Capital and Private Equity Country Attractiveness Indices", *Journal of Corporate Finance*, Vol. 16, No. 2, pp. 205–224, https://doi.org/10.1016/j.jcorpfin.2009.09.003.

Gulati, R. (2022) "Global and Local Banking Crises and Risk-Adjusted Efficiency of Indian Banks: Are the Impacts Really Perspective-Dependent?", *Quarterly Review of Economics and Finance*, Vol. 84, pp. 23–39, https://doi.org/10.1016/j.qref.2022.01.004.

Gulati, R. (2023) "Beyond the Z-Score: A Novel Measure of Bank Stability for Effective Policymaking", *Journal of Public Affairs*, Vol. 23, No. 4, https://doi.org/10.1002/PA.2866.

Gulati, R., Hassan, M. K., Charles, V. (2023) "Developing a New Multidimensional Index of Bank Stability and Its Usage in the Design of Optimal Policy Interventions", *Computational Economics*, https://doi.org/10.1007/s10614-023-10401-7.

Gulati, R., Kattumuri, R., & Kumar, S. (2020). A non-parametric index of corporate governance in the banking industry: An application to Indian data. Socio-Economic Planning Sciences, 70, 100702, https://doi.org/10.1016/J.SEPS.2019.03.008.

Hadad, M. D. et al. (2011) "Banking Efficiency and Stock Market Performance: An Analysis of Listed Indonesian Banks", *Review of Quantitative Finance and Accounting*, Vol. 37, No. 1, pp. 1–20, https://doi.org/10.1007/s11156-010-0192-1.

Hatefi, S. M., Torabi, S. A. (2018) "A Slack Analysis Framework for Improving Composite Indicators with Applications to Human Development and Sustainable Energy Indices", *Econometric Reviews*, Vol. 37, No. 3, pp. 247–259, https://doi.org/10.1080/07474938.2016.1140286.

Hays, F. H., De Lurgio, S. A., Gilbert, A. H. (2009) "Efficiency Ratios and Community Bank Performance", *Journal of Finance and Accountancy* [Internet], pp. 1–15. Available at: <https://www.aabri.com/manuscripts/09227.pdf> [Accessed: October 3, 2024]

Henriques, I. C. et al. (2020) "Two-Stage DEA in Banks: Terminological Controversies and Future Directions", *Expert Systems with Applications*, Vol. 161, 113632, https://doi.org/10.1016/j.eswa.2020.113632.

Herring, R., Santomero, A. (1995) *The Role of the Financial Sector in Economic Performance*, Working Paper no. 95 (08), The Wharton School, University of Pennsylvania Research Paper Series. Available at: <https://ssrn.com/abstract=7647> [Accessed: October 3, 2024]

Hu, D. et al. (2012) "Network-Based Modeling and Analysis of Systemic Risk in Banking Systems", *MIS Quarterly*, Vol. 36, No. 4, pp. 1269–1291, https://doi.org/10.2307/41703507.

Huang, L.-Y. et al. (2011) "Corporate Governance and Efficiency: Evidence from U.S. Property-Liability Insurance Industry", *The Journal of Risk and Insurance*, Vol. 78, No. 3, pp. 519–550, https://doi.org/10.1111/j.1539-6975.2011.01410.x.

Hughes, J. P., Mester, L. J. (2008) Efficiency in Banking: Theory, Practice, and Evidence, FRB of Philadelphia Working Paper No. 08-1, http://dx.doi.org/10.2139/ssrn.1092220.

Hwa, V. et al. (2018) "Does Regulatory Bank Oversight Impact Economic Activity? A Local Projections Approach", *Journal of Financial Stability*, Vol. 39, pp. 167–174, https://doi.org/10.1016/J.JFS.2017.01.006.

Islami, M., Kurz-Kim, J.-R. (2013) *A Single Composite Financial Stress Indicator and Its Real Impact in the Euro Area*, Discussion Papers No. 31/2013, Deutsche Bundesbank. Available at: <https://www.bundesbank.de/discussion_paper_31_2013> [Accessed: October 3, 2024]

Kalyvas, A. N., Mamatzakis, E. (2014) "Does Business Regulation Matter for Banks in the European Union?", *Journal of International Financial Markets, Institutions and Money*, Vol. 32, pp. 278–324, https://doi.org/10.1016/j.intfin.2014.06.007.

Kim, D., Santomero, A. (1988) "Risk in Banking and Capital Regulation", *The Journal of Finance*, Vol. 43, No. 5, pp. 1219–1233, https://doi.org/10.1111/j.1540-6261.1988.tb03966.x.

Kocenda, E., Iwasaki, I. (2021) "Bank Survival Around the World: A Meta-Analytic Review", *Journal of Economic Surveys*, Vol. 36, No. 1, pp. 108–156, https://doi.org/10.1111/joes.12451.

Kuizinienė, D. et al. (2022) "Systematic Review of Financial Distress Identification Using Artificial Intelligence Methods", *Applied Artificial Intelligence*, Vol. 36, No. 1, https://doi.org/10.1080/08839514.2022.2138124.

Kumar, A. et al. (2022) "Banking Performance and Institutional Quality: Evidence from Dynamic Panel Data Analysis", *International Journal of Finance & Economics*, Vol. 28, No. 4, pp. 4717–4737, https://doi.org/10.1002/ijfe.2673.

Kyiu, A., Tawiah, V. (2023) "IFRS 9 Implementation and Bank Risk", *Accounting Forum*, pp. 1–25, https://doi.org/10.1080/01559982.2023.2233861.

Landis, R. S., Beal, D. J.,Tesluk, P. E. (2000) "A Comparison of Approaches to Forming Composite Measures in Structural Equation Models", *Organizational Research Methods*, Vol. 3, No. 2, pp. 186–207, https://doi.org/10.1177/109442810032003.

Lartey, T., James, G. A., Danso, A. (2021) "Interbank Funding, Bank Risk Exposure and Performance in the UK: A Three-Stage Network DEA Approach", *International Review of Financial Analysis*, Vol. 75, https://doi.org/10.1016/J.IRFA.2021.101753.

Lechner, P., Gatzert, N. (2018) "Determinants and Value of Enterprise Risk Management: Empirical Evidence from Germany", *The European Journal of Finance*, Vol. 24, No. 10, pp. 867–887, https://doi.org/10.1080/1351847X.2017.1347100.

Lee, B. S., Li, M.-Y. L. (2012) "Diversification and Risk-Adjusted Performance: A Quantile Regression Approach", *Journal of Banking & Finance*, Vol. 36, No. 7, pp. 2157–2173, https://doi.org/10.1016/j.jbankfin.2012.03.020.

Leventis, S., Dimitropoulos, P., Owusu-Ansah, S. (2013) "Corporate Governance and Accounting Conservatism: Evidence from the Banking Industry", *Corporate Governance – An International Review*, Vol. 21, No. 3, pp. 264–286, https://doi.org/10.1111/corg.12015.

Lozano-Vivas, A. et al. (2002) "An Efficiency Comparison of European Banking Systems Operating under Different Environmental Conditions", *Journal of Productivity Analysis*, Vol. 18, No. 1, pp. 59–77, https://doi.org/10.1023/A:1015704510270.

Malafronte, I., Starita, M. G., Pereira, J. (2018) "The Effectiveness of Risk Disclosure Practices in the European Insurance Industry", *Review of Accounting and Finance*, Vol. 17, No. 1, pp. 130–147, https://doi.org/10.1108/RAF-09-2016-0150.

Mamatzakis, E. (2015) "Risk and Efficiency in the Central and Eastern European Banking Industry under Quantile Analysis", *Quantitative Finance*, Vol. 15, No. 3, pp. 553–567, https://doi.org/10.1080/14697688.2012.715245.

Mamatzakis, E., Bermpei, T. (2014) "What Drives Investment Bank Performance? The Role of Risk, Liquidity and Fees Prior to and During the Crisis", *International Review of Financial Analysis*, Vol. 35, pp. 102–117, https://doi.org/10.1016/j.irfa.2014.07.012.

Mamatzakis, E. et al. (2023) "Measuring the Efficiency and Productivity of the U.K. Insurance Market", *International Journal of Finance & Economics*, Vol. 29, No. 1, https://doi.org/10.1002/ijfe.2723.

Maricic, M., Jeremic, V. (2023) "Imposing Unsupervised Constraints to the Benefit-of-the-Doubt (BoD) Model", *Metron*, Vol. 81, No. 3, pp. 259–296, https://doi.org/10.1007/s40300-023-00254-3.

Martín-Martín, A. et al. (2021) "Google Scholar, Microsoft Academic, Scopus, Dimensions, Web of Science, and OpenCitations' COCI: A Multidisciplinary

Comparison of Coverage via Citations”, *Scientometrics*, Vol. 126, pp. 871–906, https://doi.org/10.1007/s11192-020-03690-4.

Marton, J., Runesson, E. (2017) “The Predictive Ability of Loan Loss Provisions in Banks – Effects of Accounting Standards, Enforcement and Incentives”, *The British Accounting Review*, Vol. 49, No. 2, pp. 162–180, https://doi.org/10.1016/j.bar.2016.09.003.

Matousek, R. et al. (2015) “Bank Performance and Convergence During the Financial Crisis: Evidence from the ‘Old’ European Union and Eurozone”, *Journal of Banking & Finance*, Vol. 52, pp. 208–216, https://doi.org/10.1016/j.jbankfin.2014.08.012.

Maudos, J. et al. (2002) “Cost and Profit Efficiency in European Banks”, *Journal of International Financial Markets, Institutions and Money*, Vol. 12, No. 1, pp. 33–58, https://doi.org/10.1016/S1042-4431(01)00051-8.

McKee, G., Kagan, A. (2018) “Community Bank Structure: An X-Efficiency Approach”, *Review of Quantitative Finance and Accounting*, Vol. 51, No. 1, pp. 19–41, https://doi.org/10.1007/s11156-017-0662-9.

Meeusen, W., van Den Broeck, J. (1977) “Efficiency Estimation from Cobb-Douglas Production Functions with Composed Error”, *International Economic Review*, Vol. 18, No. 2, p. 435, https://doi.org/10.2307/2525757.

Melyn, W., Moesen, W. (1991) *Towards a Synthetic Indicator of Macroeconomic Performance: Unequal Weighting When Limited Information Is Available*, Public Economic Research Paper No. 17, CES, KU Leuven. Available at: <https://www.econbiz.de/Record/towards-a-synthetic-indicator-of-macroeconomic-performance-unequal-weighting-when-limited-information-is-available-melyn-wim/10000836584> [Accessed: October 3, 2024]

Mester, L. J. (1996) “A Study of Bank Efficiency Taking into Account Risk-Preferences”, *Journal of Banking & Finance*, Vol. 20, No. 6, pp. 1025–1045, https://doi.org/10.1016/0378-4266(95)00047-X.

Mies, M. (2024) “Empirical Research on Banks’ Risk Disclosure: Systematic Literature Review, Bibliometric Analysis and Future Research Agenda”, *International Review of Financial Analysis*, Vol. 95, https://doi.org/10.1016/J.IRFA.2024.103357.

Mohanram, P., Saiy, S., Vyas, D. (2018) “Fundamental Analysis of Banks: The Use of Financial Statement Information to Screen Winners from Losers”, *Review of Accounting Studies*, Vol. 23, No. 1, pp. 200–233, https://doi.org/10.1007/s11142-017-9430-2.

Mohsin, M. et al. (2021) “The Evaluation of Efficiency and Value Addition of IFRS Endorsement Towards Earnings Timeliness Disclosure”, *International Journal of Finance & Economics*, Vol. 26, No. 2, pp. 1793–1807, https://doi.org/10.1002/ijfe.1878.

Mongeon, P., Paul-Hus, A. (2016) "The Journal Coverage of Web of Science and Scopus: A Comparative Analysis", *Scientometrics*, Vol. 106, No. 1, pp. 213–228, https://doi.org/10.1007/s11192-015-1765-5.

Mousavi, M. M., Ouenniche, J., Xu, B. (2015) "Performance Evaluation of Bankruptcy Prediction Models: An Orientation-Free Super-Efficiency DEA-Based Framework", *International Review of Financial Analysis*, Vol. 42, pp. 64–75, https://doi.org/10.1016/J.IRFA.2015.01.006.

Mühlnickel, J., Weiß, G. N. F. (2015) "Consolidation and Systemic Risk in the International Insurance Industry", *Journal of Financial Stability*, Vol. 18, pp. 187–202, https://doi.org/10.1016/J.JFS.2015.04.005.

Murillo-Zamorano, L. R. (2004) "Economic Efficiency and Frontier Techniques", *Journal of Economic Surveys*, Vol. 18, No. 1, pp. 33–77, https://doi.org/10.1111/J.1467-6419.2004.00215.X.

Nazareth, N., Ramana Reddy, Y. V. (2023) "Financial Applications of Machine Learning: A Literature Review", *Expert Systems with Applications*, Vol. 219, 119640, https://doi.org/10.1016/J.ESWA.2023.119640.

Nippani, S., Ling, R. (2021) "Bank Size and Performance: An Analysis of the Industry in the United States in the Post-Financial-Crisis Era", *Journal of Financial Research*, Vol. 44, No. 3, pp. 587–606, https://doi.org/10.1111/jfir.12255.

OECD, European Union, & Joint Research Centre – European Commission. (2008) *Handbook on constructing composite indicators: Methodology and user guide*, OECD, https://doi.org/10.1787/9789264043466-en.

Page, M. J. et al. (2021) "The PRISMA 2020 Statement: An Updated Guideline for Reporting Systematic Reviews", *BMJ*, Vol. 372, https://doi.org/10.1136/BMJ.N71.

Paruolo, P., Saisana, M., Saltelli, A. (2013) "Ratings and Rankings: Voodoo or Science?", *Journal of the Royal Statistical Society Series A: Statistics in Society*, Vol. 176, No. 3, pp. 609–634, https://doi.org/10.1111/J.1467-985X.2012.01059.X.

Lozano Vivas, A., Pastor Ciurana, J. T., Pastor Monsálvez, J. M. (1997) *Efficiency of European Banking Systems: A Correction by Environment Variables*, Working Paper Serie EC No. 1997-12, Instituto Valenciano de Investigaciones Económicas, S.A. (Ivie). Available at: <https://www.ivie.es/downloads/working_papers/1997-12.pdf> [Accessed: October 3, 2024]

Pessarossi, P., Weill, L. (2015) "Do capital requirements affect cost efficiency? Evidence from China", *Journal of Financial Stability*, Vol 19, pp. 119–127, https://doi.org/10.1016/j.jfs.2014.11.002.

Pinto, S., Sarte, P.-D. Sharp, R. (2020) "The Information Content and Statistical Properties of Diffusion Indexes", *63rd Issue (September 2020) of the International Journal of Central Banking* [Internet] Available at: <https://www.ijcb.org/journal/ijcb20q3a2.htm> [Accessed: October 3, 2024]

Proaño-Rivera, B., Feria-Dominguez, J. M. (2024) "Are Ecuadorian Banks Enough Technically Efficient for Growth? A Clinical Study", *International Journal of Finance & Economics*, Vol. 29, No. 2, pp. 2011–2029, https://doi.org/10.1002/ijfe.2775.

Purvis, B., Genovese, A. (2023) "Better or Different? A Reflection on the Suitability of Indicator Methods for a Just Transition to a Circular Economy", *Ecological Economics*, Vol. 212, 107938, https://doi.org/10.1016/j.ecolecon.2023.107938.

Radojicic, M., Savic, G., Jeremic, V. (2018) "Measuring the Efficiency of Banks: The Bootstrapped I-Distance GAR DEA Approach", *Technological and Economic Development of Economy*, Vol. 24, No. 4, pp. 1581–1605, https://doi.org/10.3846/TEDE.2018.3699.

Rogge, N. (2018) "On Aggregating Benefit of the Doubt Composite Indicators", *European Journal of Operational Research*, Vol. 264, No. 1, pp. 364–369, https://doi.org/10.1016/j.ejor.2017.06.035.

Ruinan, L. (2019) "Comparison of Bank Efficiencies Between the US and Canada: Evidence Based on SFA and DEA", *Journal of Competitiveness*, Vol. 11, No. 2, pp. 113–129. Available at: <https://doi.org/10.7441/joc.2019.02.08> [Accessed: October 3, 2024]

Safiullah, M., Shamsuddin, A. (2019) "Risk-Adjusted Efficiency and Corporate Governance: Evidence from Islamic and Conventional Banks", *Journal of Corporate Finance*, Vol. 55, pp. 105–140, https://doi.org/10.1016/j.jcorpfin.2018.08.009.

Sahoo, B. K., Acharya, D. (2010) "An Alternative Approach to Monetary Aggregation in DEA", *European Journal of Operational Research*, Vol. 204, No. 3, pp. 672–682, https://doi.org/10.1016/j.ejor.2009.11.035.

Schaeck, K., Cihák, M. (2014) "Competition, Efficiency, and Stability in Banking", *Financial Management*, Vol. 43, No. 1, pp. 215–241, https://doi.org/10.1111/fima.12010.

Sen, I. (2023) "Regulatory Limits to Risk Management", *The Review of Financial Studies*, Vol. 36, No. 6, pp. 2175–2223, https://doi.org/10.1093/rfs/hhac083.

Shaffer, S. (1993) "Can Megamergers Improve Bank Efficiency?", *Journal of Banking & Finance*, Vol. 17, No. 2-3, pp. 423–436, https://doi.org/10.1016/0378-4266(93)90042-C.

Shakeel, M. R., Siddiqui, T. A. and Alam, S. (2023) "Feature Selection in Corporate Bankruptcy Prediction Using ML Techniques: A Systematic Literature Review". In Chakravarthy, V., Bhateja, V., Flores Fuentes, W., Anguera, J. and Vasavi, K.P. ed., *Advances in Signal Processing, Embedded Systems and IoT*, Lecture Notes in Electrical Engineering, Vol. 992, Singapore: Springer, https://doi.org/10.1007/978-981-19-8865-3_32.

Shamshur, A., Weill, L. (2019) "Does Bank Efficiency Influence the Cost of Credit?", *Journal of Banking & Finance*, Vol. 105, pp. 62–73, https://doi.org/10.1016/j.jbankfin.2019.05.002.

Simper, R., Dadoukis, A., Bryce, C. (2019) "European Bank Loan Loss Provisioning and Technological Innovative Progress", *International Review of Financial Analysis*, Vol. 63, pp. 119–130, https://doi.org/10.1016/j.irfa.2019.03.001.

Spokeviciute, L., Keasey, K., Vallascas, F. (2019) "Do Financial Crises Cleanse the Banking Industry? Evidence from US Commercial Bank Exits", *Journal of Banking & Finance*, Vol. 99, pp. 222–236, https://doi.org/10.1016/j.jbankfin.2018.12.010.

Srairi, S. A. (2010) "Cost and Profit Efficiency of Conventional and Islamic Banks in GCC Countries", *Journal of Productivity Analysis*, Vol. 34, No. 1, pp. 45–62, https://doi.org/10.1007/s11123-009-0161-7.

Stulz, R. M. (2023) *Crisis Risk and Risk Management*, Fisher College of Business Working Paper No. 2023-010, Charles A. Dice Working Paper No. 2023-10, http://dx.doi.org/10.2139/ssrn.4439633.

Sun, L., Chang, T.-P. (2011) "A Comprehensive Analysis of the Effects of Risk Measures on Bank Efficiency: Evidence from Emerging Asian Countries", *Journal of Banking & Finance*, Vol. 35, No. 7, pp. 1727–1735, https://doi.org/10.1016/j.jbankfin.2010.11.017.

Tan, Y., Tsionas, M. G. (2022) "Modelling Sustainability Efficiency in Banking", *International Journal of Finance & Economics*, Vol. 27, No. 3, pp. 3754–3772, https://doi.org/10.1002/ijfe.2349.

Učkar, D., Petrović, D. (2021a) "Efficiency of Banks in Croatia", *Zbornik Radova Ekonomskog Fakulteta u Rijeci*, Vol. 39, No. 2, https://doi.org/10.18045/zbefri.2021.2.349.

Učkar, D., Petrović, D. (2021b) "Financial Institutions Efficiency: Theory, Methods and Empirical Evidence". In *Economic and Social Development: 64th International Scientific Conference on Economic and Social Development: Book of Proceedings, 22 January 2021*. Zagreb, Croatia: Varazdin Development and Entrepreneurship Agency, pp. 63–77. Available at: <https://www.bib.irb.hr/1106438> [Accessed: October 3, 2024]

van der Cruijsen, C., de Haan, J., Roerink, R. (2023) "Trust in Financial Institutions: A Survey", *Journal of Economic Surveys*, Vol. 37, No. 4, pp. 1214–1254, https://doi.org/10.1111/JOES.12468.

van Puyenbroeck, T., Rogge, N. (2018) "Geometric Mean Quantity Index Numbers with Benefit-of-the-Doubt Weights", *European Journal of Operational Research*, Vol. 256, No. 3, pp. 1004–1014, https://doi.org/10.1016/j.ejor.2016.07.038.

Verbunt, P., Rogge, N. (2018) "Geometric Composite Indicators with Compromise Benefit-of-the-Doubt Weights", *European Journal of Operational Research*, Vol. 264, No. 1, pp. 388–401, https://doi.org/10.1016/j.ejor.2017.06.061.

Visser, M., van Eck, N. J., Waltman, L. (2021) "Large-Scale Comparison of Bibliographic Data Sources: Scopus, Web of Science, Dimensions, Crossref, and Microsoft Academic", *Quantitative Science Studies*, Vol. 2, No. 1, pp. 20–41, https://doi.org/10.48550/arXiv.2005.10732.

VOSviewer (2024) VOSviewer software 1.6.20. Available at: <https://www.vosviewercom/> [Accessed: December 18, 2024]

Walker, J. T. et al. (2019) "What Influences Business Academics' Use of the Association of Business Schools (ABS) List? Evidence from a Survey of UK Academics", *British Journal of Management*, Vol. 30, No. 3, pp. 730–747, https://doi.org/10.1111/1467-8551.12294.

Williams, J. (2004) "Determining Management Behaviour in European Banking", *Journal of Banking & Finance*, Vol. 28, No. 10, pp. 2427–2460, https://doi.org/10.1016/j.jbankfin.2003.09.010.

Williams, J., Gardener, E. (2003) "The Efficiency of European Regional Banking", *Regional Studies*, Vol. 37, No. 4, pp. 321–330, https://doi.org/10.1080/0034340032000074361.

Williams, L. J., O'Boyle, E. (2011) "The Myth of Global Fit Indices and Alternatives for Assessing Latent Variable Relations", *Organizational Research Methods*, Vol. 14, No. 2, pp. 350–369, https://doi.org/10.1177/1094428110391472.

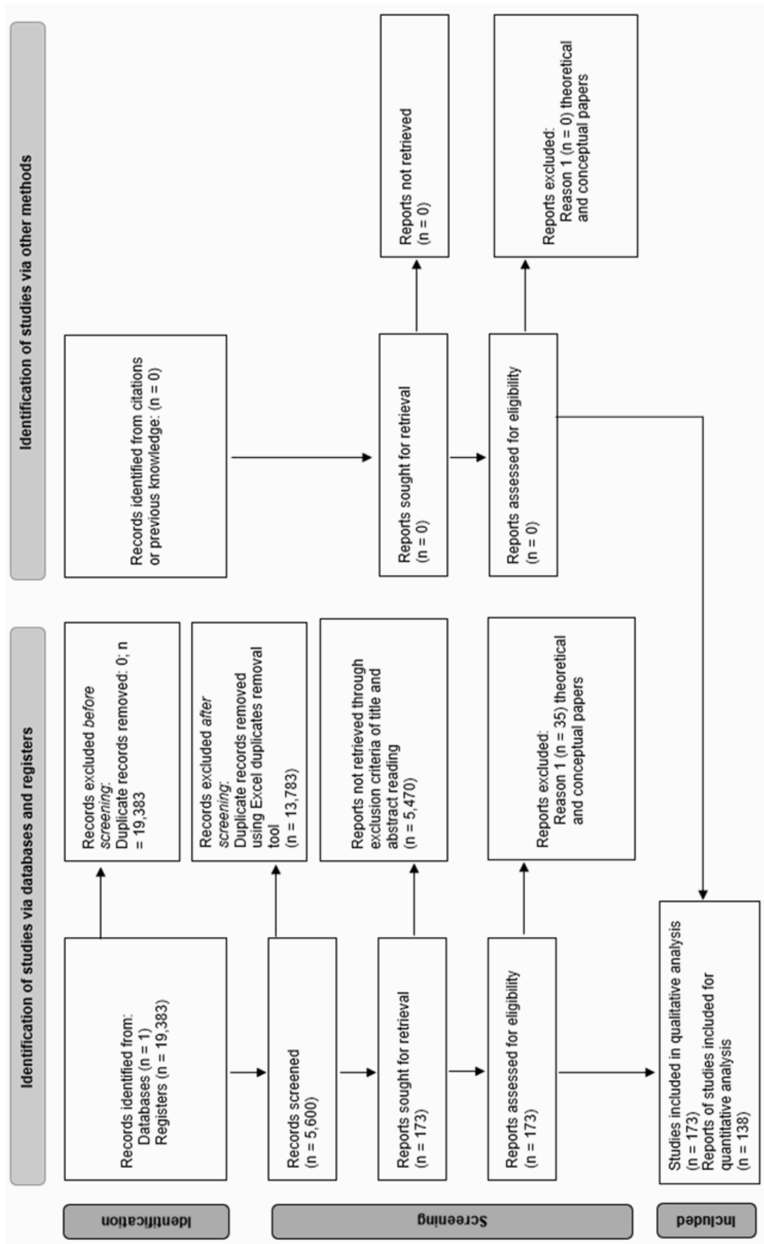
Zamore, S., Beisland, L. A., Mersland, R. (2023) "Excessive Focus on Risk? Non-Performing Loans and Efficiency of Microfinance Institutions", *International Journal of Finance & Economics*, Vol. 28, No. 2, pp. 1290–1307, https://doi.org/10.1002/ijfe.2477.

Zhang, J. et al. (2013) "Market Concentration, Risk-Taking, and Bank Performance: Evidence from Emerging Economies", *International Review of Financial Analysis*, Vol. 30, pp. 149–157, https://doi.org/10.1016/J.IRFA.2013.07.016.

Zhu, J., Liu, W. (2020) "A Tale of Two Databases: The Use of Web of Science and Scopus in Academic Papers", *Scientometrics*, Vol. 123, No. 1, pp. 321–335, https://doi.org/10.1007/s11192-020-03387-8.

Appendix

Figure A: PRISMA Flow Diagram



Source: Author's construction based on Page et al. (2021)

Efikasnost financijskih institucija: Sistematski pregled literature

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Sažetak

U ovom istraživanju provodi se sistematski pregled literature utjecaja upravljanja rizicima na efikasnost financijskih institucija. Koristeći se PRISMA metodom, analizirano je 173 članaka objavljenih u razdoblju od 1990. do 2023. godine i to u časopisima rangiranim prema Akademskom vodiču časopisa objavljenom od strane Udruge poslovnih škola u 2021. godini. Rezultati pokazuju kako se parametarski i ne parametarski modeli podjednako koriste u procjeni efikasnosti financijskih institucija. Rezultati istraživanja ističu ograničenja spomenutih metodologija, kako i nedostatak konsenzusa u klasifikaciji varijabli. Rezultati također pokazuju kako se recentna empirijska istraživanja prvenstveno usmjeravaju na efekte spajanja i pripajanja, regulaciju i upravljanje rizicima na efikasnost banaka i osiguravajućih društava. Analizom recentnih empirijskih istraživanja ističe se trend razvijanja i uporabe kompozitnih indeksa u procjeni efikasnosti. Rezultati ovog istraživanja mogu biti od koristi akademicima, istraživačima, menadžerima financijskih institucija, regulatorima i kreatorima monetarne politike čiji je interes efikasnost financijskih institucija.

Ključne riječi*: efikasnost, upravljanje rizicima, financijske institucije, kompozitni indeksi*

JEL klasifikacija*: C61, G21, G22*

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9.4 APPENDED SCIENTIFIC PAPER 2: BANK RISK-ADJUSTED EFFICIENCY USING A COMPOSITE RISK MANAGEMENT INDEX

Bank Risk-Adjusted Efficiency Using a Composite Risk Management Index

Petrović, D., Dasilas, A. & Karanović, G. (2025)

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Bank Risk-Adjusted Efficiency Using a Composite Risk Management Index

Purpose – The purpose of this paper is to examine the relationship between risk management and efficiency. To achieve this, risk-adjusted efficiency is calculated on a longitudinal sample of 589 banks over a period from 2015 to 2021.

Design/methodology/approach – This study employs a Data Envelopment Analysis "Benefit-of-the-Doubt" (DEA BoD) model to construct a Risk Management Index (RMI) based on the CAMEL (Capital Adequacy, Asset Quality, Management Efficiency, Earnings, and Liquidity) framework. The attained RMI is then used to empirically test the relationship between risk management and bank efficiency.

Findings – The empirical analysis shows that there is a positive and significant relationship between bank RMI and efficiency, with a strong negative and significant relationship between earnings and efficiency. The authors conclude that using a composite RMI is valuable as it facilitates the ranking and comparison of bank risk management quality.

Originality – This paper is among the first to develop a RMI for the estimation of risk-adjusted efficiency. Risk proxies, including Loan Loss Reserves and Non-Performing Loans, are integrated within a specific CAMEL framework to construct the RMI. Utilizing the RMI as a performance measure, rather than relying solely on profitability ratios, is deemed more appropriate as it aids in identifying critical areas for effective risk management, such as Asset Quality.

Keywords: banks, risk-adjusted efficiency, composite risk management index, DEA BoD.

JEL Classifications: C14, D24, G21

Paper type: Research paper

1. Introduction

Banks play a pivotal role in contemporary economies by facilitating the transformation of savings into credit, efficiently allocating resources, and mitigating costs and risks associated with economic activities. Through their capital allocation and risk-pooling functions, banks contribute significantly to economic development and the improvement of living standards (Herring and Santomero, 1995). Empirical research indicates a positive correlation between enhanced bank efficiency, stability, and increased shareholder value (Matousek *et al.*, 2015; Schaeck and Cihák, 2014; Shamshur and Weill, 2019). Efficiency, characterized by the minimization of inputs and maximization of outputs (profits), can sometimes result in a misalignment between manager and shareholder objectives, leading to agency problems (Demsetz, 1988; Hughes and Mester, 2008; Scholtens and van Wensveen, 2000; Seward, 1990). Furthermore, while effective risk management may temporarily reduce profits, it stabilizes cash flows and promotes long-term resilience (Assaf *et al.*, 2019), as outlined by Sun and Chang (2011), Simper *et al.* (2017), and Gulati (2022).

However, recent banking crises, including the failures of Silicon Valley Bank and Credit Suisse, highlight the potential instability when risk management practices are inadequate, even in globally connected banks (Böni *et al.*, 2024; Vo and Le, 2023). Herring and Santomero (1995) postulate the self-reinforcing nature of bank runs, while recent banking crises are studied by Akhtaruzzaman *et al.* (2023), Bhattacharya and Reddy (2022), and Fiordelisi *et al.* (2021). The Great Financial Crisis exposed systemic vulnerabilities associated with poor risk management and the high-risk behaviors encouraged within banks that are considered “Too Big to Fail” banks, which corroborated risk management decomposition by Berger and DeYoung (1997) into external (“bad luck”) and internal (“bad management”) factors. Recent crises emphasize how factors such as bank size, liquidity, and operational efficiency can influence resilience (Martins, 2024), and stress the importance of effective regulatory oversight since large banks do not become only Too Big To Fail, but also "Too Interconnected to Fail" and "Too Big to Regulate and Supervise". Consequently, Rossi (2023) advocated structural reforms to constrain bank crediting activities, since managers driven by shareholder expectations and personal incentives, might be enticed to engage in risky behaviors that increase the bank’s vulnerability to crises (Finucane *et al.*, 2000; Mishra, 2014; Slovic *et al.*, 2004).

This study develops a new composite Risk Management Index (RMI) using the Data Envelopment Analysis “Benefit of the Doubt” (DEA BoD) model to address the gap in the literature concerning the impact of risk management on bank efficiency. The DEA BoD model is superior due to its data-driven weight allocation, providing a more objective alternative to traditional weighting methods, such as expert opinions and equal weighting schemes. To the extent of the authors’ knowledge, this is the first study of its kind. The existing research primarily develops composite indices focusing on various aspects of banking, including stability (Gulati et al., 2023; Gulati, 2023), governance (Gulati et al., 2020), financial risk (Çolak, 2021), portfolio optimization (Li and Gao, 2025), and country-wide geopolitical risk (Caldara and Iacoviell, 2022). However, it lacks direct measures of how risk management impacts the efficiency of individual banks. Previous models have often relied on equal weighting or stochastic dominance (Agliardi *et al.,* 2012), though this introduces subjectivity into composite index construction.

The present study empirically tests the proposed RMI on a longitudinal international sample of 589 banks from 2015 to 2021, applying the DEA BoD model to reduce subjectivity in weighting. Unlike previous studies (Gaganis et al., 2021) that developed country-wide risk indices, our approach proposes a refined, bank-level risk management measure. Furthermore, to specifically focus on individual banks we have incorporated Loan Loss Reserves (LLR) ratios alongside Non-Performing Loans (NPL) as key indicators of credit risk. Despite bank efficiency and stability being well researched, the relationship between risk management and efficiency is still insufficiently understood. Considering this issue, this study examines how internal risk management practices impact banking efficiency. By developing a composite RMI based on the CAMEL framework (encompassing the factors of Capital Adequacy, Asset Quality, Management Efficiency, Earnings, and Liquidity), this study seeks to quantify the influence of risk management on operational efficiency, thereby offering valuable insights for managers and regulators. Two hypotheses we posited for consideration:

H1: There is a significant relationship between bank-specific risks (CAMEL) and composite risk management index.

H2: There is a significant relationship between the risk management index and bank efficiency.

The first hypothesis aims to construct an RMI using the CAMEL framework to evaluate the adequacy of a bank's risk management. The CAMEL framework has been extensively used in research on profitability (Muhmad and Hashim, 2015; Pekkaya and Demir, 2018; Qureshi and Siddiqui, 2023; Trung, 2021), stability (Shukla, 2015), and risk (Bhatti *et al.*, 2022; Danlami *et al.*, 2022; Handorf, 2016; Risal and Panta, 2019). The second hypothesis examines the relationship between RMI and bank efficiency, supporting prior studies on risk management and efficiency (Boussemart *et al.*, 2019; Lartey *et al.*, 2021; Luu *et al.*, 2023; Mamatzakis, 2015; Mamatzakis and Bermpei, 2014; Marton and Runesson, 2017; Safiullah and Shamsuddin, 2019; Simper *et al.*, 2019; Zamore *et al.*, 2023). Although risk management activities entail significant costs, it ultimately contributes to reduced income volatility and fewer loan losses (Assaf *et al.*, 2019; Badunenko *et al.*, 2022).

Analyzing these hypotheses will shed light on the relationship between risk management and operational efficiency, enabling supervisors to identify high-risk banks and intervene more effectively. Understanding how risk management components impact efficiency can also enable managers to address internal vulnerabilities. Studies by Tron *et al.* (2022) and Berger *et al.* (2016) stress the importance of risk management, particularly during crises. Recent research further indicates that banks with higher efficiency are often more resilient in times of crisis (Gulati, 2023; Schaeck and Cihák, 2014; Shaddady and Moore, 2019). The relationship between risk management and bank operational efficiency is critical, as the recent collapse of Silicon Valley Bank and the Credit Suisse takeover might have been avoided with the implementation of adequate risk management practices.

The paper is organized as follows: Section 2 presents a brief theoretical framework, and Section 3 reviews the relevant literature. Section 4 outlines the methodology employed in this study and Section 5 discusses the dataset used. Section 6 presents the empirical results and offers a brief discussion, and Section 7 concludes the paper.

2. Theoretical framework

Efficiency in the banking sector pertains to the optimal utilization of inputs to enhance outputs while concurrently minimizing resource consumption, with a focus cost minimisation or profit maximization. To evaluate risk-adjusted efficiency, this study draws on a theoretical framework that incorporates the theories of financial intermediation, theory of the firm, agency theory, and microeconomic production theory, all of which contribute to the construction of the RMI used here.

Microeconomic production theory emphasizes the necessity of minimizing inputs while maximizing outputs a principle that underlies the efficiency-focused aspects of RMI. This is particularly reflected in both the Management Efficiency (ME) dimension, which captures both operational and cost efficiency, and the Earnings (E) dimension, which pertains to profit maximization. The theory of the firm, as articulated by Coase (1937), emphasizes the importance of maximizing shareholder value. This perspective aligns with the RMI's inclusion of profitability measures in the E dimension, which assesses how effectively a bank manages risks while generating value. Agency theory addresses the alignment of managerial and shareholders objectives to prevent conflicts that could impact risk management effectiveness (Jensen and Meckling, 1976; Stulz, 1984). This concept supports the RMI's focus on managerial efficiency as a critical component of effective risk management, recognizing that good governance aligns operational decisions with shareholders' best interests.

In this context, agency theory emphasizes two key trade-offs: the first between profits and cost efficiency, as reflected in the ME dimension, and the second between capitalization and profit maximization, represented in the Capital Adequacy (CA) dimension. To mitigate potential losses, management must maintain sufficient capital, which consequently limits the funds available for income-generating activities such as lending, asset acquisitions, and other investments. Agency problems occur when lenient credit scoring requirements and insufficient monitoring—reflected in the AQ dimension—result in increased lending and reduced overhead costs in the short term. Over time, this can lead to a higher incidence of NPLs, weakening LLRs and capital, ultimately diminishing shareholder value and jeopardizing bank stability. As financial institutions, particularly banks, expand and become extremely large, their role in maintaining financial and economic stability increases. However, they may also become "Too Big to Fail", complicating management, regulation, and oversight. This fosters a moral hazard, as bank managers may prioritize profit maximization over prudent risk management, relying on the expectation of government intervention to avert any failure. Such incentives can encourage riskier financial behavior. A similar challenge arises in liquidity management, as banks must maintain sufficient liquidity to prevent bank runs—an issue reflected in the Liquidity (L) dimension of the proposed RMI.

The theory of financial intermediation (Santomero, 1984; Scholtens and van Wensveen, 2000; Seward, 1990) highlights the role of banks in reducing transaction costs and facilitating capital allocation, thereby promoting economic efficiency. While traditional financial intermediation theory did not emphasize risk management, contributions from Scholtens and van Wensveen (2000), Allen and Santomero (1997), and Oldfield and Santomero (1970) argue that risk management adds substantial value to intermediation. This theoretical foundation underpins the liquidity and asset quality components of the RMI, which reflect a bank's ability to effectively manage liquidity (in the L dimension) and credit risk (in the AQ dimension). Furthermore, Demsetz (1988, p. 144), along with earlier contributions from Knight (1921) and Markowitz (1952), characterizes firms as institutions designed to efficiently share risk. Erel *et al.* (2015) introduced the theory of risk capital, advocating for its internal development as a strategic approach to risk management. This approach, focused on the deliberate allocation of risk capital, aligns with the CA component of the RMI, measuring the bank's ability to absorb potential losses from its activities. Similarly, governance and crisis management, emphasized by Stulz (2023), contribute to the resilience of financial institutions, underscoring the long-term benefits of investments in risk management for stability. This theoretical foundation supports the CA, AQ, and L dimensions of the RMI. Together, these dimensions reflect a bank's ability to allocate sufficient capital to maintain stability, manage credit risk through effective credit scoring and monitoring, and generate adequate reserves through LLRs to mitigate NPLs. Furthermore, it ensures efficient capital allocation while addressing liquidity requirements, thereby safeguarding deposits and reinforcing overall bank stability.

Finally, studies by Santomero (1997), Kim and Santomero (1988), and Oldfield and Santomero (1970) highlight the critical role of risk management in enhancing banking efficiency and stability. These contributions support the construction of the RMI, which aggregates the CAMEL components into a composite index for evaluating a bank's overall risk management. The integration of these theories into the RMI allows for a comprehensive measure of risk-adjusted efficiency, providing valuable insights into how risk management impacts operational efficiency across financial institutions.

3. Literature review

The efficiency of banking institutions has been extensively studied, with seminal work and key principles established by Hughes and Mester (2008), Mester (1996) and Berger and Humphrey (1997). Recent reviews by Ardia *et al.* (2023), Ahmad *et al.* (2020), de Abreu *et al.* (2019), Bhatia *et al.* (2018), and Aiello and Bonanno (2017) provide valuable insights into advancements in efficiency research. Studies on measurement approaches highlight both parametric and non-parametric methodologies, as discussed by Murillo-Zamorano (2004). Aiello and Bonanno (2017) point out that differences in methodological approaches, estimation techniques, and the selection of variables impact efficiency outcomes. Consequently, Henriques *et al.* (2020) advocate for standardized variables and methodologies to improve comparability across studies.

Data Envelopment Analysis (DEA) is a popular non-parametric method in multiple disciplines (with over 1,000 publications annually; Emrouznejad and Yang, 2018), is widely used to assess efficiency, focusing on factors like bank size, mergers, and acquisitions (Almaqtari *et al.,* 2019; Andrievskaya and Semenova, 2016; Kumar *et al.,* 2022; McKee and Kagan, 2018; Nippani and Ling, 2021; Proaño-Rivera *et al.,* 2023; Tan and Tsionas, 2022). Other studies have examined the impact of regulation and ownership structure (Abedifar *et al*., 2013; Ayadi *et al*., 2016; Barra *et al*., 2022; Barth *et al*., 2013; Bischof *et al*., 2022; Kyiu and Tawiah, 2023; Mohsin *et al*., 2021; O'Hanlon, 2013). Georgis *et al.* (2021) argue that the DEA methodology remains popular due to its computational simplicity and capacity to benchmark multiple inputs and outputs. Recent studies have concentrated on enhancing the performance of DEA models by refining algorithms to better manage large datasets (Dellnitz, 2022), and integrating machine learning techniques for risk management (Jomthanachai *et al.,* 2021). Li *et al.* (2021) analyze China's basic pension insurance using a three-stage DEA model. The determinants of bank efficiency were examined by Ullah *et al.* (2023), who also consider enterprise risk management as an important internal factor influencing bank efficiency.

Research examining the impact of risk management on efficiency has built on the Berger and DeYoung (1997) classification of risk as stemming from external factors ("bad luck") and internal factors ("bad management"), alluding to the positive effect of adequate risk management on long-term efficiency and stability. Studies on loan quality and capital allocation reveal that banks allocate more capital for operational risk than for market risk (Chang, 1999; Fontnouvelle *et al*., 2006). International studies by Sun and Chang (2011) and Fredriksson and Moro (2014) demonstrate that risk measures significantly affect efficiency across different countries and periods. Key risk indicators, such as NPLs, LLRs, and loan loss provisions (LLRs), are widely used to assess risk management. Studies by Mamatzakis (2015), Ghosh (2015), and Zha *et al.* (2016) confirm the adverse impact of NPLs and LLPs on operational efficiency. Tarchouna *et al.* (2019) emphasize the importance of considering NPLs when assessing bank efficiency. They advocate for stricter credit scoring practices and prudent lending to minimize NPL levels, thereby validating their inclusion in the AQ dimension of the RMI.

Berger *et al.* (2009) further note that inefficiency is more pronounced in larger banks, especially during periods of profitability. Milne and Onorato (2012) emphasized the importance of addressing the risk exposure of each asset to allocate capital efficiently. Finally, Badunenko *et al.* (2022) argue that declines in short-term cost efficiency precede deterioration in asset quality, which aligns with Berger and DeYoung (1997) hypotheses on "skimping" and poor risk management. Pessarossi and Weill (2015) observed that implementing stricter capital requirements enhances cost efficiency. Furthermore, Safiullah and Shamsuddin (2019) conducted a comparative analysis of Islamic and conventional banks, revealing that while Islamic banks exhibit greater cost efficiency, they tend to be less profit efficient. Boussemart *et al.* (2019) observe that improving credit risk efficiency may inadvertently reduce overall economic efficiency. Finally, Zamore *et al.* (2023) identified a non-linear relationship between NPLs and inefficiency in microfinance institutions, where initial increases in NPLs enhance efficiency but further increases result in inefficiency. Sensarma and Jayadev (2009) report that bank risk management capabilities positively influence stock returns, thereby enhancing shareholder value. Similarly, Ng *et al.* (2012) find that the presence of a risk management committee reduces risk-taking among insurers.

This study specifically focuses on risk-adjusted efficiency, with a central aim of developing a RMI based on the CAMEL framework that defines indicators of bank risk and efficiency as supported by previous research (de Abreu and de Camargos, 2022; Bhatti *et al.*, 2022; Muhmad and Hashim, 2015; Pekkaya and Demir, 2018; Qureshi and Siddiqui, 2023; Risal and Panta, 2019; Shaddady and Moore, 2019; Trung, 2021). The CAMEL framework is widely regarded as an effective tool for monitoring the health and risk levels of financial institutions (for a more in-depth analysis, see Ngatia *et al.,* 2024). Roman and Şargu (2013) argue that the CAMEL framework, and the CAMELS framework which includes an "S" for sensitivity to market risk, are frequently employed to assess bank the performance and soundness. Al-Najjar and Assous (2021) utilize the CAMEL rating framework to evaluate Saudi banks, while Chockalingam *et al.* (2018) investigate capital adequacy in relation to strategic risk, focusing on Basel requirements. These studies identify key financial indicators for the CA dimension of the RMI, including various capital ratios, such as the Tier 1 ratio. Studies by Simper *et al*. (2017) and Gulati *et al.* (2023) highlight the importance of incorporating a combination of equity, LLPs, and NLPs to accurately evaluate risk-adjusted efficiency. Ozili (2019) finds that banking sectors with higher regulatory capital and liquidity requirements tend to report lower levels of NPLs. Meanwhile, Gulati (2022) examines the impact of banking crises on risk-adjusted efficiency, using NPLs and equity capital as risk proxies. Marton and Runesson (2017) demonstrate that higher accounting standards improve the predictive capacity of LLPs for future losses, supporting the use of LLPs and similar metrics in an RMI. Bratten *et al.* (2020) observed that the discretionary application of LLPs is affected by the proportions of fair-value assets. Baule and Tallau (2021) established a theoretical connection between expected losses and asset volatility, recommending Basel risk weights for banks with low to medium risk levels while cautioning that these weights may become inadequate for high-risk banks or during periods of crisis. Recent work by Bhat *et al.* (2021) and Luu *et al.* (2023) shows that banks often use LLPs to stabilize earnings, which can enhance risk management and increase stability. Recent studies on LLPs have primarily focused on capital allocation within a given year based on management projections of future NPLs. However, the present study introduces a novel approach by incorporating LLRs as cumulative reserves for NPLs. These studies collectively provide a foundation for constructing the RMI, integrating CAMEL-based risk indicators into the AQ dimension by identifying its key financial indicators.

The identification of key financial indicators for the remaining CAMEL framework dimensions—ME), E, and L—is relatively straightforward. Management Efficiency can be assessed using non-interest expenses, the cost-to-income ratio as a measure of cost efficiency, and net loans relative to total assets. Earnings are best captured through common profitability indicators such as Return on Assets (ROA), Return on Equity (ROE), and Net Interest Margin (NIM). Finally, the Liquidity relies on widely used liquidity ratios in financial performance estimation, with a particular emphasis on bank deposits.

Despite the comprehensive examination of bank efficiency and risk management in prior studies, there is a gap in the synthesis of risk management practices and their impact on operational efficiency. Previous studies predominantly focus either on efficiency metrics or risk indicators in insolation, rather than combining them into a single composite measure such as the RMI. Tan *et al.* (2017) use the Lerner index as a proxy for assessing market power and competition in their efficiency estimation of Chinese banks. In contrast, Shi and Yu (2021) employ a DEA-PCA method for risk management analysis and propose a risk evaluation index, though their approach is limited in both scope and variable selection.

Composite indices are widely used in economic and financial research to evaluate multidimensional phenomena. The Human Development Index exemplifies how composite indices simplify complex assessments while maintaining a multidimensional perspective by combining health, education, and income indicators (UNDP, 1990; 2023). The OECD has also provided guidelines for constructing composite indices, as demonstrated by the Technology Achievement Index. In the aviation industry, the Composite Risk Index methodology was proposed by the Performance Review Commission (PRC, 2019) as a valuable tool for stakeholders to ensure that all aspects of safety management systems prioritize the safety of all parties involved. Caldara and Iacoviell (2022) propose a Geopolitical Risk Index, while Li and Gao (2025) develop a risk index for portfolio optimization. Similarly, Çolak (2021) introduces a novel multivariate approach for assessing corporate financial risk using Multiple Discriminant Analysis (MDA).

Similarly, in the financial sector, composite indices have been developed to measure bank stability, governance (Gulati *et al.,* 2020), and financial risk (Gaganis *et al*., 2021; Gulati *et al*., 2023). Consistent with previous research, the RMI proposed in this study integrates key risk management indicators into a single measure, facilitating a more comprehensive evaluation of bank risk-adjusted efficiency and the influence of risk management on that efficiency. This study aims to fill a gap in the literature concerning how risk management affects bank efficiency by developing a new composite RMI using the DEA BoD model. To the authors' knowledge, this is the first study of its kind.

By employing the CAMEL framework, this study clearly defines key financial indicators related to capital adequacy, asset quality, management efficiency, earnings, and liquidity. Our study is among the first to incorporate LLR ratios alongside NPL ratios as key indicators of AQ, distinguishing it from previous studies based on LLPs. Furthermore, we empirically test the proposed RMI on a longitudinal international sample of 589 banks from 2015 to 2021, applying the DEA BoD model to minimize subjectivity in weighting, as it is a fully data-driven process. This approach contrasts with studies that rely on average CAMEL values for performance evaluation (Roman and Şargu, 2013). Unlike previous studies (Gaganis *et al.,* 2021) that developed country-wide risk indices, our approach introduces a more nuanced, bank-level risk management measure.

Consequently, this study uniquely addresses the gap in the literature concerning the effect of risk management on efficiency by proposing a new composite RMI that integrates the CAMEL components, thereby offering a comprehensive assessment of risk-adjusted efficiency.

4. Methodology

This study outlines the development of RMI employing the DEA BoD model, in accordance with the guidelines from the OECD *et al*. (2008) handbook on composite indicators. The BoD model, as non-parametric DEA method, is extremely sensitive to data accuracy, as DEA does not incorporate an error term like parametric methods. Thus, data errors are attributed to inefficiency, potentially skewing results if inaccuracies are present. To minimize this risk, data selection and transformation are conducted carefully to ensure alignment with the dataset's origin and structure. The RMI construction employs a constrained DEA BoD model following recommendations from Maricic and Jeremic (2023), who argue that a restricted model can improve robustness by limiting excessive weighting flexibility. This approach optimizes the data-driven allocation of weights across the RMI's components, based on the CAMEL framework (Afzal *et al.,* 2020; Alzayed *et al.*, 2023; Hwa *et al*., 2018; Kumar *et al.,* 2022). Constraining the DEA BoD model helps manage subjectivity and weight allocation. As underscored by Gulati (2023), among other benefits, such as seamless application to small samples and ease of use, data-driven weight distribution is a primary advantage.

Composite indices condense complex information into single measures, increasing their utility in efficiency studies. However, Cherchye *et al.* (2004) caution that composite indices can provide an overly simple and deceptive picture, inciting users to draw simplistic policy conclusions. This study acknowledges that while developing composite indices it is crucial to carefully approach its development, to minimize the risk of misleading information. Several studies focused on the development of composite indices. For example, Agliardi *et al.* (2012) developed a country risk index specifically tailored for emerging markets, while Hu *et al.* (2012) examined the systemic risk within the banking sector. Abou-El-Sood (2016) investigated the role of capital adequacy ratios in predicting bank failure and suggested that well-capitalized banks are better positioned to invest in riskier assets. Radojicic *et al.* (2018) categorize the variables frequently used in bank efficiency studies. Schaeck and Cihák (2014) examine the interplay between competition, efficiency, and stability, concluding that competition enhances efficiency and enables robust banks to withstand market shocks. Gaganis *et al.* (2021) propose a framework for evaluating banks' social, environmental, and financial performance, while Abendschein and Grundke (2022) evaluate measures of systemic risk.

The BoD model is also susceptible to extreme values and data outliners, and since the DEA lacks an error term, outliners can disproportionately impact results. Therefore, following the steps in OECD's Handbook, winsorization is also applied to the data in this study to enhance its robustness. While the constrained BoD model applied in this study limits excessive weight allocation, the risk of bias is reduced but not eliminated. Moreover, the bias in the selection of variables is reduced by implementing the CAMEL framework, as a widely accepted basis for defining RMI sub-indicators and its components.

As previously stated, we use the CAMEL framework because it effectively monitors the health and risk levels of financial institutions. In this study, it clearly defines the key financial indicators essential for the RMI. Capital Adequacy assesses a bank's resilience to unexpected financial shocks and reflects its capitalization. As a component of the proposed composite RMI, it is defined through capital ratios. Asset Quality addresses one of the most critical aspects of a bank's risk management—credit risk. This dimension plays a central role in the proposed composite RMI and uniquely incorporates LLRs alongside NPLs to evaluate a bank's ability to effectively manage credit risk. Management Efficiency focuses on a bank's ability to control non-interest costs efficiently, represented by the cost-to-income ratio and non-interest expenses. The Earnings dimension is characterized by common profitability indicators, such as ROA, ROE, and NIM, which reflect a bank's ability to maximize profits and ensure long-term financial sustainability. Finally, Liquidity is represented by liquidity ratios, which are essential for maintaining public trust and safeguarding against sudden liquidity crises.

The CAMEL-driven dimensions of the proposed RMI comprehensively represent risk-adjusted efficiency and align with established financial assessment frameworks (AL-Najjar and Assous, 2021; de Abreu and de Camargos, 2022; Bhatti *et al.* 2022; Ngatia *et al.*, 2024). One of the primary challenges in constructing composite indices is determining the appropriate weight distribution of each sub-indicator and dimension. Traditionally, weight allocation is conducted through feedback from industry professionals, gathered via questionnaires or interviews, which are then averaged and distributed, rendering the process highly subjective. Several methodological approaches exist for defining weight distribution, including equal weighting (EW), Factor Analysis (FA), Principal Component Analysis (PCA), MDA, and others. In this study, the constrained DEA BoD model is employed due to its advantages over alternative approaches.

Equal weighting, as used in the Human Development Index, assumes all dimensions contribute equally, which may oversimplify and introduce subjectivity. Given that risk management practices differ among banks, applying a uniform weighting scheme would be inappropriate and highly subjective. Consequently, this study employs the constrained DEA BoD model, a data-driven approach that minimizes subjectivity by optimally adjusting weights for each bank.

Statistical methods such as Factor Analysis (FA) and Principal Component Analysis (PCA) derive weights based on statistical variance, with the goal of maximizing components according to statistical distinction rather than economic meaning. While Stochastic Frontier Analysis (SFA) is commonly employed in efficiency estimation studies, its application in constructing composite indices is limited as production function and variable weights need to be predefined, thereby introducing a degree of subjectivity (Shi and Yu, 2021, p. 2). Furthermore, SFA is restricted in its ability to measure the performance of a single output (Li *et al.*, 2021, p. 3336). In contrast, the constrained DEA BoD model derives weights from performance efficiency, making it more suitable for benchmarking.

The MDA is employed in the construction of the widely recognized Altman's Z-score and assumes linear separability—a condition that may not be applicable in complex financial environments. In contrast, DEA BoD is a non-parametric model that does not require restrictive distributional assumptions. Furthermore, while MDA produces binary classifications rather than continuous efficiency scores, the DEA BoD model offers a continuous efficiency scale, enabling a more granular analysis of risk-adjusted efficiency.

By integrating the constrained DEA BoD model, this study reduces the subjectivity associated with traditional composite index construction methods—such as reliance on expert opinions and equal weighting—while also addressing the statistical limitations of FA and PCA, and the classification constraints of MDA. This approach ensures a more robust and interpretable measure of risk-adjusted efficiency.

The DEA BoD model was first introduced by Melyn and Moesen (1991) and later expanded by Cherchye *et al.* (2004) and Cherchye *et al.* (2007). The methodological framework of this study was based on insights from Gulati (2023) and Maricic and Jeremic (2023). This methodology is consistent with the approaches adopted by various institutions to guide policy discussions (Paruolo *et al.*, 2013). Despite its limitations, the constrained DEA BoD model is chosen due to its data-driven nature, allowing the RMI to reduce subjectivity in weight allocation. The RMI developed in this study therefore serves as the basis for analyzing the relationship between risk management and bank efficiency.

A visual representation of the dimensions and sub-indicators of the RMI is presented in Figure 1. The symbols +/- indicate the polarity of the sub-indicators, signifying whether a higher (+) or a lower (-) value is recommended. The RMI is developed based on five sub-indicators that adhere to the CAMEL framework:

Capital adequacy is defined by three variables: tier 1 capital, the total capital ratio, and the equity to total assets ratio. These ratios evaluate bank compliance with regulatory capital requirements. Higher ratios signify more robust capital reserves that serve as safety cushions that help banks absorb losses and maintain stability. Consequently, higher levels of CA are advantageous to risk management and financial stability. Nevertheless, augmented capital requirements may also constrain the capital available for income-generating activities, potentially limiting profitability.

[Figure 1 about here]

Asset quality is measured using three variables: LLR/gross loans, LLR/NPL, and NPL/gross loans. These ratios serve to assess the effectiveness with which a bank manages credit risk and performs due diligence during the credit scoring process:

- LLR/gross loans reflect the management's most informed estimate of potential future NPLs. A high ratio indicates that management anticipates higher default rates. Conversely, a low ratio indicates strong confidence in risk management practices and effective credit scoring processes.
- LLR/NPL measures the coverage of LLRs relative NPLs, indicating how well management predicted potential losses. A low ratio suggests that additional losses may necessitate coverage through capital, thus potentially compromising bank stability.
- NPL/gross loans ratio shows the proportion of loans in default. A low NPL ratio indicates effective risk management practices, whereas an increasing ratio may erode a bank's capital, thereby increasing the risk of default.

Management efficiency in this study is assessed through three variables: cost to income ratio, net loans/total assets, and non-interest expenses/average assets. Management is deemed more efficient when it can:

- maintain a lower cost to income ratio, reflecting greater efficiency in managing operational costs relative to income;
- generate a higher proportion of net loans relative to total assets;
- reduce non-interest expenses, particularly administrative costs, relative to average assets.

Earnings are a key measure of a bank's profitability and are represented by three variables: Return on Average Assets (ROAA), Return on Average Equity (ROAE), and NIM. Higher values of these ratios indicate greater profitability, reflecting the bank's ability to generate returns on its assets, equity, and interest-related activities.

Liquidity is a crucial dimension in banking, defined by four variables: net loans/deposits and short-term funding, net loans/total deposits and borrowed funds, liquid assets/deposits and short-term funding, and liquid assets/total deposits and borrowed funds:

- The net loans/deposits and short-term funding ratio should be maintained below 1 (100%) to signify that the bank preserves liquidity and has not completely allocated all deposits and short-term funding.
- The net loans/total deposits and borrowed funds indicate the extent to which loans are financed by deposits and borrowed funds. A value approaching 1 (100%) may signify potential liquidity issues, as it implies that the bank has allocated nearly all its available funds to loans.
- The liquid assets/deposits and short-term funding ratio assesses the bank's capacity to swiftly convert its assets into cash to meet deposit withdrawal demands. Ensuring an appropriate balance is crucial to mitigate the risk of liquidity shortages and avoid potential bank runs.
- The liquid assets/total deposits and borrowed funds ratio consider leverage by incorporating borrowed funds. An increase in liquid assets can mitigate liquidity risk; however, it may also constrain profitability because liquid assets generally yield lower returns.

Despite the widespread application of the CAMEL framework in evaluating bank performance due to its comprehensive coverage of key financial indicators, it has several limitations that hinder its ability to fully capture risk-adjusted efficiency. Its ability to predict future risk is constrained, as it relies on historical financial data and thus reflects past performance rather than potential future risks. The framework could be improved by incorporating alternative risk measures, such as stress test results or the Value at Risk model, to provide more forward-looking insights. Additionally, the CAMEL framework does not account for market fluctuations, which is addressed within the CAMELS framework that includes an 'S' for Sensitivity to market risk.

Similarly, the CAMEL framework excludes macroprudential risk measures (e.g., systemic risk, political risk, country risk premium), as well as environmental, social, and governance indicators, and broader economic factors such as gross domestic product, purchasing power parity, inflation, nominal interest rates, employment, and policy frameworks. Due to the lack of a clear definition and the absence of consensus on key financial indicators, along with data limitations in this study, market sensitivity and macroprudential indicators were not incorporated. These factors represent an area for improvement in future research. The CAMEL framework utilized in this study focuses on individual bank performance. Future research could investigate the integration of additional macroprudential indicators, as well as qualitative data, such as information from risk management boards, to further enhance the proposed RMI.

While the DEA BoD model offers several advantages, certain considerations must be taken into account. One observation is that, in the absence of constraints, the DEA BoD may occasionally assign disproportionately high weights to a single dominant dimension, potentially skewing the resulting efficiency scores. To address this issue, this study employs a constrained DEA BoD model that incorporates weight restrictions, ensuring that all dimensions contribute meaningfully. This approach prevents distortions, where a bank may appear efficient by excelling in just one category while neglecting others, as noted by Maricic and Jeremic (2023). As a non-parametric model, DEA constructs an efficiency frontier; however, it is susceptible to extreme values. To mitigate this vulnerability, winsorization and normalization procedures are applied to the sample data, as recommended by OECD et al. (2008), Gulati et al. (2023), and

Gulati (2023). While DEA methodology is effective with small samples, it can lead to inflated efficiency scores when generating the efficiency frontier from an extremely limited dataset. However, the study's extensive longitudinal international sample of 589 banks over a seven-year period mitigates this risk. Furthermore, some key financial indicators used in constructing the proposed RMI may take on negative values, which the DEA cannot process. To address this issue, data transformations are applied to ensure consistency and maintain the integrity of results, while also considering the polarity of the financial indicators (Figure I).

By employing the constrained DEA BoD model, this study reduces the subjectivity associated with traditional composite indices—such as professional opinions and equal weighting—while enhancing economic interpretability compared to purely statistical methods (e.g., FA, PCA, MDA). This approach ensures that the RMI offers a balanced, empirically robust, and practically meaningful measure of risk-adjusted efficiency in the banking sector.

5. Data

This study analyzes a longitudinal sample obtained from the Orbis database, encompassing 589 banks across 34 countries, each possessing assets exceeding USD 1 billion. This size threshold is commonly employed in banking efficiency research (eg. Tarchouna *et al.,* 2019) to ensure comparability, data reliability, and consistency with prior studies. The data spans from 2015 to 2021 and includes only banks with complete data across all seven years.

The initial larger sample was narrowed down by excluding all banks missing data for any year, creating a balanced panel and reduced the risk of data imputation biases. While this approach ensures data completeness, it introduces selection bias by excluding banks that lack full records, potentially affecting generalizability if these banks differ systematically from those retained. For example, smaller or less stable banks, which are more likely to have missing data, may also exhibit different risk management and efficiency profiles. Therefore, the sample may be biased forward to more established banks with better data availability. The financial variables used for the RMI (outlined in Figure 1 and Table I) are derived from bank financial statements, which are typically credible data sources. However, despite the robustness of financial statement data, we acknowledge the possibility of discrepancies due to different accounting practices across countries. Such variations may influence the comparability of financial data, even with standardization techniques applied in this study. The sample can be categorized into five geographical regions: Asia (71 banks; 12%), Australia and Oceania (6 banks; 1%), Europe (144 banks; 24%), North America (363; 62%), and South America (5 banks; 1%). A detailed country-wise distribution is provided in Appendix Table A, along with a geographical spread visualization in Appendix Figure A.

Table I presents variable summary statistics.

[Table I about here]

To mitigate the impact of outliers and to develop the RMI, we followed the two-step method described by Gulati (2023). First, we applied winsorization at the 90th percentile to reduce the influence of extreme values in the five sub-indicators. Then, we employed min-max normalization to scale values between 0 and 1, based on variable polarity (Gulati, 2023, p. 5), using min-max for positive polarity variables and max-min for negative ones. This was followed by Z-normalization (mean = 100, standard deviation = 10) to ensure all 16 financial variables yield values above zero, thus preventing variables from being excluded during RMI construction. The Compind package in R (Vidoli and Fusco, 2018) was used to calculate, weight, and aggregate BoD values for each sub-indicator into the RMI. We implemented the constrained BoD model in accordance with the methodologies established by Gulati (2023), Gulati *et al.* (2020), and Vidoli and Fusco (2018). We set bounds of 10% to 80% for all sub-indicators to prevent the dominance of any single financial indicator. The upper bound for the liquidity sub-indicator was adjusted to 70%, while the aggregation of sub-indicators into the RMI used a cap of 60% to balance the influence of each component and enhance the sensitivity of the composite index.

The influence of economic cycles and bank size is recognized as a limiting factor in the methodology. Their potential moderating role will be further examined in the results section. A sensitivity analysis, using Variance Inflation Factor VIF tests, is presented in Appendix Table B, confirming the stability of the model specifications. Furthermore, to evaluate the relationship between the RMI and its components, and the relationship between bank efficiency and risk management, panel data fixed effects models with robust standard errors are employed. This approach accounts for both inter-bank differences (heterogeneity) and intra-bank changes over time. Consequently, simple linear correlations between the proposed RMI and bank efficiency could yield misleading results and therefore are not reported in this study.

Due to data constraints, conducting sub-period analyses, such as those for pre-2015 and pre/post-pandemic periods, was not feasible. This limitation is acknowledged, and future studies are encouraged to broaden the temporal scope to evaluate risk-efficiency dynamics across various crisis periods.

6. Results and discussion

The analysis of the proposed RMI and its sub-indicators offers valuable insights into bank risk management across 589 banks from 2015 to 2021. The highest average RMI was recorded in 2016 (0.9508), and the lowest was in 2017 (0.9371), resulting in an overall average of 0.9453. Among the sub-indicators, AQ and ME achieved the highest efficiency, whereas the E, L, and CA dimensions received lower scores. Weight analysis further indicates that AQ and ME are the most influential sub-indicators in constructing the RMI. Notably, the weight of the AQ indicator increased during the COVID-19 pandemic, peaking in 2020. This underscores the importance of effective credit management and a bank's ability to maintain low levels of NPLs during times of crisis.

Subsequent panel data analysis confirms that all CAMEL sub-indicators positively and significantly influence the RMI, with ME and AQ exerting the most substantial impact. Additional econometric analysis indicates that the RMI has a positive, albeit marginally significant, effect on bank efficiency, while E demonstrates a strong negative impact. This suggests that increased profitability may come at the expense of bank efficiency. Overall, the empirical results indicate that effective risk management practices enhance a bank's operational efficiency and stability, although they may come at the cost of profitability.

Implementing BoD models enables unbiased weight generation, though they have limitations, as noted by Maricic and Jeremic (2023). A typical robustness check involves evaluating individual indicators' contributions, though this method is not suitable for BoD models with entity-specific weights. Gulati (2023) conducted robustness checks by examining variations in bank rankings using Z-score, FA, equal weighting, and constrained BoD, ultimately finding a

10% lower bound to be optimal after testing bounds between 5% and 20%. Table II displays the RMI and sub-indicator results for 589 banks over seven years. The AQ sub-indicator (0.9270) shows that banks need to improve by 0.073 to reach the efficiency frontier, while ME is approaching with a score of 0.8889. The dimensions E, L and CA have lower scores, averaging 0.8528, 0.8342, and 0.8410, respectively.

[Table II about here]

Table III's weight analysis indicates AQ (0.3632), and ME (0.2305) have the highest average weights, whereas L (0.1524), CA, and E are lower. These findings suggest that AQ and ME are the primary factors in evaluating the RMI.

During the COVID-19 pandemic in 2020, AQ saw an increase, reaching its highest weight of 0.4382, highlighting the importance of maintaining low NPL ratios. In contrast, ME held the highest weight in 2015, after which its relevance has since declined as AQ has become the dominant factor. The sub-indicators CA and E continue to have the lowest weights.

[Table III about here]

Table IV presents a weight analysis of the CAMEL sub-indicators. For CA, the equity to total assets ratio (0.5706) is the most prominent, with tier 1 capital and total capital ratio having similar importance. Within AQ, the LLR to gross loans ratio (0.4148) and NPL to gross loans ratio (0.4285) are key, underscoring the importance of default forecasts and current default rates. In ME, the net loans to total assets ratio (0.4762) and cost-to-income ratio (0.3196) indicate that banks near the efficiency frontier focus on core banking activities and cost minimization. Of all sub-indicators, E is the closest to equal weighting, with ROAA achieving a slightly lower weight. Liquidity is mainly influenced by the net loans to deposits and short-term funding ratio (0.4445) and liquid assets to total deposits and borrowed funds ratio (0.2266), highlighting the importance of managing short-term funding and liquidity.

[Table IV about here]

In this longitudinal study, an analysis of top-performing banks (RMI = 1, indicating good/adequate risk management) reveals that their average weights differ from those previously noted. For these banks, CA receives the highest weight (0.25), followed by E and L, each at 0.20. AQ (0.17) and ME (0.19) receive the lowest weights. Conversely, the worst-performing banks prioritize ME and L, while neglecting AQ and minimizing the emphasis on CA and E.

To test H1: There is a significant relationship between bank-specific risks (CAMEL) and the composite risk management index, we construct the following econometric model (1)

$$RMI_{it} = \beta_{0i} + \beta_1 CA_{1t} + \beta_2 AQ_{2t} + \beta_3 ME_{3t} + \beta_4 E_{4t} + \beta_5 L_{5t} + u_{it} \quad (1)$$

$$i = 1,2,\ldots,589;\ t = 1,2,\ldots,7$$

Where is denoted:

- β_{0i} – is the intercept of bank *i*,
- RMI_{it} – is the dependent variable, and the Risk Management Index for bank *i* at time *t*

- CA_{1t} – independent variable Capital Adequacy sub-indicator for bank *i* at time *t*
- AQ_{2t} – independent variable Asset Quality sub-indicator for each bank *i* at time *t*
- ME_{3t} – independent variable Management Efficiency sub-indicator bank *i* at time *t*
- E_{4t} – independent variable Earnings sub-indicator for bank *i* at time *t*
- L_{5t} – independent variable Liquidity sub-indicator for bank *i* at time *t*
- u_{it}- is the error term.

The evaluated model is as follows:

$$RMI_{it} = \hat{\beta}_{0i} + \hat{\beta}_1 CA_{1t} + \hat{\beta}_2 AQ_{2t} + \hat{\beta}_3 ME_{3t} + \hat{\beta}_4 E_{4t} + \hat{\beta}_5 L_{5t} + e_{it} \quad (2)$$
i = 1,2,…,589: t = 1,2,…, 7

Based on the results of the Hausman test (p-value = 1.92705e-13), presented in Appendix Table B, we employ fixed effects panel data analysis with robust (HAC) standard errors to address potential concerns related to autocorrelation and heteroscedasticity. The findings are summarized in Table V.

[Table V about here]

The results show that all components of the CAMEL framework have a positive and statistically significant relationship with the RMI ($p < 0.0001$). The highest coefficients are seen for ME and AQ, with a one-unit increase in ME leading to a 0.2296 increase in RMI, and a one-unit increase in AQ resulting in a 0.1796 increase. The model explains over 91% of the variance in RMI (LSDV R-squared = 0.9109), with a R-squared of 0.5819, indicating that 58% of the variation within individual banks is due to the CAMEL components. The Durbin-Watson statistic of 2.035 confirms that autocorrelation was addressed with robust standard errors. Thus, we reject the null hypothesis for H1, confirming the presence of a significant positive relationship between bank-specific risks (measured by CAMEL components) and RMI.

To test H2: There is a significant relationship between the risk management index and the bank's efficiency we construct the following econometric model:

$$ER_{it} = \beta_{0i} + \beta_1 RMI_{1t} + \beta_2 CA_{2t} + \beta_3 AQ_{3t} + \beta_4 ME_{4t} + \beta_5 E_{5t} + \beta_6 L_{6t} + u_{it} \quad (3)$$
i = 1,2,…,589; t = 1,2,…, 7

where the dependent variable, referred to as the Efficiency Ratio (ER), is defined as the ratio of bank overheads to the sum of interest income and net fees. The independent variables consisted of the RMI and the components of the CAMEL framework. The model under evaluation was follows:

$$ER_{it} = \hat{\beta}_{0i} + \hat{\beta}_1 RMI_{1t} + \hat{\beta}_2 CA_{2t} + \hat{\beta}_3 AQ_{3t} + \hat{\beta}_4 ME_{4t} + \hat{\beta}_5 E_{5t} + \hat{\beta}_6 L_{6t} + e_{it} \quad (4)$$
i = 1,2,…,589; t = 1,2,…, 7

Based on the results of the Hausman test (p-value = 3.78194e-16), as presented in Appendix Table B, Table VI shows the results of the fixed effects panel data analysis, including robust (HAC) standard errors for H2.

[Table VI about here]

As mentioned previously, additional sensitivity tests were conducted to rule out the presence of multicollinearity. Variance Inflation Factors were computed and are presented in Appendix Table B, with all components of the RMI receiving values less than 10.

RMI shows a positive but marginally significant effect on the ER, with a coefficient of 0.2676 and a p-value of 0.0563, indicating that a one-unit increase in RMI leads to a 0.2676 increase in the efficiency ratio, though this relationship is relatively weak. RMI shows a positive but marginally significant effect on the ER, with a coefficient of 0.2676 and a p-value of 0.0563, indicating that a one-unit increase in RMI leads to a 0.2676 increase in the ER, though the relationship is relatively weak. Conversely, the negative coefficient for E of -0.3634 ($p < 0.0001$) reveals a strong, statistically significant inverse relationship with efficiency, suggesting that higher earnings are linked to lower efficiency, potentially due to profit maximization at the cost of minimizing expenses. The LSDV R-squared value of 0.9423 shows it explains 94% of the variation in the ER, while the R-squared of 0.0359 indicates that explanatory power mainly arises from differences between banks rather than from time-based changes within individual banks. In conclusion, the findings indicate a positive, yet marginally significant, relationship between RMI and bank efficiency, whereas earnings have a substantial negative impact on efficiency. Thus, we reject the null hypothesis for H2, confirming a marginally positive relationship exists between RMI and efficiency, with earnings playing a larger role in driving inefficiency.

These findings provide actionable insights for bank managers, underscoring that the positive and significant relationship between risk management, as measured by the RMI, supports the value of investing in robust risk management practices to enhance operational efficiency. The empirical results indicate a trade-off between enhanced efficiency and stability, which can be achieved through effective risk management practices, and profitability. This suggests that managers should prioritize risk management and focus on addressing areas of weakness to reap the benefits of increased efficiency and stability. By strengthening credit risk management through rigorous credit scoring processes, client monitoring, and analysis, banks can reduce future NPLs and, consequently, LLRs. Adequate capitalization would enhance stability, providing a safety cushion in times of financial distress. Similarly, maintaining sufficient liquidity reserves would decrease the likelihood of bank runs, thereby fostering trust and stability within the financial institution.

Furthermore, improvements in operational efficiency through digitalization and the adoption of modern technologies, such as machine learning and artificial intelligence, can enhance cost efficiency and operational stability. Although these initiatives may reduce short-term profitability, the long-term benefits of increased efficiency and stability improve the bank's ability to withstand economic downturns, as evidenced during recent crises. These insights could guide both banks and regulators to prioritize efficiency and stability, potentially shifting shareholder objectives toward long-term sustainability. This shift would encourage bank management to place less emphasis on immediate profitability and to minimize overall risk exposure.

For policymakers, the RMI can be a diagnostic tool that helps to identify banks with weaker risk management practices. This allows for early intervention, reducing the likelihood of losses and enhancing stability within the banking sector. Additionally, the study's findings can inform the development of regulatory guidelines that encourage banks to adopt specific risk management practices shown to enhance efficiency, potentially leading to sector-wide improvements in stability and resilience. To the best of our knowledge, this study represents the first attempt to develop a composite RMI using CAMEL-specific financial indicators and employing the DEA BoD model. The empirical results have significant implications for bank management, regulation, education, and future research, providing both economic advantages (such as cost reduction and stability) and commercial benefits (including improved market positioning). Furthermore, this study has the potential to influence public policy by shaping regulations and indirectly benefiting society through enhanced financial stability, improved quality of life, and increased public confidence in banks.

Despite the robustness of the methodology, there are several limitations worth acknowledging in this study. First, while the constrained DEA BoD model minimizes bias in weighting constraints, it could be further improved by incorporating the unsupervised DEA BoD model proposed by Maricic and Jeremic (2023). Although the study utilizes a large, longitudinal international sample, there may still be selection bias, as it focuses exclusively on large banks from 2015 to 2021. This limitation could affect the generalizability of the findings, particularly for smaller banks or those located in underrepresented geographic regions. Future research could expand the dataset to include a wider range of smaller banks and those in underrepresented areas to enhance the generalizability of the RMI.

The study's time frame, spanning seven years and concluding during the COVID-19 pandemic, presents a limitation that may affect the findings. The pandemic likely influenced risk management priorities, potentially altering the relationships between the RMI, CAMEL components, and bank efficiency due to increased risk aversion and regulatory interventions. Evaluating the risk-adjusted efficiency of banks using the proposed RMI under varying economic conditions (e.g., prior to 2015 and after the COVID-19 pandemic) could yield valuable insights. Due to data limitations, these evaluations were not conducted; however, future studies could expand the analysis to include periods to and beyond the current timeframe to determine whether these relationships persist across different economic climates and in post-pandemic financial environments.

Despite its widespread use and reliability, the CAMEL framework has certain limitations, particularly its dependence on specific financial data and its exclusion of broader macroeconomic and qualitative factors. This study also did not examine the impact of moderating variables such as bank size, ownership structure, and economic development. Future research could address these gaps to provide a more comprehensive understanding of how risk management activities affect bank efficiency.

7. Conclusion

This study explores the relationship between bank-specific risks, represented by CAMEL components, and the composite RMI, as well as between RMI and bank efficiency. Analyzing a sample of 589 banks across 34 countries from 2015 to 2021 reveals several key findings. The results confirm a significant positive relationship between bank-specific risks (via CAMEL components) and RMI, with ME and AQ as the largest contributors, highlighting their importance in effective risk management. While RMI has a positive but marginal effect on bank efficiency, a strong inverse relationship between earnings and efficiency aligns with the profitability-efficiency trade-off.

7.1. Trade-off between short-term profit and bank efficiency

The primary empirical findings regarding the relationship between bank-specific risks, as assessed by the CAMEL framework, and the RMI indicate a limited effect, despite the marginally positive relationships between RMI and bank efficiency. This suggests that banks may prioritize short-term profitability at the expense of long-term efficiency. The weak relationship between risk management and efficiency points to a potential trade-off between managing risk and maximizing short-term profits. Nevertheless, banking managers should adopt a long-term perspective, focusing on robust risk management policies that enhance operational efficiency and strengthen institutional stability and resilience, particularly during periods of economic volatility, even if this approach might compromise short-term profitability. Bank management should prioritize the establishment of clear business policies that emphasize investments in risk management, particularly in the AQ and ME dimensions, as these factors exert the greatest influence on the RMI.

These findings suggest that banks should focus on improving ME and AQ to strengthen risk management, while regulators can use RMI as a tool to identify banks at risk of inefficiency. Effective risk management correlates positively with bank-specific risks but has a limited impact on efficiency, underscoring the need for balancing profitability and operational efficiency. Against the backdrop of recent banking crises, regulators can leverage the RMI to identify underperforming banks vulnerable to financial distress. Regulatory policies can then be formulated to incentivize risk management practices associated with long-term financial stability. Regulators should encourage banks to implement early-warning mechanisms based on the RMI and CAMEL sub-indicators to mitigate systemic risks. This study contributes to the existing literature by proposing a new composite RMI that empirically examines the impact of risk management activities on bank operational efficiency. The empirical results from this international longitudinal study indicate that there is a weakly positive relationship between risk management and bank efficiency, and reveals a short-term trade-off between operational efficiency and profitability.

The theoretical and empirical research presented in this study has valuable applications in bank management, regulation, education, and further research, offering both economic (cost reduction, stability) and commercial (market positioning) advantages. This research can influence public policy by shaping regulations and indirectly benefiting society through enhanced financial stability, improved quality of life, and increased public confidence in banks. Despite the growing emphasis on risk management in the banking sector, few studies have systematically examined the direct relationship between the RMI and operational efficiency. By addressing this gap, this study contributes to the ongoing discourse on balancing risk management priorities with operational efficiency, providing valuable insights for both academic research and practical implementation.

However, several limitations must be acknowledged. The analysis focuses on banks with total assets exceeding USD 1 billion, which may not fully represent the global banking sector. The reliance on the constrained DEA BoD model for weight generation may introduce bias due to the definition of the constraints. Additionally, while the widely used CAMEL framework is applied, it is limited in its selection of indicators, excluding other risk measures, macroeconomic factors, and qualitative data. Limitations include the DEA BoD model's sensitivity and the CAMEL framework's general approach to variable selection, along with a regional focus on larger, U.S.-based banks. Future studies could refine the RMI by selecting variables more specific to CAMEL components, focusing on smaller banks or specific regions, and enhancing the DEA model by introducing an error term and unsupervised constraints.

Finally, this study encompasses part of the COVID-19 pandemic, which significantly altered risk management behaviors.

Future research could enhance the RMI framework by integrating additional macroeconomic variables or exploring alternative weighting methods, such as the unconditional constrained DEA BoD model. To further validate the robustness of the findings, future studies could include smaller banks or those located in underrepresented geographic regions, thereby addressing bank heterogeneity driven by accounting practices, economic conditions, cultural, and other factors. Questions regarding moderating variables, such as bank size and ownership structures, should be examined to gain a deeper understanding of how risk management affects efficiency. Future research could also investigate the impact of economic cycles on risk management priorities, particularly in the context of post-pandemic financial conditions. Furthermore, the application of the RMI in diversified economic environments, and the influence of macroeconomic factors beyond the banking sector on the RMI, would yield valuable insights into the effect of risk management on operational efficiency in banks.

References

Abedifar, P., Molyneux, P. and Tarazi, A. (2013), "Risk in Islamic Banking*", *Review of Finance*, Vol. 17 No. 6, pp. 2035–2096, doi: 10.1093/rof/rfs041.

Abendschein, M. and Grundke, P. (2022), "On the ranking consistency of systemic risk measures: empirical evidence*", *The European Journal of Finance*, Routledge, Vol. 28 No. 3, pp. 261–290, doi: 10.1080/1351847X.2021.1946413.

Abou-El-Sood, H. (2016), "Are regulatory capital adequacy ratios good indicators of bank failure? Evidence from US banks", *International Review of Financial Analysis*, North-Holland, Vol. 48, pp. 292–302, doi: 10.1016/J.IRFA.2015.11.011.

de Abreu, D.P.A. and de Camargos, M.A. (2022), "Applying the CAMELS Model to Evaluate the Profitability of the Brazilian Banking Sector", *Revista Evidenciacao Contabil & Financias*, Vol. 10 No. 3, pp. 100–117, doi: 10.22478/ufpb.2318-1001.2022v10n3.61571.

de Abreu, E.S., Kimura, H. and Sobreiro, V.A. (2019), "What is going on with studies on banking efficiency?", *Research in International Business and Finance*, Vol. 47, pp. 195–219, doi: 10.1016/j.ribaf.2018.07.010.

Afzal, A., Mirza, N. and Arshad, F. (2020), "Market discipline in South Asia: Evidence from commercial banking sector", *International Journal of Finance & Economics*, Vol. 26 No. 2, pp. 2251–2262, doi: 10.1002/ijfe.1904.

Agliardi, E., Agliardi, R., Pinar, M., Stengos, T. and Topaloglou, N. (2012), "A new country risk index for emerging markets: A stochastic dominance approach", *Journal of Empirical Finance*, Vol. 19 No. 5, pp. 741–761, doi: 10.1016/j.jempfin.2012.08.003.

Ahmad, N., Naveed, A., Ahmad, S. and Butt, I. (2020), "Banking Sector Performance, Profitability, and Efficiency: A Citation-Based Systematic Literature Review", *Journal of Economic Surveys*, John Wiley & Sons, Ltd, Vol. 34 No. 1, pp. 185–218, doi: 10.1111/JOES.12346.

Aiello, F. and Bonanno, G. (2017), "On the Sources of Heterogeneity in Banking Efficiency Literature", *Journal of Economic Surveys*, John Wiley & Sons, Ltd, Vol. 32 No. 1, pp. 194–225, doi: 10.1111/JOES.12193.

Akhtaruzzaman, M., Boubaker, S. and Goodell, J.W. (2023), "Did the collapse of Silicon Valley Bank catalyze financial contagion?", *Finance Research Letters*, Elsevier, Vol. 56, p. 104082, doi: 10.1016/J.FRL.2023.104082.

AL-Najjar, D. and Assous, H.F. (2021), "Key determinants of deposits volume using CAMEL rating system: The case of Saudi banks", *PloS One*, Vol. 16 No. 12, doi: 10.1371/JOURNAL.PONE.0261184.

Allen, F. and Santomero, A. (1997), "The theory of financial intermediation", *Journal of Banking & Finance*, Vol. 21 No. 11–12, pp. 1461–1485, doi: 10.1016/S0378-4266(97)00032-0.

Almaqtari, F.A., Al-Homaidi, E.A., Tabash, M.I. and Farhan, N.H. (2019), "The determinants of profitability of Indian commercial banks: A panel data approach", *International Journal of Finance & Economics*, John Wiley & Sons, Ltd., Vol. 24 No. 1, pp. 168–185, doi: 10.1002/IJFE.1655.

Alzayed, N., Eskandari, R. and Yazdifar, H. (2023), "Bank failure prediction: corporate governance and financial indicators", *Review of Quantitative Finance and Accounting*, Vol. 61 No. 2, pp. 601–631, doi: 10.1007/s11156-023-01158-z.

Andrievskaya, I. and Semenova, M. (2016), "Does banking system transparency enhance bank competition? Cross-country evidence", *Journal of Financial Stability*, Elsevier, Vol. 23, pp. 33–50, doi: 10.1016/J.JFS.2016.01.003.

Ardia, D., Bluteau, K. and Meghani, M.A. (2023), "Thirty years of academic finance", *Journal of Economic Surveys*, John Wiley & Sons, Ltd, doi: 10.1111/JOES.12571.

Assaf, A.G., Berger, A.N., Roman, R.A. and Tsionas, M.G. (2019), "Does efficiency help banks survive and thrive during financial crises?", *Journal of Banking & Finance*, Vol. 106, pp. 445–470, doi: 10.1016/j.jbankfin.2019.07.013.

Ayadi, R., Naceur, S. Ben, Casu, B. and Quinn, B. (2016), "Does Basel compliance matter for bank performance?", *Journal of Financial Stability*, Vol. 23, pp. 15–32, doi: 10.1016/j.jfs.2015.12.007.

Badunenko, O., Dadoukis, A., Fusi, G. and Simper, R. (2022), "The impact of efficiency on asset quality in banking", *The European Journal of Finance*, Vol. 28 No. 6, pp. 596–620, doi: 10.1080/1351847X.2021.1946117.

Barra, C., Papaccio, A. and Ruggiero, N. (2022), "Basel accords and banking inefficiency: Evidence from the Italian local market", *International Journal of Finance & Economics*, Vol. 28 No. 4, pp. 4079–4119, doi: 10.1002/ijfe.2637.

Barth, J.R., Lin, C., Ma, Y., Seade, J. and Song, F.M. (2013), "Do bank regulation, supervision and monitoring enhance or impede bank efficiency?", *Journal of Banking & Finance*, Vol. 37 No. 8, pp. 2879–2892, doi: 10.1016/j.jbankfin.2013.04.030.

Baule, R. and Tallau, C. (2021), "The risk sensitivity of Basel risk weights and loan loss provisions: evidence from European banks", *The European Journal of Finance*, Routledge, Vol. 27 No. 18, pp. 1855–1886, doi: 10.1080/1351847X.2021.1918207.

Berger, A.N. and DeYoung, R. (1997), "Problem loans and cost efficiency in commercial banks", *Journal of Banking & Finance*, Vol. 21 No. 6, pp. 849–870, doi: 10.1016/S0378-4266(97)00003-4.

Berger, A.N., Hasan, I. and Zhou, M. (2009), "Bank ownership and efficiency in China: What will happen in the world's largest nation?", *Journal of Banking & Finance*, Vol. 33 No. 1, pp. 113–130, doi: 10.1016/j.jbankfin.2007.05.016.

Berger, A.N. and Humphrey, D.B. (1997), "Efficiency of financial institutions: International survey and directions for future research", *European Journal of Operational Research*, Vol. 98 No. 2, pp. 175–212, doi: 10.1016/S0377-2217(96)00342-6.

Berger, A.N., Imbierowicz, B. and Rauch, C. (2016), "The Roles of Corporate Governance in Bank Failures during the Recent Financial Crisis", *Journal of Money, Credit and Banking*, John Wiley & Sons, Ltd, Vol. 48 No. 4, pp. 729–770, doi: 10.1111/JMCB.12316.

Bhat, G., Lee, J.A. and Ryan, S.G. (2021), "Using Loan Loss Indicators by Loan Type to Sharpen the Evaluation of Banks' Loan Loss Accruals", *Accounting Horizons*, Vol. 35 No. 3, pp. 69–91, doi: 10.2308/HORIZONS-18-014.

Bhatia, V., Basu, S., Mitra, S.K. and Dash, P. (2018), "A review of bank efficiency and productivity", *OPSEARCH 2018 55:3*, Springer, Vol. 55 No. 3, pp. 557–600, doi: 10.1007/S12597-018-0332-2.

Bhattacharya, A. and Reddy, R.R. (2022), "Credit Suisse–Greensill Saga: A Case of Risk Management Failure", *Https://Doi.Org/10.1177/09721509221117369*, SAGE PublicationsSage India: New Delhi, India, doi: 10.1177/09721509221117369.

Bhatti, M.A., Sadiq, M., Albarq, A.N. and Juhari, A.S. (2022), "Risk Management and Financial Performance of Banks: An Application of CAMEL Framework", *Cuadernos de Economia - Spain*, Vol. 45 No. 128, pp. 113–123, doi: 10.32826/cude.v1i128.713.

Bischof, J., Rudolf, N. and Schmundt, W. (2022), "How Do Non-Performing Loans Evolve Along the Economic Cycle? The Role of Macroeconomic Conditions and Legal Efficiency", *European Accounting Review*, Routledge, Vol. 31 No. 5, pp. 1149–1174, doi: 10.1080/09638180.2022.2071960.

Böni, P., Zimmermann, · Heinz, Böni, P. and Zimmermann, H. (2024), "The Credit Suisse bailout in hindsight: not a bitter pill to swallow, but a case to follow", Vol. 38, pp. 1–35, doi: 10.1007/s11408-023-00443-0.

Boussemart, J.P., Leleu, H., Shen, Z., Vardanyan, M. and Zhu, N. (2019), "Decomposing banking performance into economic and credit risk efficiencies", *European Journal of Operational Research*, North-Holland, Vol. 277 No. 2, pp. 719–726, doi: 10.1016/J.EJOR.2019.03.006.

Caldara, D. and Iacoviell, M. (2022), "Measuring Geopolitical Risk", *American Economic Review*, American Economic Association, Vol. 112 No. 4, pp. 1194–1225, doi: 10.1257/AER.20191823.

Chang, C.-C. (1999), "The Nonparametric Risk-Adjusted Efficiency Measurement: An Application to Taiwan's Major Rural Financial Intermediaries", *American Journal of Agricultural Economics*, John Wiley & Sons, Ltd, Vol. 81 No. 4, pp. 902–913, doi: 10.2307/1244333.

Cherchye, L., Knox Lovell, C.A., Moesen, W. and Van Puyenbroeck, T. (2007), "One market, one number? A composite indicator assessment of EU internal market dynamics", *European Economic Review*, Vol. 51 No. 3, pp. 749–779, doi: 10.1016/j.euroecorev.2006.03.011.

Cherchye, L., Moesen, W. and Van Puyenbroeck, T. (2004), "Legitimately Diverse, yet Comparable: On Synthesizing Social Inclusion Performance in the EU*", *JCMS: Journal of Common Market Studies*, John Wiley & Sons, Ltd, Vol. 42 No. 5, pp. 919–955, doi: 10.1111/J.0021-9886.2004.00535.X.

Coase, R.H. (1937), "The Nature of the Firm", *Economica*, Vol. 4 No. 16, pp. 386–405, doi: 10.1111/j.1468-0335.1937.tb00002.x.

Chockalingam, A., Dabadghao, S. and Soetekouw, R. (2018), "Strategic risk, banks, and Basel III: estimating economic capital requirements", *Journal of Risk Finance*, Emerald Group Holdings Ltd., Vol. 19 No. 3, pp. 225–246, doi: 10.1108/JRF-11-2016-0142/FULL/PDF.

Çolak, M.S. (2021), “A new multivariate approach for assessing corporate financial risk using balance sheets”, *Borsa Istanbul Review*, Elsevier, Vol. 21 No. 3, pp. 239–255, doi: 10.1016/J.BIR.2020.10.007.

Danlami, M.R., Abduh, M. and Razak, L.A. (2022), “CAMELS, risk-sharing financing, institutional quality and stability of Islamic banks: evidence from 6 OIC countries”, *Journal of Islamic Accounting and Business Research*, Vol. 13 No. 8, pp. 1155–1175, doi: 10.1108/JIABR-08-2021-0227.

Dellnitz, A. (2022), “Big data efficiency analysis: Improved algorithms for data envelopment analysis involving large datasets”, *Computers & Operations Research*, Pergamon, Vol. 137, p. 105553, doi: 10.1016/J.COR.2021.105553.

Demsetz, H. (1988), “The Theory of the Firm Revisited”, *Journal of Law, Economics, & Organization*, Vol. 4 No. 1, pp. 141–161.

Emrouznejad, A. and Yang, G. liang. (2018), “A survey and analysis of the first 40 years of scholarly literature in DEA: 1978–2016”, *Socio-Economic Planning Sciences*, Pergamon, Vol. 61, pp. 4–8, doi: 10.1016/J.SEPS.2017.01.008.

Erel, I., Myers, S.C. and Read, J.A. (2015), “A theory of risk capital”, *Journal of Financial Economics*, Vol. 118 No. 3, pp. 620–635, doi: 10.1016/j.jfineco.2014.10.006.

Finucane, M.L., Alhakami, A., Slovic, P. and Johnson, S.M. (2000), “The affect heuristic in judgments of risks and benefits”, *Journal of Behavioral Decision Making*, Vol. 13 No. 1, pp. 1–17, doi: 10.1002/(SICI)1099-0771(200001/03)13:1<1::AID-BDM333>3.0.CO;2-S.

Fiordelisi, F., Radić, N. and Weyman-Jones, T. (2021), “Detecting zombie banks”, *The European Journal of Finance*, Vol. 27 No. 15, pp. 1459–1488, doi: 10.1080/1351847X.2021.1893200.

Fontnouvelle, P. de, DeJesus-Rueff, V., Jordan, J.S. (John S. and Rosengren, E.S. (2006), “Capital and Risk: New Evidence on Implications of Large Operational Losses”, *Journal of Money, Credit, and Banking*, Vol. 38 No. 7, pp. 1819–1846, doi: 10.1353/mcb.2006.0088.

Fredriksson, A. and Moro, A. (2014), “Bank-SMEs relationships and banks’ risk-adjusted profitability”, *Journal of Banking & Finance*, Vol. 41, pp. 67–77, doi: 10.1016/j.jbankfin.2013.12.026.

Gaganis, C., Pasiouras, F., Tasiou, M. and Zopounidis, C. (2021), “CISEF: A composite index of social, environmental and financial performance”, *European Journal of Operational Research*, Vol. 291 No. 1, pp. 394–409, doi: 10.1016/j.ejor.2020.09.035.

Georgios, C., Evangelia, F., Christos, M. and Maria, N. (2021), “Exploring cost-efficient bundling in a multi-cloud environment”, *Simulation Modelling Practice and Theory*, Elsevier, Vol. 111, p. 102338, doi: 10.1016/J.SIMPAT.2021.102338.

Ghosh, A. (2015), “Banking-industry specific and regional economic determinants of non-performing loans: Evidence from US states”, *Journal of Financial Stability*, Elsevier, Vol. 20, pp. 93–104, doi: 10.1016/j.jfs.2015.08.004.

Gulati, R. (2022), “Global and local banking crises and risk-adjusted efficiency of Indian banks: Are the impacts really perspective-dependent?”, *The Quarterly Review of Economics and Finance*, North-Holland, Vol. 84, pp. 23–39, doi: 10.1016/J.QREF.2022.01.004.

Gulati, R. (2023), “Beyond the Z-score: A novel measure of bank stability for effective policymaking”, *Journal of Public Affairs*, John Wiley & Sons, Ltd, Vol. 23 No. 4, p. e2866, doi: 10.1002/PA.2866.

Gulati, R., Hassan, M.K. and Charles, V. (2023), “Developing a New Multidimensional Index of Bank Stability and Its Usage in the Design of Optimal Policy Interventions”, *Computational Economics*, doi: 10.1007/s10614-023-10401-7.

Gulati, R., Kattumuri, R. and Kumar, S. (2020), “A non-parametric index of corporate governance in the banking industry: An application to Indian data”, *Socio-Economic Planning Sciences*, Pergamon, Vol. 70, p. 100702, doi: 10.1016/J.SEPS.2019.03.008.

Handorf, W.C. (2016), “CAMEL to CAMELS: The risk of sensitivity”, *Journal of Banking Regulation*, Vol. 17 No. 4, pp. 273–287, doi: 10.1057/jbr.2015.24.

Henriques, I.C., Sobreiro, V.A., Kimura, H. and Mariano, E.B. (2020), “Two-stage DEA in banks: Terminological controversies and future directions”, *Expert Systems with Applications*, Vol. 161, p. 113632, doi: 10.1016/j.eswa.2020.113632.

Herring, R. and Santomero, A. (1995), “The Role of the Financial Sector in Economic Performance”, *Center for Financial Institutions Working Papers 95-08, Wharton School Center for Financial Institutions, University of Pennsylvania.*

Hu, D., Zhao, J.L., Hua, Z. and Wong, M.C.S. (2012), “Network-Based Modeling and Analysis of Systemic Risk in Banking Systems”, *MIS Quarterly*, Vol. 36 No. 4, pp. 1269–1291, doi: https://doi.org/10.2307/41703507.

Hughes, J.P. and Mester, L.J. (2008), “Efficiency in banking: theory, practice, and evidence”, *Oxford Handbook of Banking*, doi: https://dx.doi.org/10.2139/ssrn.1092220.

Hwa, V., Kapinos, P. and Ramirez, C.D. (2018), “Does regulatory bank oversight impact economic activity? A local projections approach”, *Journal of Financial Stability*, Elsevier, Vol. 39, pp. 167–174, doi: 10.1016/J.JFS.2017.01.006.

Jensen, M.C. and Meckling, W.H. (1976), “Theory of the firm: Managerial behavior, agency costs and ownership structure”, *Journal of Financial Economics*, Vol. 3 No. 4, pp. 305–360, doi: 10.1016/0304-405X(76)90026-X.

Jomthanachai, S., Wong, W.P. and Lim, C.P. (2021), “An Application of Data Envelopment Analysis and Machine Learning Approach to Risk Management”, *IEEE Access, Institute of Electrical and Electronics Engineers Inc.*, Vol. 9, pp. 85978–85994, doi: 10.1109/ACCESS.2021.3087623.

Kim, D. and Santomero, A. (1988), “Risk in Banking and Capital Regulation”, *The Journal of Finance*, Vol. 43 No. 5, pp. 1219–1233, doi: 10.1111/j.1540-6261.1988.tb03966.x.

Knight, F.H. (1921), *Risk, Uncertainty and Profit*, University of Illinois at Urbana-Champaign’s Academy for Entrepreneurial Leadership Historical Research Reference in Entrepreneurship.

Kumar, A., Ahmed, K., Bhayo, M.-R. and Kalhoro, M.R. (2022), “Banking performance and institutional quality: Evidence from dynamic panel data analysis”, *International Journal of Finance & Economics*, Vol. 28 No. 4, pp. 4717–4737, doi: 10.1002/ijfe.2673.

Kyiu, A. and Tawiah, V. (2023), “IFRS 9 implementation and bank risk”, *Accounting Forum*, Vol. 0 No. 0, pp. 1–25, doi: 10.1080/01559982.2023.2233861.

Lartey, T., James, G.A. and Danso, A. (2021), “Interbank funding, bank risk exposure and performance in the UK: A three-stage network DEA approach”, *International Review of Financial Analysis*, North-Holland, Vol. 75, p. 101753, doi: 10.1016/J.IRFA.2021.101753.

Li, B. and Gao, Q. (2025), “Uncertain bi-objective portfolio programming models of risky assets with liquidity and entropy constraints under uncertainty theory based DEA efficiency measures”, *Journal of Computational and Applied Mathematics*, North-Holland, Vol. 461, p. 116442, doi: 10.1016/J.CAM.2024.116442.

Li, Z., Si, X., Ding, Z., Li, X., Zheng, S., Wang, Y., Wei, H., et al. (2021), "Measurement and Evaluation of the Operating Efficiency of China's Basic Pension Insurance: Based on Three-Stage DEA Model", *Risk Management and Healthcare Policy,* Risk Manag Healthc Policy, Vol. 14, pp. 3333–3348, doi: 10.2147/RMHP.S320479.

Luu, H.N., Nguyen, L.H. and Wilson, J.O.S. (2023), "Organizational culture, competition and bank loan loss provisioning", *The European Journal of Finance*, Vol. 29 No. 4, pp. 393–418, doi: 10.1080/1351847X.2022.2053732.

Mamatzakis, E. (2015), "Risk and efficiency in the Central and Eastern European banking industry under quantile analysis", *Quantitative Finance*, Vol. 15 No. 3, pp. 553–567, doi: 10.1080/14697688.2012.715245.

Mamatzakis, E. and Bermpei, T. (2014), "What drives investment bank performance? The role of risk, liquidity and fees prior to and during the crisis", *International Review of Financial Analysis*, Vol. 35, pp. 102–117, doi: 10.1016/j.irfa.2014.07.012.

Maricic, M. and Jeremic, V. (2023), "Imposing unsupervised constraints to the Benefit-of-the-Doubt (BoD) model", *Metron*, Springer-Verlag Italia s.r.l., Vol. 81 No. 3, pp. 259–296, doi: 10.1007/S40300-023-00254-3/METRICS.

Markowitz, H. (1952), "Portfolio Selection", *The Journal of Finance*, Vol. 7 No. 1, pp. 77–91, doi: 10.2307/2975974.

Martins, A.M. (2024), "The collapse of Silicon Valley Bank and Credit Suisse and their impact on other U.S. Banks", *Applied Economics Letters*, Routledge, doi: 10.1080/13504851.2024.2302862.

Marton, J. and Runesson, E. (2017), "The predictive ability of loan loss provisions in banks – Effects of accounting standards, enforcement and incentives", *The British Accounting Review*, Vol. 49 No. 2, pp. 162–180, doi: 10.1016/j.bar.2016.09.003.

Matousek, R., Rughoo, A., Sarantis, N. and Assaf, A.G. (2015), "Bank performance and convergence during the financial crisis: Evidence from the 'old' European Union and Eurozone", *Journal of Banking & Finance*, Vol. 52, pp. 208–216, doi: https://doi.org/10.1016/j.jbankfin.2014.08.012.

McKee, G. and Kagan, A. (2018), "Community bank structure an x-efficiency approach", *Review of Quantitative Finance and Accounting*, Vol. 51 No. 1, pp. 19–41, doi: 10.1007/s11156-017-0662-9.

Melyn, W. and Moesen, W. (1991), "Towards a synthetic indicator of macroeconomic performance : unequal weighting when limited information is available", *Public Economic Research Paper 17, CES, KU Leuven*, Leuven.

Mester, L.J. (1996), "A study of bank efficiency taking into account risk-preferences", *Journal of Banking & Finance*, North-Holland, Vol. 20 No. 6, pp. 1025–1045, doi: https://doi.org/10.1016/0378-4266(95)00047-X.

Milne, A. and Onorato, M. (2012), "Risk-Adjusted Measures of Value Creation in Financial Institutions", *European Financial Management*, John Wiley & Sons, Ltd, Vol. 18 No. 4, pp. 578–601, doi: 10.1111/J.1468-036X.2010.00540.X.

Mishra, S. (2014), "Decision-Making Under Risk: Integrating Perspectives From Biology, Economics, and Psychology", *Personality and Social Psychology Review: An Official Journal of the Society for Personality and Social Psychology, Inc*, Vol. 18 No. 3, pp. 280–307, doi: 10.1177/1088868314530517.

Mohsin, M., Nurunnabi, M., Zhang, J., Sun, H., Iqbal, N., Iram, R. and Abbas, Q. (2021), "The evaluation of efficiency and value addition of IFRS endorsement towards earnings timeliness disclosure", *International Journal of Finance & Economics*, Vol. 26 No. 2, pp. 1793–1807, doi: 10.1002/ijfe.1878.

Muhmad, S.N. and Hashim, H.A. (2015), "Using the CAMEL Framework in Assessing Bank Performance in Malaysia", *International Journal of Economics Management and Accounting*, Vol. 23 No. 1, pp. 109–127, doi: https://doi.org/10.31436/ijema.v23i1.292.

Murillo-Zamorano, L.R. (2004), "Economic Efficiency and Frontier Techniques", *Journal of Economic Surveys*, John Wiley & Sons, Ltd, Vol. 18 No. 1, pp. 33–77, doi: 10.1111/J.1467-6419.2004.00215.X.

Ng, T.H., Chong, L.L. and Ismail, H. (2012), "Is the risk management committee only a procedural compliance?: An insight into managing risk taking among insurance companies in Malaysia", *Journal of Risk Finance*, Emerald Group Publishing Ltd., Vol. 14 No. 1, pp. 71–86, doi: 10.1108/15265941311288112/FULL/XML.

Ngatia, J., Makori, D. and Theuri, M.J. (2024), "Camel Financial Indicators and Performance of Tier Three Commercial Banks in Kenya", *Journal of Finance and Accounting*, Vol. 8 No. 9, pp. 80–99, doi: 10.53819/81018102T7035.

Nippani, S. and Ling, R. (2021), "Bank size and performance: An analysis of the industry in the United States in the post-financial-crisis era", *Journal of Financial Research*, Vol. 44 No. 3, pp. 587–606, doi: 10.1111/jfir.12255.

OECD, European Union and Joint Research Centre - European Commission. (2008), *Handbook on Constructing Composite Indicators: Methodology and User Guide*, OECD, doi: 10.1787/9789264043466-en.

O'Hanlon, J. (2013), "Did loan-loss provisioning by UK banks become less timely after implementation of IAS 39?", *Accounting and Business Research*, Vol. 43 No. 3, pp. 225–258, doi: 10.1080/00014788.2013.747260.

Oldfield, G. and Santomero, A. (1970), "The Place of Risk Management in Financial Institutions", *Sloan Management Review*, Vol. 39.

Ozili, P.K. (2019), "Non-performing loans and financial development: new evidence", *Journal of Risk Finance*, Emerald Group Holdings Ltd., Vol. 20 No. 1, pp. 59–81, doi: 10.1108/JRF-07-2017-0112/FULL/PDF.

Paruolo, P., Saisana, M. and Saltelli, A. (2013), "Ratings and Rankings: Voodoo or Science?", *Journal of the Royal Statistical Society Series A: Statistics in Society*, Oxford Academic, Vol. 176 No. 3, pp. 609–634, doi: 10.1111/J.1467-985X.2012.01059.X.

Pekkaya, M. and Demir, F.E. (2018), "Determining the Priorities of CAMELS Dimensions Based on Bank Performance", in Dincer, H., Hacioglu, U. and Yuksel, S. (Eds.), *Global Approaches in Financial Economics, Banking, and Finance*, pp. 445–463, doi: 10.1007/978-3-319-78494-6_21.

Performance Review Commission (PRC) (2019), PRR 2018: Performance Review Report – Preliminary Concept of the Composite Risk Index (CRI), *Eurocontrol*, Brussels, Belgium, available at: https://www.eurocontrol.int/sites/default/files/2019-06/prr-2018.pdf (24.3.2025)

Pessarossi, P. and Weill, L. (2015), "Do capital requirements affect cost efficiency? Evidence from China", *Journal of Financial Stability*, Vol. 19, pp. 119–127, doi: 10.1016/j.jfs.2014.11.002.

Proaño-Rivera, B., José, |, Feria-Dominguez, M., Azuay, D. and Feria-Dominguez, J.M. (2023), "Are Ecuadorian banks enough technically efficient for growth? A clinical study", *International Journal of Finance & Economics*, John Wiley & Sons, Ltd, doi: 10.1002/IJFE.2775.

Qureshi, A.S. and Siddiqui, D.A. (2023), "The Impact of the CAMEL Model on Banks' Profitability", *SSRN Electronic Journal*, Elsevier BV, doi: 10.2139/SSRN.4432257.

Radojicic, M., Savic, G. and Jeremic, V. (2018), "Measuring the efficiency of banks: the bootstrapped I-distance GAR DEA approach", *Technological and Economic Development of Economy*, Vilnius Gediminas Technical University, Vol. 24 No. 4, pp. 1581–1605, doi: 10.3846/TEDE.2018.3699.

Risal, H.G. and Panta, S.B. (2019), "CAMELS-Based Supervision and Risk Management: What Works and What Does Not", *Fortune Institute of International Business (FIIB) Business Review*, Vol. 8 No. 3, pp. 194–204, doi: 10.1177/2319714519873747.

Roman, A. and Şargu, A.C. (2013), "Analysing the Financial Soundness of the Commercial Banks in Romania: An Approach based on the Camels Framework", *Procedia Economics and Finance*, Elsevier BV, Vol. 6, pp. 703–712, doi: 10.1016/S2212-5671(13)00192-5.

Rossi, S. (2023), "The banking crisis of Credit Suisse: Origins, consequences, and reform proposals", *Investigación Económica*, Universidad Nacional Autónoma de México, Facultad de Economía, Vol. 82 No. 325, pp. 21–36, doi: 10.22201/FE.01851667P.2023.325.86135.

Safiullah, M. and Shamsuddin, A. (2019), "Risk-adjusted efficiency and corporate governance: Evidence from Islamic and conventional banks", *Journal of Corporate Finance*, Vol. 55, pp. 105–140, doi: 10.1016/j.jcorpfin.2018.08.009.

Santomero, A. (1984), "Modeling the Banking Firm: A Survey", *Journal of Money, Credit and Banking*, Vol. 16 No. 4, pp. 576–602, doi: 10.2307/1992092.

Santomero, A. (1997), "Commercial Bank Risk Management: An Analysis of the Process", *Journal of Financial Services Research*, Vol. 2/3, doi: 10.1023/A:1007971801810.

Schaeck, K. and Cihák, M. (2014), "Competition, Efficiency, and Stability in Banking", *Financial Management*, Vol. 43 No. 1, pp. 215–241, doi: 10.1111/fima.12010.

Scholtens, B. and van Wensveen, D. (2000), "A critique on the theory of financial intermediation", *Journal of Banking & Finance*, Vol. 24 No. 8, pp. 1243–1251, doi: 10.1016/S0378-4266(99)00085-0.

Sensarma, R. and Jayadev, M. (2009), "Are bank stocks sensitive to risk management?", *Journal of Risk Finance*, Emerald Group Publishing Limited, Vol. 10 No. 1, pp. 7–22, doi: 10.1108/15265940910924463/FULL/XML.

Seward, J.K. (1990), "Corporate Financial Policy and the Theory of Financial Intermediation", *The Journal of Finance*, Vol. 45 No. 2, pp. 351–377, doi: 10.1111/j.1540-6261.1990.tb03694.x.

Shaddady, A. and Moore, T. (2019), "Investigation of the effects of financial regulation and supervision on bank stability: The application of CAMELS-DEA to quantile regressions", *Journal of International Financial Markets Institutions and Money*, Vol. 58, pp. 96–116, doi: 10.1016/j.intfin.2018.09.006.

Shamshur, A. and Weill, L. (2019), "Does bank efficiency influence the cost of credit?", *Journal of Banking and Finance*, Vol. 105, pp. 62–73, doi: 10.1016/j.jbankfin.2019.05.002.

Shi, X. and Yu, W. (2021), "Analysis of Chinese Commercial Banks' Risk Management Efficiency Based on the PCA-DEA Approach", *Mathematical Problems in Engineering*, John Wiley & Sons, Ltd, Vol. 2021 No. 1, p. 7306322, doi: 10.1155/2021/7306322.

Shukla, S.S. (2015), "Analysing Financial Strength of Public and Private Sector Banks: A CAMEL Approach", *Pacific Business Review International*, Vol. 7 No. 8, pp. 44–50, doi: http://www.pbr.co.in/2015/2015_month/February/6.pdf.

Simper, R., Dadoukis, A. and Bryce, C. (2019), "European bank loan loss provisioning and technological innovative progress", *International Review of Financial Analysis*, Vol. 63, pp. 119–130, doi: 10.1016/j.irfa.2019.03.001.

Simper, R., Hall, M.J.B., Liu, W. Bin, Zelenyuk, V. and Zhou, Z. (2017), "How relevant is the choice of risk management control variable to non-parametric bank profit efficiency analysis? The case of South Korean banks", *Annals of Operations Research*, Springer New York LLC, Vol. 250 No. 1, pp. 105–127, doi: 10.1007/S10479-015-1946-X/METRICS.

Slovic, P., Finucane, M.L., Peters, E. and MacGregor, D.G. (2004), "Risk as analysis and risk as feelings: some thoughts about affect, reason, risk, and rationality", *Risk Analysis: An Official Publication of the Society for Risk Analysis*, Vol. 24 No. 2, pp. 311–322, doi: 10.1111/j.0272-4332.2004.00433.x.

Stulz, R.M. (1984), "Optimal Hedging Policies", *The Journal of Financial and Quantitative Analysis*, Vol. 19 No. 2, pp. 127–140, doi: 10.2307/2330894.

Stulz, R.M. (2023), *Crisis Risk and Risk Management*, National Bureau of Economic Research, doi: http://dx.doi.org/10.2139/ssrn.4439633.

Sun, L. and Chang, T.-P. (2011), "A comprehensive analysis of the effects of risk measures on bank efficiency: Evidence from emerging Asian countries", *Journal of Banking and Finance*, Vol. 35 No. 7, pp. 1727–1735, doi: 10.1016/j.jbankfin.2010.11.017.

Tan, Y. and Tsionas, M.G. (2022), "Modelling sustainability efficiency in banking", *International Journal of Finance & Economics*, Vol. 27 No. 3, pp. 3754–3772, doi: 10.1002/ijfe.2349.

Tan, Y., Floros, C. and Anchor, J. (2017), "The profitability of Chinese banks: Impacts of risk, competition and efficiency", *Review of Accounting and Finance*, Emerald Group Publishing Ltd., Vol. 16 No. 1, pp. 86–105, doi: 10.1108/RAF-05-2015-0072/FULL/XML.

Tarchouna, A., Jarraya, B. and Bouri, A. (2019), "Shadow prices of non-performing loans and the global financial crisis: Empirical evidence from US commercial banks", *Journal of Risk Finance*, Emerald Group Holdings Ltd., Vol. 20 No. 5, pp. 411–434, doi: 10.1108/JRF-03-2018-0030/FULL/PDF.

Tron, A., Dallocchio, M., Ferri, S. and Colantoni, F. (2022), "Corporate governance and financial distress: lessons learned from an unconventional approach", *Journal of Management and Governance 2022 27:2*, Springer, Vol. 27 No. 2, pp. 425–456, doi: 10.1007/S10997-022-09643-8.

Trung, N.K.Q. (2021), "Determinants of bank performance in Vietnamese commercial banks: an application of the CAMELS model", *Cogent Business & Management*, Vol. 8 No. 1, doi: 10.1080/23311975.2021.1979443.

Ullah, S., Majeed, A. and Popp, J. (2023), "Determinants of bank's efficiency in an emerging economy: A data envelopment analysis approach", *PLOS ONE*, *Public Library of Science*, Vol. 18 No. 3, p. e0281663, doi: 10.1371/JOURNAL.PONE.0281663.

United Nations Development Programme (UNDP) (1990), Human Development Report 1990: Concept and Measurement of Human Development, *Oxford University Press*, New York, NY. Available at: https://hdr.undp.org/system/files/documents/hdr1990encompletenostats.pdf (24.3.2025)

United Nations Development Programme (UNDP) (2023), Human Development Report 2023: The Future of Development in a Changing World, *UNDP*, New York, NY. Available at: https://hdr.undp.org/content/human-development-report-2023-24 (24.3.2025)

Vidoli, F. and Fusco, E. (2018), *Compind: Composite Indicators Functions Based on Frontiers in R (Compind Package Version 2.0)*.

Vo, L. Van and Le, H.T.T. (2023), "From Hero to Zero: The case of Silicon Valley Bank", *Journal of Economics and Business*, Elsevier, Vol. 127, p. 106138, doi: 10.1016/J.JECONBUS.2023.106138.

Zamore, S., Beisland, L.A. and Mersland, R. (2023), "Excessive focus on risk? Non-performing loans and efficiency of microfinance institutions", *International Journal of Finance & Economics*, Vol. 28 No. 2, pp. 1290–1307, doi: 10.1002/ijfe.2477.

Zha, Y., Liang, N., Wu, M. and Bian, Y. (2016), "Efficiency evaluation of banks in China: A dynamic two-stage slacks-based measure approach", *Omega*, Pergamon, Vol. 60, pp. 60–72, doi: 10.1016/J.OMEGA.2014.12.008.

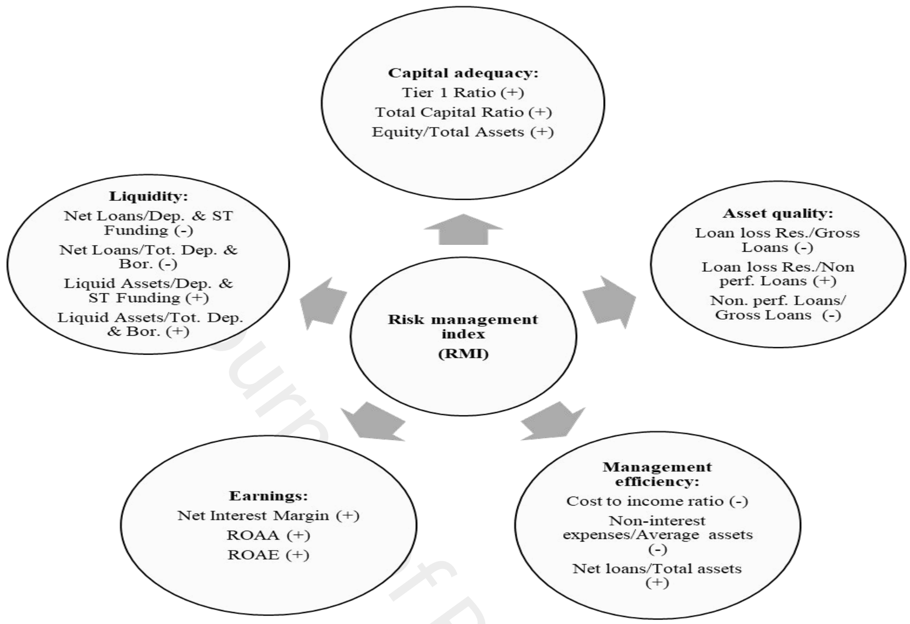
Appendix

[Table A about here]

[Figure A about here]

[Table B about here]

Figure 1 Risk management index composition



Source: Authors' construction

Table I Summary statistics of 16 indicators

RMI Components	Variables	Max	Min	Average	SD
Capital Adequacy	Tier 1 Ratio	0.9896	0.0488	0.1474	0.0606
	Total Capital Ratio	0.9896	0.0572	0.1617	0.0605
	Equity / Total assets	0.5070	0.0154	0.1043	0.0368
Asset Quality	Loan Loss Res. / Gross Loans	0.3031	-0.0225	0.0214	0.0286
	Loan Loss Res. / Non Perf. Loans	9.9158	-0.1180	1.5827	1.4503
	Non Perf. Loans / Gross Loans	0.6104	0.0002	0.0267	0.0519
Management Efficiency	Cost to Income Ratio	6.0299	-3.4744	0.6138	0.2006
	Non Int. Exp. / Avg Assets	0.3000	-0.0120	0.0293	0.0210
	Net Loans / Total assets	0.9792	0.0461	0.6368	0.1500
Earnings	Net Interest Margin	0.2630	-0.0018	0.0340	0.0231
	Return on Avg Assets (ROAA)	0.0994	-0.0943	0.0098	0.0089
	Return on Avg Equity (ROAE)	0.8797	-0.8713	0.0947	0.0769
Liquidity	Net Loans / Dep. & ST Funding	2.5287	0.0667	0.7934	0.2149
	Net Loans / Tot. Dep. & Bor.	1.2546	0.0534	0.7378	0.1724
	Liquid Assets / Dep. & ST Funding	2.3252	0.0004	0.1781	0.2046
	Liquid Assets / Tot. Dep. & Bor.	1.9769	0.0004	0.1565	0.1602

Source: Author's calculation

Table II RMI and sub-indicators results

Year	Capital Adequacy	Asset Quality	Management Efficiency	Earnings	Liquidity	RMI
2015	0.8342	0.9241	0.8924	0.8528	0.8228	0.9430
2016	0.8308	0.9208	0.8948	0.8490	0.8207	0.9508
2017	0.8410	0.9225	0.8948	0.8516	0.8229	0.9371
2018	0.8418	0.9243	0.8938	0.8645	0.8315	0.9463
2019	0.8488	0.9299	0.8926	0.8605	0.8299	0.9480
2020	0.8458	0.9311	0.8810	0.8351	0.8480	0.9450
2021	0.8443	0.9360	0.8727	0.8562	0.8637	0.9468
Average	0.8410	0.9270	0.8889	0.8528	0.8342	0.9453

Source: Author’s calculations

Table III Average RMI sub-indicators weights

Year	Capital Adequacy	Asset Quality	Management Efficiency	Earnings	Liquidity
2015	0.1233	0.2854	0.3146	0.1314	0.1453
2016	0.1179	0.4083	0.1978	0.1245	0.1515
2017	0.1195	0.3033	0.3060	0.1226	0.1486
2018	0.1226	0.3702	0.2289	0.1220	0.1563
2019	0.1249	0.3350	0.2424	0.1339	0.1638
2020	0.1370	0.4382	0.1566	0.1258	0.1424
2021	0.1320	0.4021	0.1674	0.1393	0.1593
Average	0.1253	0.3632	0.2305	0.1285	0.1524

Source: Author's calculations

Table IV Average RMI sub-indicators weights

	Sub-indicator	2015	2016	2017	2018	2019	2020	2021	Average
CA	Tier 1 Capital	0.1463	0.1511	0.1986	0.1951	0.2010	0.2521	0.2557	0.2000
	Total Capital Ratio	0.1856	0.2628	0.2260	0.2284	0.2141	0.2379	0.2509	0.2294
	Equity/Total Assets	0.6681	0.5861	0.5754	0.5766	0.5849	0.5100	0.4934	0.5706
AQ	Loan loss Res./Gross Loans	0.4900	0.4399	0.4102	0.3496	0.5138	0.3829	0.3175	0.4148
	Loan loss Res./Non perf. Loans	0.1585	0.1677	0.1487	0.1428	0.1341	0.1713	0.1737	0.1567
	Non. perf. Loans/ Gross Loans	0.3515	0.3924	0.4411	0.5076	0.3521	0.4458	0.5088	0.4285
ME	Non-Interest Expenses /Average Assets	0.2450	0.2236	0.2035	0.1915	0.1856	0.2046	0.1756	0.2042
	Cost To Income Ratio	0.4898	0.2699	0.2655	0.2699	0.2818	0.2997	0.3603	0.3196
	Net Loans/Total Assets	0.2652	0.5065	0.5311	0.5385	0.5326	0.4958	0.4640	0.4762
E	Net Interest Margin	0.4126	0.4209	0.4161	0.3246	0.3282	0.4090	0.2284	0.3628
	Return On Average Assets	0.2022	0.2236	0.2557	0.3365	0.3579	0.2604	0.3413	0.2825
	Return On Average Equity	0.3852	0.3555	0.3282	0.3389	0.3139	0.3306	0.4304	0.3547
L	Net Loans/Dep. & ST Funding	0.5044	0.4881	0.4688	0.4138	0.4046	0.4066	0.4250	0.4445
	Net Loans/Tot. Dep. & Bor.	0.1784	0.1958	0.1560	0.1153	0.1346	0.1224	0.1336	0.1480
	Liquid Assets/Dep. & ST Funding	0.1530	0.1550	0.1733	0.2070	0.2039	0.2131	0.1611	0.1809
	Liquid Assets/Tot. Dep. & Bor.	0.1642	0.1611	0.2019	0.2640	0.2569	0.2579	0.2803	0.2266

Source: Author’s calculations, CA – Capital adequacy; AQ – Asset Quality; ME – Management Efficiency; E – Earnings; L – Liquidity

Table V Fixed effects panel data analysis with robust (HAC) standard errors

Variables	Results
Capital Adequacy (CA)	0.1062*** (0.0063)
Asset Quality (AQ)	0.1796*** (0.0084)
Management Efficiency (ME)	0.2296*** (0.0112)
Earnings (E)	0.1342*** (0.0046)
Liquidity (L)	0.1493*** (0.0073)
Constant	0.2464*** (0.0172)
Observations	4,123
R-squared	0.9109
R-squared within	0.5819

Note: The table reports the results from the panel fixed effect with robust (HAC) standard errors regression on the relationship between bank-specific risks denoted by the CAMEL sub-indicators and the composite risk management index (RMI). The dependent variable is the composite risk management index (RMI) as constructed in previous sections using the constrained DEA BoD model. Standard errors are reported in parenthesis. *, **, *** indicates significance levels at the 10%, 5%, and 1% respectively.

Source: Author's calculations

Table VI Fixed effects panel data analysis with robust (HAC) standard errors

Variables	Results
Risk Management Index (RMI)	0.2676* (0.1399)
Capital Adequacy (CA)	−0.0497 (0.0778)
Asset Quality (AQ)	0.0814 (0.0637)
Management Efficiency (ME)	0.03607 (0.1404)
Earnings (E)	−0.3634*** (0.0673)
Liquidity (L)	0.0609 (0.0849)
Constant	0.5623*** (0.1494)
Observations	4,123
R-squared	0.9423
R-squared within	0.0359

Note: The table reports the results from the panel fixed effect with robust (HAC) standard errors regression on the relationship between the RMI with its components and operational efficiency. The dependent variable is the Efficiency ratio (ER) defined as the ratio of bank overheads to the sum of interest income and net fees. Standard errors are reported in parenthesis. *, **, *** indicates significance levels at the 10%, 5%, and 1% respectively.

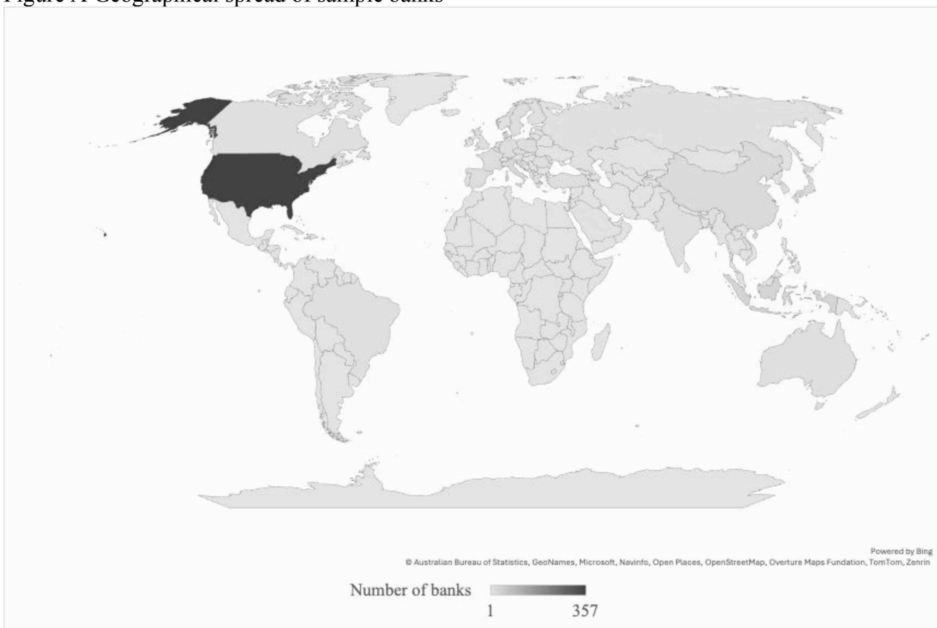
Source: Author's calculations

Table A Bank distribution by country

	Countries	Number of banks	Percentage	Location
1	Australia	6	1.02%	Australia and Oceania
2	Austria	2	0.34%	Europe
3	Belgium	4	0.68%	Europe
4	Brazil	5	0.85%	South America
5	Canada	6	1.02%	North America
6	China	17	2.89%	Asia
7	Croatia	3	0.51%	Europe
9	Czechia	6	1.02%	Europe
10	Denmark	10	1.70%	Europe
11	Estonia	1	0.17%	Europe
12	Finland	4	0.68%	Europe
13	France	9	1.53%	Europe
14	Germany	7	1.19%	Europe
15	Greece	4	0.68%	Europe
16	India	5	0.85%	Europe
17	Indonesia	28	4.75%	Asia
16	Ireland	3	0.51%	Europe
19	Italy	22	3.74%	Europe
20	Japan	15	2.55%	Asia
21	Luxembourg	2	0.34%	Europe
22	Malta	1	0.17%	Europe
23	Netherlands	7	1.19%	Europe
24	Poland	7	1.19%	Europe
25	Portugal	4	0.68%	Europe
26	Romania	8	1.36%	Europe
27	Russia	1	0.17%	Europe
28	Saudi Arabia	2	0.34%	Asia
29	South Korea	9	1.53%	Asia
30	Spain	10	1.70%	Europe
31	Sweden	10	1.70%	Europe
32	Turkey	8	1.36%	Europe
33	United Kingdom	6	1.02%	Europe
34	United States of America	357	60.61%	North America
	Total	**589**	**100.00%**	

Source: Author's calculation

Figure A Geographical spread of sample banks



Source: Author’s construction

Table B Additional diagnostic tests

Random effects (GLS) with standard errors clustered by unit (Testing H1)

Variables	Results
Capital Adequacy (CA)	0.1313*** (0.0036)
Asset Quality (AQ)	0.1880*** (0.0046)
Management Efficiency (ME)	0.2174*** (0.0078)
Earnings (E)	0.1404*** (0.0033)
Liquidity (L)	0.15423*** (0.0048)
Constant	0.2190*** (0.0116)
Observations	4,123
Joint test of regressors	8605.08***
Breusch-Pagan	1076.52***
Hausman test	68.6816***

Note: The table reports the results from the panel random effect with standard errors clustered by unit regression on the relationship between bank-specific risks denoted by the CAMEL sub-indicators and the composite risk management index (RMI). The dependent variable is the composite risk management index (RMI) as constructed in previous sections using the constrained DEA BoD model. Standard errors are reported in parenthesis. *, **, *** indicates significance levels at the 10%, 5%, and 1% respectively.

Variance Inflation Factors -VIF (Testing H1)

Variables	Results
Capital Adequacy (CA)	1.060
Asset Quality (AQ)	1.214
Management Efficiency (ME)	2.557
Earnings (E)	1.461
Liquidity (L)	2.185

Note: Minimum possible value = 1.0, Values > 10.0 may indicate a collinearity problem

Random effects (GLS) with standard errors clustered by unit (Testing H2)

Variables	Results
Risk Management Index (RMI)	0.3121** (0.1450)
Capital Adequacy (CA)	-0.0566 (0.1360)

Asset Quality (AQ)	0.1029* (0.0581)
Management Efficiency (ME)	-0.0671 (0.1385)
Earnings (E)	-0.370838*** (0.0659)
Liquidity (L)	-0.0022 (0.0834)
Constant	0.6568*** (0.1450)
Observations	4,123
Joint test of regressors	57.7546***
Breusch-Pagan	9894.96***
Hausman test	84.7149***

Note: The table reports the results from the panel random effect with standard errors clustered by unit regression on the relationship between the RMI with its components and operational efficiency. The dependent variable is the Efficiency ratio (ER) defined as the ratio of bank overheads to the sum of interest income and net fees. Standard errors are reported in parenthesis. *, **, *** indicates significance levels at the 10%, 5%, and 1% respectively.

Variance Inflation Factors -VIF (Testing H2)

Variables	Results
Risk Management Index (RMI)	6.550
Capital Adequacy (CA)	2.085
Asset Quality (AQ)	3.305
Management Efficiency (ME)	3.946
Earnings (E)	2.698
Liquidity (L)	3.555

Note: Minimum possible value = 1.0, Values > 10.0 may indicate a collinearity problem

Source: Author's calculations

9.5 APPENDED SCIENTIFIC PAPER 3: INSURANCE COMPANIES RISK-ADJUSTED EFFICIENCY USING A COMPOSITE RISK MANAGEMENT INDEX

Insurance Companies Risk-Adjusted Efficiency Using a Composite Risk Management Index

Petrović, D., Dasilas, A. & Karanović, G. (2025)
Review of Accounting and Finance, pp. 1-23. doi: https://doi.org/10.1108/RAF-11-2024-0492

Review of Accounting and Finance

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Insurance Companies Risk-Adjusted Efficiency Using a Composite Risk Management Index

Journal:	*Review of Accounting and Finance*
Manuscript ID	RAF-11-2024-0492.R2
Manuscript Type:	Research Paper
Keywords:	Financial institutions, Risk management, Data envelopment analysis

Insurance Companies Risk-Adjusted Efficiency Using a Composite Risk Management Index

Purpose: This study investigates the relationship between risk management practices and operational efficiency in insurance companies using risk-adjusted efficiency data from a sample of 744 insurers from 2012 to 2021. The study aim is to determine how specific risk management practices impact operating efficiency.

Design/methodology/approach: A Data Envelopment Analysis "Benefit-of-the-Doubt" (DEA BoD) model is employed to construct a Risk Management Index (RMI) composed of five sub-indicators: Capital Adequacy, Asset Quality, Management Efficiency, Earnings, and Solvency. This proposed RMI to assesses the relationship between insurers' risk management practices and operational efficiency.

Findings: The findings indicate a positive and statistically significant relationship between RMI solvency and operational efficiency. In contrast, the other RMI components demonstrate a significant but negative relationship with operational efficiency, implying that the composite RMI is an effective tool for ranking and comparing the quality of insurers' risk management practices.

Originality: This study is among first to develop an RMI for estimating risk-adjusted efficiency for insurance companies. By employing RMI as a performance measure instead of conventional profitability ratios, this methodology underscores critical areas for the improvement of risk management practices, including capital adequacy and solvency.

Keywords: insurance companies, risk-adjusted efficiency, composite risk management index, DEA BoD.

JEL Classifications: C14, D24, G22

Paper type: Research paper

1. Introduction

Insurance companies are vital financial institutions that offer risk assessments, pooling, diversification, and hedging services. By combining financial intermediation with risk management, insurers contribute significantly to economic growth. Given their critical importance, efficient operations and robust risk management practices are essential. Stable and efficient insurers reduce transaction costs throughout the economy, thereby fostering sustainable growth.

While insurer efficiency has been extensively studied (Alhassan and Biekpe, 2015; Drake et al., 2017; Eling and Jia, 2018; Eling and Luhnen, 2010; Ferro and León, 2018; Jurčević and Mihelja Žaja, 2013; Mamatzakis et al., 2023; Mühlnickel and Weiss, 2015), fewer studies have examined how risk management affects operational efficiency. The seminal study by Stulz (1984) emphasized the importance of effective risk management in stabilizing performance, while Oldfield and Santomero (1970) underscored its critical role in financial institutions. Santomero and Babbel (1997) further argued that effective risk management, despite its associated costs, can enhance firm profitability.

This study addresses the gap between risk management and operational efficiency by developing a novel composite Risk Management Index (RMI) for insurers. The RMI captures key firm-specific risks, enabling a systematic analysis of their impact on efficiency. Specifically, this paper tests two hypotheses:

H1: There is a significant relationship between insurance company specific risks (capital, assets, operational, and solvency) and the composite risk management index.

H2: There is a significant relationship between the risk management index and insurance company efficiency.

To construct the RMI, this study introduces the CAMES framework – an adaptation of the CAMEL model (Capital Adequacy, Asset Quality, Management Efficiency, Earnings, and Liquidity) commonly used in banking, in which Liquidity is replaced with Solvency, reflecting its greater relevance in the insurance industry. Hypothesis H1 tests the internal validity of the CAMES-derived RMI, while H2 examines its relationship with operational efficiency. The RMI is constructed using a constrained Data Envelopment Analysis "Benefit of Doubt" (DEA BoD) model, providing objective, data-driven weights that are less subjective to equal or expert-based weighting methods. This study is among the first to develop a composite RMI specifically tailored for insurers and to incorporate solvency-specific indicators, such as the solvency ratio, total gross provisions to gross written premiums, and the retention ratio, as key measures of solvency risk.

Despite the acknowledged significance of risk management for insurer stability, few studies empirically quantify its relationship with operational efficiency using firm-level risk indicators. This study addresses that gap by providing new insights into how risk management influences efficiency. For policymakers, the RMI serves as an early warning tool to identify deficiencies in insurers' risk management before they escalate into systemic threats. For managers, it underscores how specific risk factors affect operational efficiency facilitating targeted enhancements in internal risk management practices. To our knowledge, this is one of the first studies to develop a risk-adjusted efficiency framework specifically designed for insurers, building upon and significantly enhancing previous research that primarily focused on risk disclosures (Malafronte et al., 2016, 2018), and providing a comprehensive and quantifiable framework that directly links risk management to operational efficiency within the insurance sector.

The paper is organized as follows: Section 2 outlines the theoretical framework; Section 3 reviews the literature; Section 4 describes the methodology; Section 5 presents the dataset; Section 6 discusses the results; and Section 7 concludes with implications and suggestions for future research.

2. Theoretical background

The operational efficiency of insurance companies is supported by several economic and financial theories, upon which the study hypotheses regarding the impact of risk management impact on firm efficiency are based. This section outlines the theoretical rationale behind RMI development and its expected impact on insurer efficiency.

Microeconomic production theory emphasizes minimizing inputs while maximizing outputs, which directly supports H2: that RMI, particularly through operational and cost efficiency, influences overall insurer efficiency. This is captured in two dimensions: Management Efficiency (ME) reflecting cost efficiency, and the Earnings (E) emphasizing profit maximization. The theory of the firm (Coase, 1937) emphasizes the maximization of shareholder value, which is reflected in the E dimension through profitability measures. This provides a theoretical foundation for H2, suggesting that effective risk management practices enhance operational efficiency while creating shareholder value.

Agency theory (Jensen and Meckling, 1976; Stulz, 1984) emphasizes the importance of aligning managerial and shareholder interests to mitigate conflicts that can undermine risk management, particularly in relation to risk-taking and cost efficiency. This theory supports both H1 and H2 by framing managerial efficiency as central to effective risk management and operational efficiency, captured through the ME dimension. It also reveals the trade-off between maintaining Capital Adequacy (CA) and Asset Quality (AQ) versus profit maximization. Higher capital buffers can reduce risk but may limit the availability of funds for revenue-generating activities. Similarly, Solvency (S) reflects the balance between underwriting risks and financial stability, and this trade-off is captured by metrics such as solvency and retention ratios. Collectively, CA, AQ, ME, and S embody the agency theory framework within the RMI, supporting its hypothesized relationship with efficiency (H2).

The theory of financial intermediation, outlined by Scholtens and van Wensveen (2000) and Seward (1990), underscores the role of insurers in minimizing transaction costs and effectively allocating capital, as represented in the AQ dimension. Although traditional theory does not explicitly address risk management, extensions by Scholtens and van Wensveen (2000) and Oldfield and Santomero (1970) highlight that prudent risk management (reflected in the CA, AQ and S dimensions) enhances operational efficiency. This framework supports H1 by linking all five RMI dimensions (CA, AQ, ME, E, S) to insurer risk profiles, underpins H2 by suggesting that stronger RMI leads to improved efficiency.

Demsetz (1988, p. 144), building on the works of Knight (1921) and Markowitz (1952), conceptualizes firms as mechanisms for efficient risk sharing; a central function for insurers, reflected in the AQ and S dimensions. Erel et al. (2015) further develop the theory of risk capital, emphasizing its internal development as a strategic risk management tool; this aligns with the CA dimension that captures an insurer's ability to absorb losses. Similarly, Stulz (2023), underscores the significance of governance and crisis management in fostering resilience, thereby reinforcing the roles of CA and ME in effective risk management. This theoretical framework reinforces H1 by explaining the connection between the RMI and its components.

Bomhard (2005), de Castries (2005), and Santomero and Babbel (1997) emphasize that risk management is essential for resilience and long-term stability of the insurance industry. Their research underpins RMI development, consolidating the CA, AQ, ME, E, S sub-indicators into a comprehensive measure of risk management. This framework supports both hypotheses, demonstrating that robust risk management directly enhances operational efficiency.

3. Literature review

Research on the efficiency of insurance companies has extensively examined profitability and efficiecy metrics (Bhuyan et al., 2022; Ferro and León, 2018; Grmanová and Strunz, 2017; Klotzki et al., 2018; Mamatzakis, 2015; Okura and Yanase, 2013; Učkar and Petrović, 2022; Wanke and Barros, 2016), though most studies have assessed efficiency in isolation, without integrating key risk factors. Recent literature increasingly advocates for a holistic approach that reflects the evolving risk landscape of the insurance industry. Additionally, studies highlight the influence of ownership structure (Cummins and Xie, 2016), corporate governance (Huang et al., 2011) and consolidation (Cummins et al., 1999; Mühlnickel and Weiss, 2015) on efficiency. These findings support the inclusion of the ME sub-indicator in the RMI, as effective governance is essential for sustaining operational efficiency.

Systemic and macroeconomic risks are increasingly emphasized in the literature. Mühlnickel and Weiss (2015) highlight the impact of systemic risk, exemplified by the collapse of the American International Group. Drake et al. (2017) and Jurčević and Mihelja Žaja (2013) examine the efficiency of the insurance sector during financial crises. Both underscore the interrelationship between risk management and operational efficiency, supporting the inclusion of CA and S sub-indicators in the RMI to capture a firm resilience to financial shocks.

Micro-level risk management significantly influences insurer efficiency. Huang and Paradi (2011) demonstrate that insurers with robust risk management practices, particularly in risk reserves and underwriting, achieve higher efficiency. This finding supports the inclusion of provisions and retention ratios in the S sub-indicator. Cheng and Weiss (2013) positively link capital and risk, thereby justifying the CA sub-indicator. Similarly, Eling and Schaper (2017) and Peng and Lian (2021) show that diversification improves efficiency, reinforcing the inclusion of the AQ sub-indicator. In contrast, Eling and Jia (2018) emphasize that technical inefficiency, measured by the ME sub-indicator, combined with business volatility, heightens the risk of failure, highlighting the critical role of stability measures within the RMI.

Recent empirical studies support the RMI's multidimensional structure and its components. Goyal and Gulati (2024) identify key insurer-specific risks (underwriting, investment, insolvency, and total risk) that correspond to the RMI's CAMES framework: ME (underwriting risk), AQ (investment risk), S (insolvency risk), and CA (overall risk exposure). Similarly, Abu Al-Haija and Houcine (2023) emphasize the significance of equity and financial leverage, thereby validating the CA sub-indicator. Zweifel (2019) highlights the increasing importance of the Solvency III framework, reinforcing the relevance of solvency ratios and retention measures in the CA and S dimensions. Bressan (2018) finds that while lower retention (indicating more reinsurance) improves solvency by alleviating capital strain, it may also reduce profitability – a trade-off captured in the S sub-indicator. Sharif et al. (2024) demonstrate that effective management of solvency and underwriting risk enhances performance, underscoring the necessity of risk-adjusted efficiency measures. Aouini and Abdennadher (2022) link risk premiums and asset levels to ROA, justifying their inclusion in the E sub-indicator. Finally, Abel and Marire (2021) apply the Boone indicator to assess competition, while Caporale et al. (2017) emphasize how credit and liquidity risks contribute to insolvency to further support the comprehensive nature of the RMI.

Despite research on insurance efficiency and risk management, most studies evaluate risk factors individually, overlooking their combined impact on operational efficiency. This study addresses that gap by developing a composite RMI of five key risk dimensions. The RMI serves as a novel, insurer-specific, and risk-adjusted tool for assessing operational efficiency, providing significant contributions to both academic research and regulatory practice.

4. Methodology

This study develops the RMI using the constrained DEA BoD model, following OECD (2008) guidelines for composite indicators. DEA, introduced by Charnes et al. (1978) and extended by Banker et al. (1984). It was adapted into the BoD model by Melyn and Moesen (1991) and further refined by Cherchye et al. (2004, 2007, 2008). Following Gulati (2023), who applied this methodology to create a Bank Stability Index (BSI) for Indian banks, we adopt the constrained DEA BoD model. The constrained form of the DEA BoD provides a more objective and data-driven RMI by minimizing subjectivity in weight allocation.

The constrained BoD model employs a non-parametric DEA approach, providing flexibility for benchmarking. Since the DEA does not incorporate an error term to account for random variability, inaccuracies in the data may be misinterpreted as inefficiencies. To mitigate this issue, we meticulously clean and preprocess the data. Winsorisation at the 5th and 95th percentiles mitigates outliers, followed by min-max normalization to scale values between 0 and 1, for variables with positive, and max-min scaling for variables with negative effects on the composite index, as required by the DEA BoD model (Gulati, 2023). Finally, Z-normalization (mean = 100, standard deviation = 10) ensures that all 15 financial variables remain positive, thereby preserving their integrity in the construction of the RMI. The variables are subsequently weighted and aggregated into BoD scores for each RMI sub-indicator using the Compind package in R (Vidoli and Fusco, 2018). Weight constraints are implemented, with limits set at 10-80% at the sub-indicator level and a 60% cap at the final RMI level to prevent any single sub-indicator from dominating the results. This methodology aligns the findings of Vidoli and Fusco (2018), Gulati et al. (2020), Gulati (2023), and Maricic and Jeremic (2023), who emphasize that such constraints help to avoid overfitting and inflated efficiency scores, typical of unconstrained DEA, enhancing transparency and interpretability, while reducing subjectivity compared to equal or expert-based weighting.

The proposed composite RMI consists of five dimensions/sub-indicators (CA, AQ, ME, E, S) collectively referred to as the CAMES framework. This framework is adapted from the banking-focused CAMEL model, substituting liquidity (L) with S to more effectively capture the long-term financial resilience that is essential in the insurance industry (Gulati et al., 2020, 2023; Pekkaya and Demir, 2018; Shaddady and Moore, 2019).

Since the DEA BoD model is data-driven, bias may occur if variables are poorly specified, making robust variable selection and weighting constraints essential. Variable selection is guided by the literature and empirical relevance to ensure RMI robustness. For instance, the capital and surplus to total assets ratio and the solvency ratio correspond to the CA and S sub-indicators, effectively capturing insurers' financial resilience. The expense ratio and ROA represent ME and E, measuring cost efficiency and profitability, respectively. Investment yield serves as a key component for AQ, reflecting investment performance. Additionally, the ratio of net premiums written to capital and surplus addresses underwriting (CA), investment yield also captures investment-related risk (AQ), and retention ratio indicates the insurers' risk appetite (S). Collectively, these variables provide a comprehensive view of insurer risk profiles, reinforcing the RMI's role as an integrated measure that links risk management to operational efficiency.

Figure 1 illustrates the sub-indicators of the RMI, with (+) or (–) symbols indicating whether higher or lower values are preferable.

[Figure 1 about here]

Capital Adequacy is assessed using three key indicators that collectively evaluate whether an insurer is adequately capitalized to manage its risks:

- Capital and surplus to total assets ratio indicates the proportion of an insurer's assets financed by equity. A higher ratio indicates enhanced financial stability and provides a large safety cushion against unforeseen losses.
- Net premiums written to capital to surplus ratio measures underwriting volume relative to the capital base. Lower values are preferred, as conservative underwriting strategies limit exposure to claims relative to available capital.
- Total gross provisions to capital and surplus ratio evaluates the scale of reserves set aside relative to capital. Higher values may indicate expectations of increased future liabilities. Lower values suggest confidence in the current risk exposure and effective risk management.

Asset Quality is assessed using three key indicators that collectively provide insight into asset allocation efficiency, investment performance, and the balance between core underwriting and investment activities:

- Total investment to total assets ratio indicates the proportion of an insurer's assets allocated to investments. Higher values suggest stronger revenue generation through investments; however, they can also increase exposure to market risks. Since insurers are not solely investment entities, an excessive focus on investments may indicate a shift away from core insurance operations.
- Investment yield measures the returns relative to an investment portfolio. A higher yield indicates better investment performance; however, it may also indicate higher risk exposure if driven by riskier investments.
- Underwriting results to net investment income ratio compares profitability from underwriting activities relative to investment income. Higher ratios are preferred, as they indicate a stronger reliance on core insurance operations rather than on investment returns, signaling healthier underwriting performance.

Management efficiency is assessed using three key indicators that reflect insurers' operational efficiency in underwriting core operations:

- Balance on the combined technical account represents the net result from underwriting after deducting claims, expenses, and reinsurance costs. A positive balance indicates effective risk management and cost control, contributing to profitability.
- Underwriting expenses to underwriting income ratio reflects the share of income consumed by expenses, and it can be characterized as the efficiency ratio for insurers. Lower values are preferred, as they indicate higher operational efficiency.

- Expense ratio compares underwriting expense to earned premiums. A lower ratio indicates more effective cost management in relation to revenue, thereby enhancing profitability.

Earnings are assessed through three key indicators: Return on Assets (ROA), Profit Margin, and Return on Equity (ROE), all calculated based on profit/loss before tax. These indicators capture an insurer's profitability in relation to its assets, equity, and revenue retention. Higher values across these indicators signify stronger profitability, improved cost management, and more efficient resource utilization. Together, they provide a comprehensive overview of an insurer's financial performance and operational efficiency.

Solvency is a critical component of the proposed RMI, assessed through three key metrics that demonstrate an insurers' financial resilience and capacity for effective risk-management:

- Solvency ratio measures an insurer's capital and surplus in relation to its total assets, indicating its ability to meet long-term obligations. Higher values signify stronger financial stability and a greater capacity to absorb losses.
- Total gross provisions to gross written premiums assesses the amount an insurer reserves for future claims in relation to its premiums. A higher ratio indicates prudent risk management and financial stability; however, excessively high reserves may limit profitability.
- Retention ratio, calculated as net premiums written divided by gross premiums written, reflects an insurer's risk retention in relation to reinsurance. A higher ratio indicates greater risk retention, which may enhance profitability but also increases exposure to potential losses. Conversely, lower values suggest a more conservative approach, resulting in reduced risk.

This study employs the constrained DEA BoD model due to its advantages over other weighting methods such as Equal Weighting (EW), expert-based weighting, Factor Analysis (FA), Principal Component Analysis (PCA), and Multiple Discriminant Analysis (MDA). EW and expert-based weighting opinions are highly subjective, with EW oversimplifying by assuming equal importance across all dimensions. Although FA and PCA are objective, they derive weights from statistical variance, often lacking economic interpretability. MDA is better suited for classification tasks rather than for generating continuous efficiency scores. In contrast, the constrained DEA BoD model produces data-driven weights, thereby reducing subjectivity and avoiding reliance on purely statistical variation. This study implements rigorous data preprocessing, outlier treatment, and weight constraints, along with careful variable selection grounded in both theoretical frameworks and recent empirical evidence. Consequently, the proposed RMI offers a balanced, reliable, and economically meaningful measure of risk-adjusted efficiency for the insurance sector.

5. Data

This study analyzes a longitudinal sample obtained from the Orbis database over the period from 2012 to 2021, comprising 744 insurance companies across 31 countries, each exceeded USD 1 billion in total assets. This threshold is frequently used in financial efficiency studies to ensure both comparability and relevance. While focusing on larger insurers enhances data reliability, it may also introduce selection bias by excluding smaller or less stable firms -

particularly from emerging markets - that are more likely to be omitted due to incomplete records. Such firms may exhibit distinct risk management practices and efficiency characteristics, potentially limiting the generalizability of the findings. The financial data used to construct the RMI (Figure 1, Table 1) are sourced from insurer's financial statements, which are generally regarded as reliable. Nevertheless, variations in accounting standards across countries may affect data comparability, and standardization techniques were applied, as detailed in the Methodology section.

The dataset's balanced panel structure promotes reliability by using complete longitudinal data. The final sample reflects a strong representation of firms from developed economies, particularly North America (460; 61.83%) and Europe (226; 30.38%), with limited representation from other regions, i.e., Asia (42; 5.65%), South America (7; 0.94%), Africa (1; 0.13%), and Australia (8; 1.08%). This geographical concentration may shape the interpretation of results, which likely reflect the practices of large, well-capitalized insurers, thus potentially limiting the applicability of the RMI to insurance companies in emerging economies. Appendix Table A lists the countries included, and Appendix Figure A provides a visual distribution. Summary statistics for all financial variables are presented in Table I.

[Table I about here]

While the study design enhances internal validity, future research should explore more inclusive samples - particularly involving smaller insurers and emerging economies - to broaden the applicability of the RMI framework.

6. Results and discussion

The analysis of the proposed RMI and its sub-indicators offers valuable insights into the effectiveness of risk management across the included insurance companies. The average RMI was highest in 2015 (0.9536) and lowest in 2017 (0.9233), with an overall average of 0.9295. Among the sub-indicators, CA achieved the highest efficiency (0.9248), suggesting that insurance companies must improve by 0.0752 to attain the efficiency frontier. This was followed closely by AQ and S (each 0.91) while ME and E produced lower scores (Table II). Weight analysis further indicates that CA is the most influential sub-indicator in constructing the RMI. Panel data analysis confirms that all sub-indicators positively and significantly influence the RMI, with AQ and S contributing the most.

[Table II about here]

To evaluate the relationship between the RMI and its components, and the relationship between insurer efficiency and risk management, panel data fixed effects models with robust standard errors are employed. This approach accounts for both differences between (heterogeneity) and within an insurance companies over time. Consequently, simple linear correlations between the proposed RMI and insurers efficiency could yield misleading results and therefore are not reported here.

Econometric analysis indicates RMI has a positive, statistically significant effect on operational efficiency. Apart from S sub-indicator, the sub-indicators CA, AQ, ME, and E display negative coefficients, indicating that higher values in these specific risk elements are associated with lower efficiency. To further validate our empirical results, the fixed effect with robust (HAC) errors was employed based on the results of the Hausman test, with sensitivity analysis using Variance Inflation Factor (VIF) tests (Appendix Table B).

Implementing BoD models facilitates the generation of unbiased weights; however, these models have limitations (Maricic and Jeremic, 2023). A conventional robustness check typically involves assessing the contributions of individual indicators, though such an approach is not applicable to BoD models that utilize entity-specific weights. Gulati (2023) reports that for financial institutions, lower bounds of 10% are most appropriate according to robustness checks performed by analyzing variations in bank rankings using Z-scores, FA, EW, and constrained BoD methodologies.

Table III displays the average weights of the RMI sub-indicators. CA has the highest average weight at 0.3152, followed by S (0.2046), and AQ (0.1951). In contrast, ME and E exhibited the lowest average weights (0.1451 and 0.1401). These findings imply that capitalization, as reflected in CA and S, play a critical role in assessing the quality of an insurer's risk management.

[Table III about here]

Table IV provides an analysis of the weights assigned to each sub-indicator. For CA, the ratio of the total gross provisions to capital and surplus (0.6102) is the most significant indicator, followed by the ratio of the net premiums written to capital and surplus (0.2481). Conversely, the ratio of capital and surplus to total assets is lowest (0.1417). These findings indicate that reserves maintained by insurers for future claims in relation to their equity represent the most critical factor in assessing CA.

[Table IV about here]

For AQ, the ratio of total investments to total assets (0.5088) is the most significant indicator of insurance companies' asset quality, followed by investment yield (0.2775). Conversely, the underwriting result for the net investment income ratio has the lowest weight (0.2138). ME is primarily assessed through the expense ratio (average 0.5861), highlighting the critical importance of cost minimization in relation to earned income. The ratio of total underwriting expenses to total underwriting income (0.2645) underscores the insurers' essential role of operational efficiency. In contrast, the balance on the combined technical account has the lowest average weight (0.1674). A detailed examination of efficient insurance companies, characterized by a RMI of 1, signifying effective risk management, indicates that their average weights exhibit slight variations from those previously documented. Analyzing risk-adjusted efficient insurance companies reveals that CA has the highest average weight (0.3035), followed by ME (0.2071), S (0.1978), AQ (0.1619) and E as lowest (0.1297). This suggests that insurance companies should prioritize maintaining robust capital levels while remaining attentive to their solvency and strive to enhance their cost efficiency. In contrast, the worst-performing insurance companies tend to disproportionately emphasize AQ (0.2633) and S (0.2596), while placing less importance on ME (0.1313) and E (0.1000). Consequently, to improve their risk-adjusted efficiency, underperforming insurance companies should redirect their focus towards capital adequacy and solvency, while reducing their emphasis on asset quality, as investing is not an insurers' primary business.

To test H1: There is a significant relationship between insurance companies' specific risks (CAMES) and the composite risk management index, we construct the following econometric model (1):

$$RMI_{it} = \beta_{0i} + \beta_1 CA_{1t} + \beta_2 AQ_{2t} + \beta_3 ME_{3t} + \beta_4 E_{4t} + \beta_5 S_{5t} + u_{it} \quad (1)$$

i = 1,2,…, 744; t = 1,2,…, 10

Where is denoted:

- β_{0i} – intercept of insurance company *i,*
- RMI_{it} – dependent variable, and the RMI for insurance company *i* at time *t*
- CA_{1t} – independent variable CA sub-indicator for insurance company *i* at time *t*
- AQ_{2t} – independent variable AQ sub-indicator for insurance company *i* at time *t*
- ME_{3t} – independent variable ME sub-indicator for insurance company *i* at time *t*
- E_{4t} – independent variable E sub-indicator for insurance company *i* at time *t*
- S_{5t} – independent variable S sub-indicator for insurance company *i* at time *t*
- u_{it}- is the error term.

The evaluated model is as follows:

$$RMI_{it} = \hat{\beta}_{0i} + \hat{\beta}_1 CA_{1t} + \hat{\beta}_2 AQ_{2t} + \hat{\beta}_3 ME_{3t} + \hat{\beta}_4 E_{4t} + \hat{\beta}_5 S_{5t} + e_{it} \quad (2)$$

i = 1,2,…, 744; t = 1,2,…, 10

The results of the Hausman test (p = 3.67498e-05) advocate for the employment of fixed effects panel data model, incorporating robust (HAC) standard errors, to address potential concerns related to autocorrelation and heteroscedasticity. To ensure the robustness of the regression model, we conducted VIF tests with all values below 2, indicating no serious multicollinearity concerns. Full additional test results are reported in the Appendix Table B. Table V presents the results of the fixed effects panel data model, including robust (HAC) standard errors for H1.

[Table V about here]

Our findings indicate that all components (CA, AQ, ME, E, S) exhibit a positive, statistically significant relationship with the composite RMI (RMI, $p < 0.0001$). Notably, S demonstrates the highest coefficient, suggesting that a one-unit increase in solvency corresponds to a 0.2471 increase in RMI, while a one-unit increase in AQ results in a 0.1779 increase in RMI. The model accounts for over 97% of the variance in the RMI (LSDV $R^2 = 0.9748$) with an overall R^2 of 0.9325, indicating that 93% of the variation within individual insurance companies can be attributed to the CAMES components of the RMI. A Durbin-Watson statistic of 1.683 indicates that autocorrelation is not a major concern. Furthermore, the Wooldridge test for autocorrelation ($p = 0.1305$) failed to reject the null hypothesis, suggesting the absence of first-order autocorrelation. The Pesaran CD test for cross-sectional dependence ($z = 82.54$, $p = 0$) indicated significant cross-sectional dependence, which is common in large panel datasets of financial institutions operating under shared macroeconomic and regulatory conditions. This cross-sectional dependence implies that some unobserved factors influence all units within the panel. The use of HAC standard errors mitigates this issue, ensuring robust inference despite cross-sectional correlation. Consequently, we reject the null hypothesis for H1, concluding that there is a significant positive relationship between the specific risks of insurance companies, as measured by the CAMES components, and the RMI, with AQ and S playing the most substantial roles in determining the RMI.

To test H2: There is a significant relationship between RMI and insurance companies' operational efficiency, we construct the following econometric model:

$$ER_{it} = \beta_{0i} + \beta_1 RMI_{1t} + \beta_2 CA_{2t} + \beta_3 AQ_{3t} + \beta_4 ME_{4t} + \beta_5 E_{5t} + \beta_6 S_{6t} + u_{it} \quad (3)$$
$$i = 1,2,\ldots,744;\ t = 1,2,\ldots,10$$

where the dependent variable is the ratio of total underwriting expenses to total underwriting income, as it reflects the efficiency of the insurer's core operations (efficiency ratio). The independent variables include the RMI and its components (CA, AQ, ME, E, S). The model under evaluation was as follows:

$$ER_{it} = \hat{\beta}_{0i} + \hat{\beta}_1 RMI_{1t} + \hat{\beta}_2 CA_{2t} + \hat{\beta}_3 AQ_{3t} + \hat{\beta}_4 ME_{4t} + \hat{\beta}_5 E_{5t} + \hat{\beta}_6 S_{6t} + e_{it} \quad (4)$$
$$i = 1,2,\ldots,744;\ t = 1,2,\ldots,10$$

Following the results of the Hausman test (p = 3.74467e-112) we employ a fixed effects panel data model, incorporating robust (HAC) standard errors, to address potential concerns related to autocorrelation and heteroscedasticity. To ensure the robustness of the regression model we conducted VIF tests, with all values below 5, and no serious multicollinearity concerns were observed, except for RMI (19.169). While the VIF for RMI exceeds the conventional threshold (> 10), this is an expected consequence given that RMI is an aggregate of the five sub-indicators. Retaining both RMI and its components allows the model to disentangle the overall effect of comprehensive risk management from the marginal influence of each risk factor, and does not affect inference on the composite index itself. Full additional test results are reported in the Appendix Table B. Table VI presents the results of the fixed effects panel data model, including robust (HAC) standard errors for H2.

The RMI shows a positive, statistically significant effect on operational efficiency, with a coefficient of 1.1375 ($p < 0.0001$). This suggests that comprehensive risk management practices positively influence operational efficiency in the insurance sector. All RMI components are significant at $p < 0.0001$. Individual components (CA, AQ, ME, and E) display negative coefficients, indicating that higher values in these specific risk elements are associated with lower efficiency, while S displayed a positive coefficient (0.6612).

The results indicate that a one-unit increase in RMI leads to an increase of 1.1375 in the efficiency ratio, defined as the ratio of total underwriting expenses to total underwriting income. In the case of S, the increase is 0.6612 in the efficiency ratio respectively. Conversely, the negative coefficient for ME (−1.1170; $p < 0.0001$), indicates a strong, statistically significant, inverse relationship with efficiency. This finding implies that a higher management efficiency is associated with a lower operational efficiency. The R^2 value of 0.7199 indicates that the model accounts for a considerable proportion of the variation in operational efficiency (72%), while a within-unit R^2 of 0.5595 reflects individual variances among insurers. The positive impact of the RMI on operational efficiency supports the theoretical proposition that a comprehensive approach to risk management can enhance operational efficiency in insurance firms. This finding aligns with previous research that highlights the efficiency benefits of robust risk management practices (Cheng and Weiss, 2013; Huang and Paradi, 2011). S and CA are core components of risk management. Bressan (2018) posits that these components can be viewed as substitutes for improving solvency. Consequently, it is reasonable to assert that solvency has a positive effect on insurer's operational efficiency.

[Table VI about here]

The inverse relationships CA, AQ, ME, and E with efficiency warrant further exploration. The negative coefficient associated with CA suggests that while maintaining adequate capital and surplus reduces risk, it may also restrict funds that could otherwise be used for operational activities, increasing underwriting costs relative to underwriting income. This relationship highlights a potential trade-off in resource allocation between stability and operational efficiency, echoing findings by Cheng and Weiss (2013) who identified a complex dynamic between capital strength and efficiency outcomes in insurers. The negative impact of AQ on efficiency may be due to the nature of insurance as a service-oriented, risk-pooling business. Insurers that prioritize asset quality and investment efficiency may resemble investment-focused entities, such as investment funds or holding companies slowly diverging from their core insurance business. This suggests that insurers heavily dependent on investment income may experience inefficiencies in their core underwriting insurance operations. The inverse relationship between ME and operational efficiency may arise from the resource-intensive characteristics of risk management functions. Adequate risk management activities require additional personnel and capital, negatively affecting operational efficiency. The negative relationship between E and efficiency corroborates the prevailing perspective that higher returns are generally associated with increased risk. The pursuit of profit maximization may compel insurers to pursue high-risk investment strategies, which can undermine cost-efficient underwriting practices.

The RMI represents a significant advancement over previous indicators, such as the Boone indicator (Abel and Marire, 2021) and the risk premium measures (Aouini and Abdennadher, 2022), which tend to focus on narrower aspects of risk management. While the Boone indicator assesses competitive efficiency in the insurance sector, it does not provide the multi-dimensional perspective required for assessing risk-adjusted operational efficiency. In contrast, the five crucial components of the RMI offers a more comprehensive measure of insurers' ability to manage risk effectively, giving nuanced insight into operational performance, and emphasizing solvency as a pivotal component of the RMI, as previously noted by Zweifel (2019). By encompassing multiple risk dimensions, the RMI improves the ability to evaluate risk-adjusted efficiency more accurately, addressing an identified gap in the insurance efficiency literature.

The study emphasizes the significance of robust risk management practices for insurance managers in improving operational efficiency. The observed positive relationship between the RMI and operational efficiency underscores the strategic importance of adopting comprehensive risk management strategies. Insurance managers should balance investment strategies with a disciplined focus on risk pooling and claims management and prioritize the optimization of resource allocation across the RMI sub-indicators, particularly CA and S.

For practitioners, the findings suggest that enhancing solvency buffers directly improves operational efficiency, while excessive focus on asset quality may divert resources from core underwriting operations. For regulators, the RMI can serve as an early-warning diagnostic tool. Regulatory guidelines may be refined to encourage insurers to optimize their capital adequacy while maintaining operational efficiency. Policymakers can use RMI as a diagnostic tool to assess the risk management quality of insurance companies. By identifying insurers with inadequate risk management, the RMI enables timely interventions that can avert systemic disruptions. Furthermore, regulators may consider using these insights to refine guidelines, advocating for adequate risk management that improve operational efficiency and increases stability of insurers. Future stress tests could incorporate the RMI framework to evaluate systemic vulnerabilities within the insurance sector.

Since this novel CAMES framework is adapted from the widely accepted CAMEL model used for evaluating bank performance, it inherits certain limitations. Specifically, it relies on historical financial data, restricting its ability to predict future risk developments. Additionally, while composite indices like the RMI simplify complex data, they risk oversimplification if not carefully designed (OECD, 2008). To address this issue, the RMI balances data complexity with interpretability, providing a practical tool for evaluating risk management. As noted by Gulati (2023), the constrained DEA BoD model reduces subjectivity while remaining effective, even with smaller sample sizes. Furthermore, by concentrating exclusively on firm-level indicators, the framework fails to account for macroeconomic factors or market sensitivity. These limitations are partly driven by data availability and the lack of a standardized definition for certain financial indicators, and merit further study.

7. Conclusion

This study investigates the relationship between insurance companies' specific risks, represented by five sub-indicators (CA, AQ, ME, E, S) referred to as the CAMES framework, and introduces a novel composite RMI to evaluate the risk-adjusted efficiency of insurance companies. It further explores how risk management, captured by the RMI, influences operational efficiency, measured as the ratio of total underwriting expenses to underwriting income. Using a large panel dataset of 744 insurers from 32 countries over 2012 - 2021, the results reveal that CA and S are the most significant drivers of adequate risk management. While the RMI and S positively affect efficiency, the remaining sub-indicators exhibit inverse relationships with operational efficiency. This highlights an important trade-off, implying that insurance companies should focus on enhancing their capital adequacy and solvency to improve their overall risk management.

The findings offer actionable insights for both practitioners and regulators. For insurers, strengthening solvency and maintaining adequate capital reserves are essential for enhancing risk-adjusted efficiency. Conversely, overemphasis on asset accumulation may reduce underwriting efficiency. Therefore, managers should balance prudential risk management with operational cost control.

For regulators, the novel RMI presents a practical diagnostic tool in identifying insurers with inadequate risk management practices. The RMI is useful in evaluating and benchmarking insurance companies, thus supporting regulators in risk-based supervision, stress testing, and early warning systems, which is particularly relevant amid increasing sensitivity and links within and between the financial sectors.

This study contributes to the literature by offering a novel, multidimensional and empirically validated composite RMI that expands beyond unidimensional approaches such as Boone indicator, risk premium measures, or focusing on risk disclosures. The proposed RMI provides a holistic, tailor-made approach for insurance companies, generating useful and practical insights.

Several limitations warrant consideration. While efficient in composite index construction, the DEA BoD framework lacks a stochastic error term and is therefore sensitive to variable selection and the accuracy of input data. Variable selection is based on the newly proposed CAMES framework and validated through several economic and financial theories and common variables. Since the CAMES framework is still new, it does not fully eliminate subjectivity in variable selection, thus more research is needed. Additionally, the observed cross-sectional dependence among firms indicates that unobserved global or systemic (macroeconomic) factors influence insurer behavior, suggesting the need to incorporate macroeconomic data. The study's emphasis on larger insurers, particularly in the USA and EU, may limit the generalizability of findings to smaller insurers or emerging markets.

Future research can enhance the RMI framework by refining variable selection to more accurately reflect the RMI sub-indicators, while integrating macroprudential data into the RMI to explore novel stress-testing frameworks to gain valuable insights into the effect of systemic risk within the insurance sector. Future studies can employ alternative methodologies such as stochastic DEA, unsupervised constraint DEA BoD models, and machine learning generated composite indices to reduce model sensitivity and improve robustness. Additionally, extending the sample to include smaller insurers or focusing on specific regions could yield valuable insights into insurers' risk management practices.

References

Abel, S. and Marire, J. (2021), "Competition in the insurance sector – An application of Boone indicator", Cogent Economics & Finance, Cogent, Vol. 9 No. 1, doi: 10.1080/23322039.2021.1974154.

Abu Al-Haija, E. and Houcine, A. (2023), "Risk management efficiency of Takaful and conventional insurance sectors in UAE and KSA", Journal of Islamic Accounting and Business Research, Emerald Publishing, Vol. ahead-of-print No. ahead-of-print, doi: 10.1108/JIABR-03-2022-0065/FULL/XML.

Alhassan, A.L. and Biekpe, N. (2015), "Efficiency, Productivity and Returns to Scale Economies in the Non-Life Insurance Market in South Africa", The Geneva Papers on Risk and Insurance. Issues and Practice, Vol. 40 No. 3, pp. 493–515.

Aouini, A. and Abdennadher, C. (2022), "Performance in the Insurance Industry (Islamic versus Conventional) and Risk Management", Journal of Financial Risk Management, Scientific Research Publishing, Vol. 11 No. 3, pp. 601–620, doi: 10.4236/JFRM.2022.113028.

Bhuyan, R., Butchey, D., Haar, J. and Talukdar, B. (2022), "CEO compensation and firm performance in the insurance industry", Managerial Finance, Emerald Group Holdings Ltd., Vol. 48 No. 7, pp. 1086–1115, doi: 10.1108/MF-04-2019-0154/FULL/XML.

Bomhard, N. von. (2005), "Risk and Capital Management in Insurance Companies", The Geneva Papers on Risk and Insurance - Issues and Practice, Vol. 30 No. 1, pp. 52–59.

Bressan, S. (2018), "The Impact of Reinsurance for Insurance Companies", Risk Governance and Control: Financial Markets & Institutions, Virtus Interpress, Vol. 8 No. 4, p. 22, doi: 10.22495/RGCV8I4P3.

Caporale, G.M., Cerrato, M. and Zhang, X. (2017), "Analysing the determinants of insolvency risk for general insurance firms in the UK", Journal of Banking & Finance, North-Holland, Vol. 84, pp. 107–122, doi: 10.1016/J.JBANKFIN.2017.07.011.

de Castries, H. (2005), "Capital Adequacy and Risk Management in Insurance", The Geneva Papers on Risk and Insurance - Issues and Practice, Vol. 30 No. 1, pp. 47–51, doi: 10.1057/palgrave.gpp.2510017.

Cheng, J. and Weiss, M.A. (2013), "Risk-Based Capital and Firm Risk Taking in Property-Liability Insurance", The Geneva Papers on Risk and Insurance - Issues and Practice, Vol. 38 No. 2, pp. 274–307, doi: 10.1057/gpp.2013.2.

Coase, R.H. (1937), "The Nature of the Firm", Economica, Vol. 4 No. 16, pp. 386–405, doi: 10.1111/j.1468-0335.1937.tb00002.x.

Cummins, J.D., Tennyson, S. and Weiss, M.A. (1999), "Consolidation and efficiency in the US life insurance industry", Journal of Banking & Finance, Vol. 23 No. 2–4, pp. 325–357, doi: 10.1016/S0378-4266(98)00089-2.

Cummins, J.D. and Xie, X. (2016), "Efficiency and Productivity in the US Property-Liability Insurance Industry: Ownership Structure, Product and Distribution Strategies", International Series in Operations Research and Management Science, Springer, Boston, MA, Vol. 238, pp. 113–163, doi: 10.1007/978-1-4899-7684-0_6.

Demsetz, H. (1988), "The Theory of the Firm Revisited", Journal of Law, Economics, & Organization, Vol. 4 No. 1, pp. 141–161.

Drake, P.P., Neale, F.R., Schorno, P.J. and Semaan, E. (2017), "Risk During the Financial Crisis: The Role of the Insurance Industry", Journal of Insurance Issues, Vol. 40 No. 2, pp. 181–214.

Eling, M. and Jia, R. (2018), "Business failure, efficiency, and volatility: Evidence from the European insurance industry", International Review of Financial Analysis, Vol. 59, pp. 58–76, doi: 10.1016/j.irfa.2018.07.007.

Eling, M. and Luhnen, M. (2010), "Efficiency in the international insurance industry: A cross-country comparison", Journal of Banking & Finance, Vol. 34 No. 7, pp. 1497–1509, doi: 10.1016/j.jbankfin.2009.08.026.

Eling, M. and Schaper, P. (2017), "Under pressure: how the business environment affects productivity and efficiency of European life insurance companies", European Journal of Operational Research, North-Holland, Vol. 258 No. 3, pp. 1082–1094, doi: 10.1016/J.EJOR.2016.08.070.

Erel, I., Myers, S.C. and Read, J.A. (2015), "A theory of risk capital", Journal of Financial Economics, Vol. 118 No. 3, pp. 620–635, doi: 10.1016/j.jfineco.2014.10.006.

Ferro, G. and León, S. (2018), "A Stochastic Frontier Analysis of Efficiency in Argentina's Non-Life Insurance Market", The Geneva Papers on Risk and Insurance - Issues and Practice, Vol. 43 No. 1, pp. 158–174.

Goyal, B. and Gulati, R. (2024), "Insurer's Risk-Taking Behavior in India: Does the Board matter?", International Journal of the Economics of Business, Routledge, Vol. 31 No. 2, pp. 131–173, doi: 10.1080/13571516.2024.2320455.

Grmanová, E. and Strunz, H. (2017), "Efficiency of insurance companies: Application of DEA and tobit analyses", Journal of International Studies, Centre of Sociological Research, Vol. 10 No. 3, pp. 250–263, doi: 10.14254/2071-8330.2017/10-3/18.

Gulati, R. (2023), "Beyond the Z-score: A novel measure of bank stability for effective policymaking", Journal of Public Affairs, John Wiley & Sons, Ltd, Vol. 23 No. 4, p. e2866, doi: 10.1002/PA.2866.

Gulati, R., Hassan, M.K. and Charles, V. (2023), "Developing a New Multidimensional Index of Bank Stability and Its Usage in the Design of Optimal Policy Interventions", Computational Economics, doi: 10.1007/s10614-023-10401-7.

Gulati, R., Kattumuri, R. and Kumar, S. (2020), "A non-parametric index of corporate governance in the banking industry: An application to Indian data", Socio-Economic Planning Sciences, Pergamon, Vol. 70, p. 100702, doi: 10.1016/J.SEPS.2019.03.008.

Huang, L.-Y., Lai, G.C., McNamara, M. and Wang, J. (2011), "Corporate Governance and Efficiency: Evidence From U.S. Property-Liability Insurance Industry", The Journal of Risk and Insurance, Vol. 78 No. 3, pp. 519–550, doi: 10.1111/j.1539-6975.2011.01410.x.

Huang, W. and Paradi, J.C. (2011), "Risk-adjusted efficiency of the insurance industry: Evidence from China", Service Industries Journal, Vol. 31 No. 11, pp. 1871–1885, doi: 10.1080/02642069.2010.503875.

Jensen, M.C. and Meckling, W.H. (1976), "Theory of the firm: Managerial behavior, agency costs and ownership structure", Journal of Financial Economics, Vol. 3 No. 4, pp. 305–360, doi: 10.1016/0304-405X(76)90026-X.

Jurčević, B. and Mihelja Žaja, M. (2013), "Banks and Insurance Companies Efficiency Indicators in the Period of Financial Crisis: The Case of the Republic of Croatia", Economic Research-Ekonomska Istraživanja, Routledge, Vol. 26 No. 1, pp. 203–224, doi: 10.1080/1331677X.2013.11517598.

Klotzki, U., Bohnert, A., Gatzert, N. and Vogelgesang, U. (2018), "Economies of scale in European life insurance", Journal of Risk Finance, Emerald Group Publishing Ltd., Vol. 19 No. 2, pp. 190–207, doi: 10.1108/JRF-03-2017-0055/FULL/XML.

Knight, F.H. (1921), Risk, Uncertainty and Profit, University of Illinois at Urbana-Champaign's Academy for Entrepreneurial Leadership Historical Research Reference in Entrepreneurship.

Malafronte, I., Porzio, C. and Starita, M.G. (2016), "The nature and determinants of disclosure practices in the insurance industry: Evidence from European insurers", International Review of Financial Analysis, North-Holland, Vol. 45, pp. 367–382, doi: 10.1016/J.IRFA.2015.02.003.

Malafronte, I., Starita, M.G. and Pereira, J. (2018), "The effectiveness of risk disclosure practices in the European insurance industry", Review of Accounting and Finance, Vol. 17 No. 1, pp. 130–147, doi: 10.1108/RAF-09-2016-0150.

Mamatzakis, E. (2015), "Risk and efficiency in the Central and Eastern European banking industry under quantile analysis", Quantitative Finance, Vol. 15 No. 3, pp. 553–567, doi: 10.1080/14697688.2012.715245.

Mamatzakis, E., Staikouras, C., Triantopoulos, C. and Wang, Z.C. (2023), "Measuring the efficiency and productivity of U.K. insurance market", International Journal of Finance & Economics, doi: 10.1002/ijfe.2723.

Maricic, M. and Jeremic, V. (2023), "Imposing unsupervised constraints to the Benefit-of-the-Doubt (BoD) model", Metron, Springer-Verlag Italia s.r.l., Vol. 81 No. 3, pp. 259–296, doi: 10.1007/S40300-023-00254-3/METRICS.

Markowitz, H. (1952), "Portfolio Selection", The Journal of Finance, Vol. 7 No. 1, pp. 77–91, doi: 10.2307/2975974.

Mühlnickel, J. and Weiss, G.N.F. (2015), "Consolidation and systemic risk in the international insurance industry", Journal of Financial Stability, Elsevier, Vol. 18, pp. 187–202, doi: 10.1016/J.JFS.2015.04.005.

OECD. (2008), Handbook on Constructing Composite Indicators: Methodology and User Guide, OECD, doi: 10.1787/9789264043466-en.

Okura, M. and Yanase, N. (2013), "What is the driving force behind consolidations in the insurance market?", Journal of Risk Finance, Emerald Group Publishing Ltd., Vol. 14 No. 2, pp. 108–119, doi: 10.1108/15265941311301152.

Oldfield, G. and Santomero, A. (1970), "The Place of Risk Management in Financial Institutions", Sloan Management Review, Vol. 39.

Pekkaya, M. and Demir, F.E. (2018), "Determining the Priorities of CAMELS Dimensions Based on Bank Performance", in Dincer, H., Hacioglu, U. and Yuksel, S. (Eds.), Global Approaches in Financial Economics, Banking, and Finance, pp. 445–463, doi: 10.1007/978-3-319-78494-6_21.

Peng, L. and Lian, Z. (2021), "Diversification and efficiency of life insurers in China and India", The Geneva Papers on Risk and Insurance - Issues and Practice, Vol. 46 No. 4, pp. 710–730.

Santomero, A. and Babbel, D.F. (1997), "Financial Risk Management by Insurers: An Analysis of the Process", The Journal of Risk and Insurance, Vol. 64 No. 2, pp. 231–270, doi: 10.2307/253730.

Scholtens, B. and van Wensveen, D. (2000), "A critique on the theory of financial intermediation", Journal of Banking & Finance, Vol. 24 No. 8, pp. 1243–1251, doi: 10.1016/S0378-4266(99)00085-0.

Seward, J.K. (1990), "Corporate Financial Policy and the Theory of Financial Intermediation", The Journal of Finance, Vol. 45 No. 2, pp. 351–377, doi: 10.1111/j.1540-6261.1990.tb03694.x.

Shaddady, A. and Moore, T. (2019), "Investigation of the effects of financial regulation and supervision on bank stability: The application of CAMELS-DEA to quantile regressions", Journal of International Financial Markets Institutions and Money, Vol. 58, pp. 96–116, doi: 10.1016/j.intfin.2018.09.006.

Sharif, Md.J., Lily, R.A. and Moniruzzaman, M. (2024), "The Impact of Risk Management on the Financial Performance of the General Insurance Companies in Bangladesh", BUFT Journal of Business & Economics, BGMEA University of Fashion & Technology, Vol. 5, doi: 10.58481/BJBE/2406.

Stulz, R.M. (1984), "Optimal Hedging Policies", The Journal of Financial and Quantitative Analysis, Vol. 19 No. 2, pp. 127–140, doi: 10.2307/2330894.

Stulz, R.M. (2023), Crisis Risk and Risk Management, National Bureau of Economic Research, doi: http://dx.doi.org/10.2139/ssrn.4439633.

Učkar, D. and Petrović, D. (2022), "Efficiency of Insurance Companies in Croatia", Ekonomska Misao i Praksa, Vol. 31 No. 1, pp. 49–79, doi: 10.17818/EMIP/2022/1.3.

Vidoli, F. and Fusco, E. (2018), Compind: Composite Indicators Functions Based on Frontiers in R (Compind Package Version 2.0).

Wanke, P. and Barros, C.P. (2016), "Efficiency drivers in Brazilian insurance: A two-stage DEA meta frontier-data mining approach", Economic Modelling, North-Holland, Vol. 53, pp. 8–22, doi: 10.1016/J.ECONMOD.2015.11.005.

Zweifel, P. (2019), "Planned Solvency III Regulation: Should It Be Adopted Outside the European Union?", Asia-Pacific Journal of Risk and Insurance, De Gruyter, Vol. 13 No. 1, doi: 10.1515/APJRI-2018-0002.

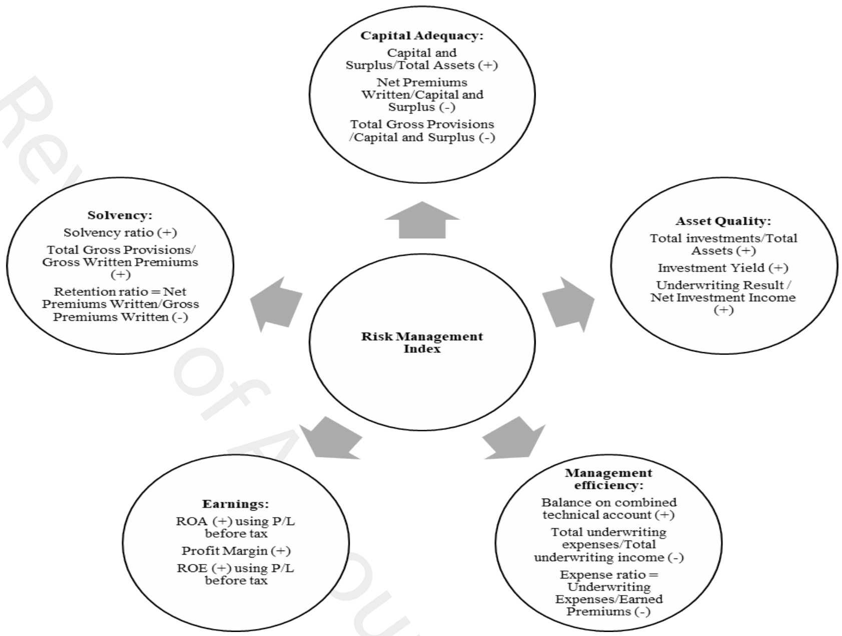
Appendix

[Table A about here]

[Figure A about here]

[Table B about here]

Figure 1 Risk Management Index (RMI)



Source(s): Authors' own work

Table I Summary statistics of 15 indicators

RMI components	Variables	Max	Min	Average	SD
Capital Adequacy	Capital and Surplus / Total Assets	1.05	-0.14	0.30	0.17
	Net Premiums Written / Capital and Surplus	106.95	-87.36	1.30	2.88
	Total Gross Provisions / Capital and Surplus	594.02	-212.12	3.99	12.90
Asset Quality	Total investments / Total Assets	1.00	0.07	0.80	0.15
	Investment Yield	0.64	-0.22	0.03	0.02
	Underwriting Result / Net Investment Income	9.96	-9.88	0.62	1.88
Management Efficiency	Balance on combined technical account in 1,000,000 USD	95,856	-16,953	430	3,321
	Total underwriting expenses / Total underwriting income	18.13	-284.78	0.88	4.08
	Expense ratio = Total Underwriting Expenses / Earned Premiums	18.13	-284.78	0.93	4.09
Earnings	ROE using P/L before tax	8.89	-9.00	0.12	0.30
	Profit margin	4.88	-2.11	0.10	0.19
	ROA using P/L before tax	0.36	-0.17	0.03	0.03
Solvency	Solvency ratio	0.97	-0.15	0.30	0.16
	Total Gross Provisions / Gross Written Premiums	52.89	-3.46	2.30	2.96
	Retention ratio = Net Premiums Written / Gross Premiums Written	1.89	-1.49	0.72	2.96

Source(s): Authors' own work

Table II Average RMI and sub-indicators results

Year	Capital Adequacy	Asset Quality	Management Efficiency	Earnings	Solvency	RMI
2012	0.9270	0.9228	0.8802	0.8346	0.9156	0.9325
2013	0.9260	0.9289	0.8569	0.8359	0.9109	0.9293
2014	0.9266	0.9125	0.8665	0.8329	0.9042	0.9269
2015	0.9272	0.9191	0.9390	0.8339	0.9631	0.9536
2016	0.9263	0.9166	0.8546	0.8275	0.9070	0.9260
2017	0.9237	0.9167	0.8771	0.8342	0.9149	0.9302
2018	0.9212	0.9130	0.8490	0.8387	0.9072	0.9233
2019	0.9231	0.9131	0.8637	0.8246	0.9037	0.9221
2020	0.9217	0.9170	0.8672	0.8260	0.9050	0.9254
2021	0.9250	0.9147	0.8651	0.8245	0.9085	0.9257
Average	0.9248	0.9174	0.8719	0.8313	0.9140	0.9295

Source(s): Authors' own work

Table III Average RMI sub-indicators weights

Year	Capital Adequacy	Asset Quality	Management Efficiency	Earnings	Solvency
2012	0.2992	0.1925	0.1504	0.1435	0.2145
2013	0.3248	0.2281	0.1244	0.1436	0.1791
2014	0.3643	0.1929	0.1346	0.1344	0.1738
2015	0.1614	0.1193	0.2445	0.1214	0.3535
2016	0.3651	0.2113	0.1330	0.1300	0.1607
2017	0.2949	0.2213	0.1432	0.1342	0.2065
2018	0.3128	0.1964	0.1208	0.1564	0.2137
2019	0.3650	0.1927	0.1334	0.1402	0.1688
2020	0.3112	0.1931	0.1327	0.1505	0.2125
2021	0.3531	0.2033	0.1342	0.1469	0.1626
Average	0.3152	0.1951	0.1451	0.1401	0.2046

Source(s): Authors' own work

Table IV Average RMI sub-indicators weights

	Sub-indicator	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	Average
Capital Adequacy	Capital and Surplus / Total Assets	0.1320	0.1188	0.1593	0.1207	0.1593	0.1480	0.1574	0.1310	0.1489	0.1416	0.1417
	Net Premiums Written / Capital and Surplus	0.2762	0.2524	0.2505	0.2468	0.2458	0.2628	0.2214	0.2496	0.2327	0.2430	0.2481
	Total Gross Provisions / Capital and Surplus	0.5918	0.6288	0.5902	0.6325	0.5949	0.5892	0.6212	0.6194	0.6184	0.6153	0.6102
Asset Quality	Total investments / Total Assets	0.5018	0.4997	0.4708	0.5062	0.5076	0.5215	0.5145	0.5160	0.5332	0.5162	0.5088
	Investment Yield	0.3023	0.3213	0.3170	0.2689	0.2777	0.2365	0.2610	0.2729	0.2486	0.2685	0.2775
	Underwriting Result / Net Investment Income	0.1959	0.1790	0.2122	0.2249	0.2147	0.2420	0.2245	0.2112	0.2181	0.2153	0.2138
Management Efficiency	Balance on combined technical account	0.1785	0.1423	0.1546	0.1744	0.1715	0.1950	0.1724	0.1593	0.1584	0.1678	0.1674
	Total underwriting expenses / Total underwriting income	0.2255	0.2176	0.1837	0.6375	0.1659	0.1894	0.2082	0.1724	0.2247	0.2396	0.2465
	Expense ratio	0.5959	0.6401	0.6617	0.1880	0.6626	0.6156	0.6194	0.6683	0.6169	0.5925	0.5861
Earnings	ROE using P/L before tax	0.3817	0.2853	0.2468	0.3079	0.3277	0.3004	0.3277	0.2882	0.3145	0.3035	0.3084
	Profit margin	0.2291	0.1997	0.2383	0.2035	0.1668	0.1762	0.2110	0.1668	0.3192	0.2096	0.2120
	ROA using P/L before tax	0.3892	0.5149	0.5149	0.4886	0.5055	0.5234	0.4613	0.5450	0.3663	0.4868	0.4796
Solvency	Solvency ratio	0.2811	0.3566	0.3835	0.4016	0.3905	0.3778	0.3922	0.3729	0.3821	0.3806	0.3719
	Total Gross Provisions / Gross Written Premiums	0.3253	0.2977	0.2608	0.4113	0.2793	0.3105	0.3027	0.3074	0.3326	0.3122	0.3140
	Retention ratio	0.3936	0.3457	0.3558	0.1871	0.3302	0.3117	0.3051	0.3198	0.2853	0.3072	0.3141

Source(s): Authors’ own work

Table V Fixed effects panel data analysis with robust (HAC) standard errors

Variables	Results
Capital Adequacy (CA)	0.1605*** (0.0053)
Asset Quality (AQ)	0.1779*** (0.0057)
Management Efficiency (ME)	0.1446*** (0.0022)
Earnings (E)	0.1445*** (0.0023)
Solvency (S)	0.2471*** (0.0046)
Constant	0.1458*** (0.0079)
Observations	7,440
R-squared	0.9748
R-squared within	0.9325

Note: The table reports the results from the panel fixed effect with robust (HAC) standard errors regression on the relationship between insurer-specific risks denoted by Capital Adequacy (CA), Asset Quality (AQ), Management Efficiency (ME), Earnings (E), and Solvency (S) sub-indicators and the composite risk management index (RMI). The dependent variable is the composite risk management index (RMI) as constructed in previous sections using the constrained DEA BoD model. Standard errors are reported in parenthesis. *, **, *** indicates significance levels at the 10%, 5%, and 1% respectively.

Source(s): Authors' own work

Table VI Fixed effects panel data analysis with robust (HAC) standard errors

Variables	Results
Risk Management Index (RMI)	1.1375*** (0.1606)
Capital Adequacy (CA)	−0.5001*** (0.0666)
Asset Quality (AQ)	−0.3687*** (0.0497)
Management Efficiency (ME)	−1.1170*** (0.0354)
Earnings (E)	−0.3776*** (0.0290)
Solvency (S)	0.6612*** (0.0554)
Constant	1.4063*** (0.0612)
Observations	7,440
R-squared	0.7199
R-squared within	0.5595

Note: The table reports the results from the panel fixed effect with robust (HAC) standard errors regression on the relationship between the RMI with its components and operational efficiency. The dependent variable is the Efficiency ratio (ER) defined as the ratio of total underwriting expenses to total underwriting income. Standard errors are reported in parenthesis. *, **, *** indicates significance levels at the 10%, 5%, and 1% respectively.

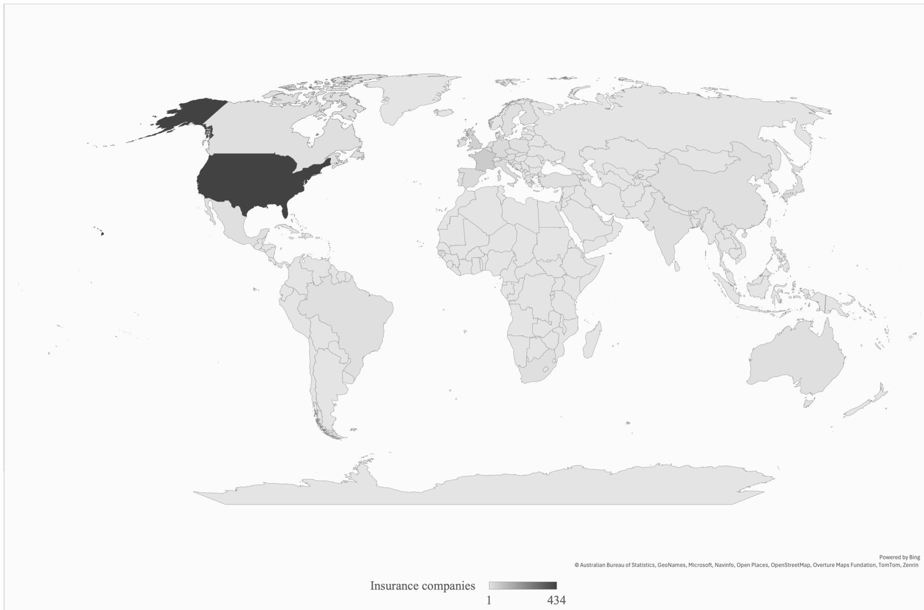
Source(s): Authors' own work

Table A Insurance companies' distribution by country

	Countries	Number of insurance companies	Percentage	Location
1	Australia	8	1.08%	Australia
2	Austria	3	0.40%	Europe
3	Belgium	8	1.08%	Europe
4	Brazil	7	0.94%	South America
5	Canada	16	2.15%	North America
6	China	15	2.02%	Asia
7	Croatia	1	0.13%	Europe
8	Czech Republic	1	0.13%	Europe
9	Denmark	3	0.40%	Europe
10	Finland	2	0.27%	Europe
11	France	63	8.47%	Europe
12	Germany	25	3.36%	Europe
13	Greece	1	0.13%	Europe
14	India	12	1.61%	Asia
15	Ireland	10	1.34%	Europe
16	Italy	22	2.96%	Europe
17	Japan	9	1.21%	Asia
18	Luxembourg	1	0.13%	Europe
19	Mexico	10	1.34%	North America
20	Netherlands	9	1.21%	Europe
21	Poland	2	0.27%	Europe
22	Portugal	1	0.13%	Europe
23	Republic of Korea	6	0.81%	Asia
24	Slovakia	1	0.13%	Europe
25	Slovenia	1	0.13%	Europe
26	South Africa	1	0.13%	Africa
27	Spain	20	2.69%	Europe
28	Sweden	3	0.40%	Europe
29	Turkey	3	0.40%	Europe
30	United Kingdom	46	6.18%	Europe
31	United States of America	434	58.33%	North America
	Total	744	100%	

Source(s): Authors' own work

Figure A Geographical spread of sample insurance companies



Source(s): Authors' own work

Table B Additional diagnostic tests

Random effects (GLS) with standard errors clustered by unit (Testing H1)

Variables	Results
Capital Adequacy (CA)	0.1478*** (0.0032)
Asset Quality (AQ)	0.1812*** (0.0049)
Management Efficiency (ME)	0.1445*** (0.0020)
Earnings (E)	0.1451*** (0.0022)
Solvency (S)	0.2484*** (0.0043)
Constant	0.1530*** (0.0066)
Observations	7,440
Joint test of regressors	35306.7***
Breusch-Pagan	6927.75***
Hausman test	27.9787***

Note: The table reports regression results from the panel random effect (GLS) with standard errors clustered by unit model on the relationship between insurer-specific risks denoted by Capital Adequacy (CA), Asset Quality (AQ), Management Efficiency (ME), Earnings (E), and Solvency (S) sub-indicators and the composite risk management index (RMI). The dependent variable is the composite risk management index (RMI) as constructed in previous sections using the constrained DEA BoD model. Standard errors are reported in parenthesis. *, **, *** indicates significance levels at the 10%, 5%, and 1% respectively.

Variance Inflation Factors -VIF (Testing H1)

Variables	Results
Capital Adequacy (CA)	1.161
Asset Quality (AQ)	1.315
Management Efficiency (ME)	1.504
Earnings (E)	1.812
Solvency (S)	1.152

Note: Minimum possible value = 1.0, Values > 10.0 may indicate a collinearity problem

Random effects (GLS) with standard errors clustered by unit (Testing H2)

Variables	Results
Risk Management Index (RMI)	0.8826*** (0.1253)
Capital Adequacy (CA)	-0.1718*** (0.0237)
Asset Quality (AQ)	-0.3252*** (0.0369)
Management Efficiency (ME)	-0.9939*** (0.0273)

Earnings (E)	-0.3422*** (0.0232)
Solvency (S)	0.2269*** (0.0441)
Constant	1.5659*** (0.0347)
Observations	7,440
Joint test of regressors	5429.22***
Breusch-Pagan	604.264***
Hausman test	534.117***

Note: The table reports regression results from the panel random effect (GLS) with standard errors clustered by unit model on the relationship between the RMI with its components and operational efficiency. The dependent variable is the Efficiency ratio (ER) defined as the ratio of total underwriting expenses to total underwriting income. Standard errors are reported in parenthesis. *, **, *** indicates significance levels at the 10%, 5%, and 1% respectively.

Variance Inflation Factors -VIF (Testing H2)

Variables	Results
Risk Management Index (RMI)	19.169
Capital Adequacy (CA)	2.774
Asset Quality (AQ)	2.782
Management Efficiency (ME)	3.487
Earnings (E)	4.449
Solvency (S)	3.810

Note: Minimum possible value = 1.0, Values > 10.0 may indicate a collinearity problem

Source(s): Authors' own work