



# CONTEMPORARY ISSUES IN FINANCE

*Edited Collection of Research Series*

Volume 06

ISSN 2827-7341 (Online)

## **Editor in Chief**

Senior Professor D.A.I. Dayaratne

## **Co-editors**

Professor D.G. Dharmarathna

Professor L.M.C.S. Menike

Professor D.N. Jayantha

Professor T.U.I. Peiris

Mr. A.A.M.D. Amarasinghe

Mrs. A.W.G.C.N. Wijethunga

Department of Accountancy and Finance  
Faculty of Management Studies  
Sabaragamuwa University of Sri Lanka

**Copyright © 2025 by Department of Accountancy and Finance**

This work is subject to copyright. All rights reserved. No part of this publication may be reproduced, stored in a retrieval system, or transmitted in any form or by any means, electronic, mechanical, photocopying, recording, or otherwise, without prior permission of the publishers.

**ISSN:** 2827-7341 (Online)

**Published by:**

Department of Accountancy and Finance  
Faculty of Management Studies  
Sabaragamuwa University of Sri Lanka  
PO. Box 02  
Belihuloya, 70140  
Sri Lanka.

**Editorial Assistant**

Ms. P.M. Shamika

**Copy Editing**

Ms. J.D.K. Ruwandika

## PREFACE

This research paper collection is the edited versions of the supervised theses of the undergraduates of the Department of Accountancy and Finance. Nearly 130 theses are supervised by the academics of the Department annually, and five outstanding papers were selected for the current volume. Therefore, all the papers considered in this volume are jointly authored by the final-year students and the respective supervisors of the Department. What primarily motivated me to initiate this edited research series was to foster a research culture among the academics and students of the Department. Secondly, disseminating intellectual knowledge to a broad spectrum of audiences contributes to the advancement of the body of knowledge in the field. The premise of all papers included in the volume is in the discipline of finance, which covers the Capital Market, Banking Sector, and Insurance Sectors.

All the papers in this volume address timely, important, and academically relevant research issues. So that readers will be well-equipped with objectively addressed and scientifically supported conclusions. As such, I believe this collection will immensely benefit the corporate sector and government policymakers. Moreover, this will be useful for students, teachers, researchers, and other public-spirited citizens interested in this subject discipline. Additionally, I witnessed the extent of work done by all the academic authors in bringing undergraduate theses up to the standards demanded by academia. I congratulate all the academics for encouraging the students to contribute papers to this publication.

As the initiator of this idea, I first compiled the concept paper for the Faculty Board and the University Senate. The comments given by the members of both bodies to further shape the idea are highly appreciated. Very importantly, I would like to express my appreciation to all the academic members of the Department of Accountancy and Finance for encouraging me to pursue my innovative idea and providing their full cooperation to bring it to reality. My Co-authors' intellectual and expert contributions are also commendable. Finally, I also appreciate the efforts of the editorial assistants and the copy editor of this edited book.

**D.A.I. Dayaratne, PhD**  
**Senior Professor in Finance**  
**Editor-in-Chief**

# CONTENT

## 01. CHAPTER ONE

- Cash Flow Risk Management and Sustainable Financial Performance of Listed Commercial Banks in Sri Lanka 5

*Madushanka R.M.V. & Amarasinghe, A.A.M.D.*

## 02. CHAPTER TWO

- Impact of Macroeconomic Determinants on Carbon Emission in Developing Countries 26

*Pieris M.H.D. & Dayaratne D.A.I.*

## 03. CHAPTER THREE

- Stock Price Reactions to Scrip Dividend Announcements: An Event Study in the Colombo Stock Exchange (CSE) 51

*Tharushi A.S. & Dharmarathna D.G.*

## 04. CHAPTER FOUR

- Accuracy of Bankruptcy Prediction Models in Forecasting Company Delisting During an Economic Crisis: Evidence from Sri Lanka 68

*Tharushika H. & Edirisinghe U.C.*

## 05. CHAPTER FIVE

- Impact of Board Gender Diversity on Sustainability Reporting Quality of Listed Commercial Banks in Sri Lanka 90

*Perera J.A.A.D. & Fernando K.D.U.D.*

## CHAPTER ONE

### Cash Flow Risk Management and Sustainable Financial Performance of Listed Commercial Banks in Sri Lanka

Madushanka R.M.V. & Amarasinghe A.A.M.D.

Department of Accountancy and Finance, Faculty of Management Studies  
Sabaragamuwa University of Sri Lanka  
[malith@mgt.sab.ac.lk](mailto:malith@mgt.sab.ac.lk)

#### Abstract

*This study examines the impact of cash flow risk management practices on the sustainable financial performance of listed commercial banks in Sri Lanka from 2014 to 2023, using a quantitative approach and dynamic panel data analysis. Key metrics—operating cash flow to total assets (TAR), liquidity coverage ratio (LCR), cash flow from operations to net income (OIR), and loan-to-deposit ratio (LDR)—were analysed as proxies for cash flow risk management, while sustainable growth rate (SGR) represented financial performance. The Random Effects (RE) model, validated by the Hausman test, was identified as the most suitable analytical framework for this study. The results indicate that TAR has a positive influence on sustainable financial performance, highlighting the importance of operational cash flow. OIR exhibited minimal impact, whereas LCR and LDR showed no significant correlation with financial performance. The findings underscore the importance of effective cash flow management in promoting long-term financial sustainability. The study recommends that bank managers improve their cash flow management practices, and regulators enforce stricter benchmarks to ensure banks effectively manage risks, particularly in volatile economic environments.*

**Keywords:** *Cash Flow Risk Management Practices, Sustainable Financial Performance, Commercial Banks.*

#### 1. Introduction

The banking sector in Sri Lanka plays a critical role in the country's financial system, contributing to economic growth, development, and stability (Wijesinghe & Pallearachchi, 2022). It encompasses both local and foreign banks, with significant evolution driven by economic localisation and globalisation (Nandalal, 2021). The Central Bank of Sri Lanka (CBSL) oversees the sector by regulating licensed commercial banks, maintaining financial stability, and implementing monetary policies.

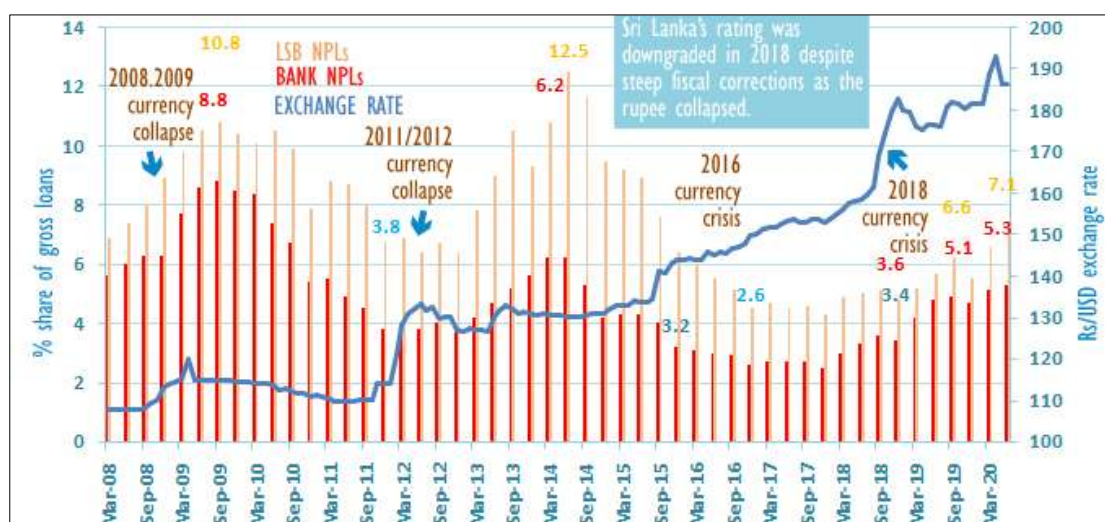
Ownership diversity characterises the sector, with state-owned banks, such as the Bank of Ceylon and People's Bank, dominating the market and supporting government initiatives, while private banks, including Commercial Bank of Ceylon and Hatton National Bank, lead in innovative financial services. Additionally, international banks such as HSBC and Standard Chartered offer global banking services (Central Bank of Sri Lanka, 2018; KPMG Sri Lanka, 2021).

Recent measures to enhance efficiency and competitiveness include financial liberalisation, the adoption of new technologies, and improved corporate governance practices, as directed by the Central Bank of Sri Lanka (CBSL, 2020). However, challenges such as economic fluctuations, political instability, and global crises, including the COVID-19 pandemic, have occasionally threatened the sector's stability, necessitating restructuring efforts post-civil war and adaptive strategies during the pandemic (Jayamaha, 2008; Central Bank of Sri Lanka, 2020). Technological advancements have significantly transformed the industry, with digital platforms, mobile banking, and automated teller machines (ATMs) improving customer satisfaction and reducing costs (Gunawardene, 2017). Furthermore, financial inclusion initiatives, including microfinance, small and medium enterprise (SME) loans, and agricultural lending, aim to serve rural and underserved populations, fostering equitable economic development (Blancher et al., 2019).

Cash flow risk management involves tools and techniques to monitor and mitigate potential adverse changes in cash movements. Effective practices ensure banks maintain liquidity for short-term needs and safeguard against long-term default risks. Methods like Value at Risk (VaR), Cash Flow at Risk (CFaR), and scenario analysis are commonly employed to address these risks (Astuti & Gunarsih, 2021; Oral & CenkAkkaya, 2015).

Sustainable finance incorporates environmental, social, and governance (ESG) considerations into financial decisions to ensure long-term profitability and sustainability. Effective cash flow risk management supports this by enabling banks to fund sustainable initiatives even during economic distress. Integrating cash flow management with ESG principles enhances stakeholder confidence, strengthens the bank's reputation, and fosters sustainable growth (Lins, Servaes & Tamayo, 2017).

Sri Lanka's banking sector, comprising domestic and foreign banks, has remained relatively stable despite economic fluctuations. However, rising non-performing loans (NPLs) indicate potential liquidity stress. By June 2020, NPLs for commercial banks had increased to 5.3% from 4.9% in March, while specialised banks had seen a rise from 6.6% to 7.1%, signalling challenges in managing cash flow risks (Central Bank of Sri Lanka, 2020).



**Figure 1.1:** NPLs and Exchange Rate Volatility in Sri Lanka's Banking Sector (2008-2020)

**Source:** Central Bank of Sri Lanka

The COVID-19 pandemic intensified liquidity pressures in Sri Lanka's banking sector due to moratoria and reduced economic activities. The Central Bank of Sri Lanka (2023) highlighted that banks with robust cash flow risk management successfully maintained liquidity and supported clients during this period. Digitalisation has significantly improved cash flow management in Sri Lankan banks, enabling more efficient transaction processing and enhanced cash flow monitoring. This has led to improved overall performance for banks that adopt digital channels (Habeeb & Wickramasinghe, 2019).

Despite progress, many Sri Lankan banks continue to rely on traditional risk management methods, which are increasingly inadequate given the complexities of modern financial products and the global economic challenges they face. This is particularly concerning as ESG considerations demand more advanced cash flow management practices (Fernando & Basnayake, 2022). From a theoretical perspective, Stakeholder Theory emphasises that banks must address the interests of all stakeholders, not just shareholders, to ensure longevity and sustainable performance (Freeman & McVea, 2001). Effective cash flow risk management aligns with this principle by fulfilling obligations to depositors, investors, and society as a whole. Similarly, Agency Cost Theory highlights the conflict between stockholders and managers, suggesting that unchecked managers may harm financial stability. Robust cash flow risk management mitigates agency risks by implementing transparent processes and controls (Jensen & Meckling, 1976).

### 1.1. Research Problem

Cash flow risk management is a persistent challenge for Sri Lanka's banking sector, a cornerstone of the nation's economic stability and development (Gowthaman, 2022). Despite

reforms and sectoral growth, listed commercial banks continue to face difficulties in maintaining effective cash flow management (Kimani & Kibera, 2023). Factors such as dynamic operational, regulatory, and economic environments further complicate risk management (Chernobai et al., 2021). The sector is also impacted by external factors, including fluctuating interest rates, volatile exchange rates, and legislative changes, making cash flow management increasingly critical (Central Bank of Sri Lanka, 2020). The COVID-19 pandemic has exacerbated these challenges, exposing weaknesses in cash flow practices due to liquidity constraints and heightened credit risks (Shabir et al., 2023).

Moreover, the slow adoption of modern financial technologies, such as digital banking and automated systems, has hindered the efficient utilisation of resources. While these technologies can enhance cash flow management, their gradual uptake increases operational risks, including system breaches and internal fraud, ultimately affecting profitability (Madushika & Wijesinghe, 2022). Globally, studies indicate that effective cash flow management is inversely correlated with profitability risks and insolvency, as observed in advanced economies (Almeida, Campello, & Weisbach, 2004). However, limited research exists on the Sri Lankan banking sector, which operates within unique economic and political frameworks. This research gap underscores the need to examine the impact of cash flow risk management practices on the financial sustainability of Sri Lanka's listed domestic commercial banks.

## **1.2. Research Objectives**

This study aims to analyse the influence of cash flow risk management practices (RMP) on the sustainable financial performance of listed commercial banks in Sri Lanka. Specifically, it aims to assess the impact of various risk management practices on financial sustainability. These include the influence of RMP on operating cash flow to total assets, liquidity coverage, cash flow from operations to net income, and loan-to-deposit ratios on the banks' sustainable financial performance. By addressing these aspects, the study provides a comprehensive understanding of the role that effective cash flow risk management plays in ensuring the financial resilience and long-term stability of Sri Lankan commercial banks.

## **1.3. Hypotheses Development**

This study is guided by the following hypotheses to explore the relationship between cash flow risk management practices and the sustainable financial performance of listed commercial banks in Sri Lanka. The primary hypothesis ( $H_{1A}$ ) posits a significant relationship between cash flow risk management practices and financial sustainability. Additionally, it examines specific dimensions of risk management practices, including the relationship



between operating cash flow to total assets ( $H_{1B}$ ), liquidity coverage ( $H_{1C}$ ), cash flow from operations to net income ( $H_{1D}$ ), and loan-to-deposit ratios ( $H_{1E}$ ) with sustainable financial performance. These hypotheses aim to provide a nuanced understanding of how distinct risk management strategies contribute to the resilience and long-term financial stability of the banking sector.

## **2. Literature Review**

### **2.1. Theoretical Review**

The study's theoretical framework incorporates Stakeholder Theory, Agency Cost Theory, Value at Risk (VaR), and Cash Flow at Risk (CFaR) to understand the impact of cash flow risk management on the financial sustainability of Sri Lankan listed commercial banks.

Freeman and McVeagh (2001) envisioned Stakeholder Theory, which suggests organising business management or ethics through the lens of morals and values. This theory posits that organisations consider all groups of stakeholders, not just the shareholders that the organisation instinctively serves, in order for the organisation to achieve and maintain decent performance and long-term survival. Within stakeholder theory and in relation to the management of cash flow risks, it is proposed that banks should develop and utilise practices that go beyond maximising shareholders' wealth alone, but also consider the interests of other stakeholders.

Agency Cost Theory highlights the importance of aligning managers' actions with shareholders' interests and mitigating risks associated with cash flow management (Jensen & Meckling, 1976; Wickramasinghe & Gunawardane, 2017). For commercial banks, this means implementing appropriate systems to control the flow of cash in and out of the organisation, ensuring the safety and security of funds for stakeholders. In Sri Lanka, given the economic uncertainties, achieving investor satisfaction and sustainable growth will depend on how agency costs associated with cash flows are managed.

VaR estimates potential losses due to market fluctuations, enabling banks to manage liquidity and mitigate risks in volatile economic environments (Astuti & Gunarsih, 2021; Central Bank of Sri Lanka, 2023). CFaR focuses specifically on predicting adverse cash flow changes, enabling banks to maintain liquidity amid challenges such as interest rate volatility and loan defaults (Oral & CenkAkkaya, 2015; Wickramasinghe & Gunawardane, 2017). Integrating these theories, the study seeks to evaluate effective cash flow risk management strategies to enhance financial stability and performance in the dynamic Sri Lankan banking sector.

## 2.2. Empirical Review

The empirical review examines existing research on cash flow risk management techniques and their influence on the sustainable performance of commercial banks, focusing on both local and global contexts. Cash flow risk management is crucial for maintaining financial stability, solvency, and profitability in the banking sector, as it addresses challenges such as economic volatility, regulatory changes, and operational risks (Kedarya et al., 2023; Nasimiyu, 2024). Practical strategies, including liquidity management, risk models like Value at Risk (VaR) and Cash Flow at Risk (CFaR), and scenario analysis, help banks mitigate risks and sustain operations during economic disruptions (Gemzik-Salwach, 2012; Astuti & Gunarsih, 2021).

Empirical studies highlight that effective cash flow management shields banks from financial shocks, ensuring stability and profitability. For example, Almeida et al. (2004) noted that organisations with better cash flow management are less sensitive to market swings. Similarly, Sri Lankan studies have shown that banks with robust cash flow systems performed better during challenges such as civil unrest and the COVID-19 pandemic, demonstrating the importance of adaptive strategies (Jayamaha, 2008; Central Bank of Sri Lanka, 2020).

Technological advancements and regulatory frameworks have a significant impact on cash flow risk management. Emerging technologies, such as artificial intelligence and machine learning, are reshaping forecasting and risk management processes, while ESG considerations are expected to further integrate sustainable strategies into cash flow management (Gunawardene, 2017; Vural, 2004). Despite these benefits, challenges such as economic instability, legal constraints, and the cost of technological implementation persist, underscoring the need for innovative and adaptive practices in managing cash flow risks.

### Global Perspectives

Numerous studies emphasise the importance of managing cash flow risk in influencing a bank's performance. According to Almeida, Campello, and Weisbach (2004), effective cash flow management provides a buffer against financial downturns, as firms with access to external funds are less affected by cash flow fluctuations. This is particularly critical for banks operating in volatile financial environments and exposed to diverse economic shocks.

Research by Ho et al. (1999) demonstrated that banks utilising Value at Risk (VAR) models to estimate potential adverse changes in cash inflows performed better due to their ability to predict and manage risks effectively. Similarly, Aktaş et al. (2012) highlighted that adopting efficient cash flow risk management practices could help banks mitigate the risk of financial crises.

Vural (2004) further explored liquidity risk management through the Cash Flow at Risk (CFaR) model, concluding that banks using this model maintained stronger cash flow positions and managed risks more effectively. Collectively, these studies highlight the importance of advanced risk management techniques in safeguarding the banking sector against substantial financial losses.

### **Sri Lankan Context**

Sri Lanka's banking sector faces distinct challenges influenced by its economic environment, regulatory structures, and competitive dynamics. Research has explored these challenges and the effectiveness of cash flow management practices, revealing varying degrees of success among banks. Gowthaman (2022) examined the impact of Sri Lanka's civil war on the banking sector, highlighting the importance of effective cash flow management during periods of instability. The study found that banks practising robust cash flow management demonstrated financial resilience, maintaining stability and performance despite the adverse effects of the war.

Wijesinghe et. al. (2018) investigated the use of digital banking technologies in Sri Lanka and their impact on cash flow management. The research indicated that technological advancements significantly enhanced cash flow management systems and contributed to improved bank performance, underscoring the transformative role of technology in modern banking operations. The Central Bank of Sri Lanka (2020) examined the impact of the COVID-19 pandemic on the banking industry, with a focus on the crucial role of adaptive cash flow strategies. Banks that swiftly adjusted their cash flow management practices to address the pandemic's economic challenges were able to sustain liquidity and provide better support to their customers. These findings underscore the importance of flexibility and responsiveness in cash flow management, enabling effective navigation of economic disruptions.

The existing literature on cash flow risk management in banking reveals several significant research gaps, particularly in the context of developing countries like Sri Lanka. The existing literature is incomplete in many aspects, particularly regarding the coupling of cash flow risk management techniques with sustainable financial performance. Whereas cash flow risk management and sustainable financial performance have attracted a large body of work separately, there are few, if any, attempts to study them in relation to each other. Most prior studies focus on traditional business financial performance indicators, with little regard for the cash flow management approach as a guarantee of long-term business sustainability, which also extends to environmental, social, and governance prospects. A majority of the empirical work regarding cash flow risk management is done in developed markets, with a few

exceptions in regions such as Sri Lanka. Technological innovations, particularly banking and financial technologies (FinTech), have prompted a paradigm shift in cash flow risk management practices (Wijesinghe, 2018). Nevertheless, this aspect of the literature has not addressed the impact of the technology used on cash flow risk management in commercial banks.

These gaps highlight areas that require further investigation to enhance understanding and practice in the field. While cash flow risk management and sustainable financial performance have been studied separately, their interplay remains underexplored. Most prior research focuses on traditional financial performance metrics, neglecting the role of effective cash flow management in supporting long-term sustainability, including Environmental, Social, and Governance (ESG) objectives. This omission is critical since stakeholders increasingly evaluate banks based on their ESG performance (Lins, Servaes, & Tamayo, 2017). Understanding the role of cash flow management in achieving broader sustainability goals is essential for developing holistic financial strategies.

Most empirical studies on cash flow risk management are concentrated in developed markets, with limited research addressing the unique economic and regulatory challenges of emerging markets, such as Sri Lanka. For instance, Gowthaman (2022) highlighted the importance of cash flow management during Sri Lanka's civil conflict, but emphasised the scarcity of studies examining how banks adapt their practices in response to evolving economic and regulatory environments. Further research is needed to understand the specific barriers and opportunities in emerging markets, which differ significantly from those in developed economies.

### **3. Methodology**

This study employs a quantitative research approach, utilising secondary data to systematically analyse financial information from listed commercial banks in Sri Lanka. The goal is to uncover patterns and relationships that provide insights into financial performance and risk management practices.

#### **3.1. Research Design**

The study employs an explanatory research design, focusing on cause-and-effect relationships between variables. This approach involves hypothesis testing and the use of quantitative methods, such as regression analysis and panel data analysis, to establish causal links between independent and dependent variables. By analysing empirical data, the study aims to validate theoretical hypotheses and elucidate the mechanisms that influence cash flow risk management and financial performance.

### 3.2. Population and Sample

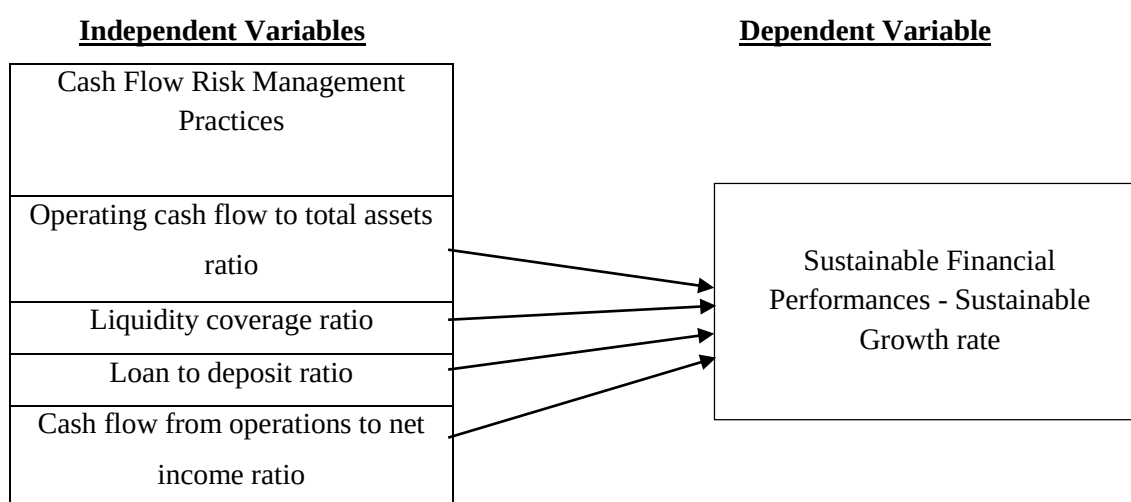
The study targets all listed commercial banks in Sri Lanka as its population, consisting of both domestic and foreign banks. However, the sample is limited to domestic private and public banks to ensure a homogeneous dataset. The exclusion of foreign banks is justified due to differences in regulatory frameworks, ownership structures, and risk management strategies, which are influenced by parent institutions abroad. Focusing on local banks ensures the findings are relevant to the Sri Lankan financial landscape and reflective of shared economic and market conditions.

The study examines data from 2014 to 2023, a period encompassing significant financial trends, regulatory changes, and the global economic impacts of the COVID-19 pandemic. This timeframe includes both pre- and post-pandemic dynamics, as well as macroeconomic turning points and one complete economic cycle, offering a comprehensive view of cash flow risk management practices and their impact on financial stability.

The study focuses on the following domestic banks: Amana Bank; Bank of Ceylon; Cargills Bank PLC; Commercial Bank of Ceylon PLC; DFCC Bank PLC; Hatton National Bank PLC; National Development Bank PLC; Nations Trust Bank PLC; Pan Asia Banking Corporation PLC; People's Bank; Sampath Bank PLC; Seylan Bank PLC; Union Bank of Colombo PLC. By concentrating on these banks, the study aims to provide findings that are valid, relevant, and applicable to Sri Lanka's domestic banking sector.

### 3.3. Conceptual Framework

The conceptual framework will illustrate how cash flow risk management practices influence sustainable financial performance.



**Figure 3.1:** Conceptual Framework

**Source:** Developed by the Researcher Based on Previous Literature

### **Sustainable Growth Rate (SGR)**

SGR represents the maximum growth a business can sustain without increasing its financial leverage or relying on external financing. It is calculated using the formula:

$$\text{SGR} = \text{ROE} \times (1 - \text{Dividend Payout Ratio})$$

This metric is essential for determining how far and how quickly a business can expand while maintaining internal financial stability. Once a company exceeds its SGR, it must resort to borrowing or external funds to facilitate additional growth (Guliyev & Muzaffarov, 2024)

### **Operating Cash Flow to Total Assets Ratio (TAR)**

The operating cash flow to total assets ratio measures a bank's operational efficiency by comparing its operating cash flow to its total assets. A higher ratio indicates that the bank is effectively utilising its assets to generate cash flows, minimising the risk of liquidity issues. This ratio is crucial for evaluating how effectively a bank manages its cash flows to meet both current and future needs, thereby reducing the likelihood of financial distress. It provides insight into the bank's operational soundness and economic structure (Eyisi & Okpe, 2014).

### **Liquidity Coverage Ratio (LCR)**

LCR, developed under the Basel III framework, ensures that banks maintain sufficient high-quality liquid assets to cover net cash outflows for at least 30 days. This metric is critical for managing short-term liquidity risks, enabling banks to withstand market shocks without resorting to unfavourable asset sales or emergency borrowing. The LCR reflects a bank's financial flexibility and its preparedness to handle liquidity demands during periods of market stress (Mashamba, 2021; Diamond & Rajan, 2001).

### **Loan to Deposit Ratio (LDR)**

LDR assesses a bank's liquidity by comparing the total loans extended to the deposits held. A low LDR indicates excess liquidity but suggests underutilization of funds, while a high LDR signals potential liquidity risks, such as the inability to meet withdrawal demands or other callable liabilities. This metric is a critical tool for evaluating how effectively a bank manages its liquidity risks and ensures its capability to meet financial obligations without jeopardising stability (Bordeleau & Graham, 2010).

### **Cash Flow from Operations to Net Income Ratio (OIR)**

The cash flow from operations to net income ratio compares actual cash generated from operations to the reported net income. This metric is crucial for assessing the quality and sustainability of earnings by verifying that actual cash flows support reported profits. It

highlights discrepancies between cash flows and earnings, which can act as a warning signal for potential financial risks. This ratio is particularly valuable in assessing a bank's liquidity and the reliability of its reported earnings (Dechow & Dichev, 2002).

**Table 3.1:** Summary of Cash Flow Ratios

| Ratio                                         | Measurement                                                                         | Used in Prior Studies                                                 |
|-----------------------------------------------|-------------------------------------------------------------------------------------|-----------------------------------------------------------------------|
| Operating Cash Flow to Total Assets (TAR)     | $\frac{\text{Operating cash flow}}{\text{Total assets}}$                            | Barth, Cram & Nelson (2001)                                           |
| Liquidity Coverage Ratio (LCR)                | $\frac{\text{High – quality liquid assets}}{\text{Net cash outflows over 30 days}}$ | Basel Committee on Banking Supervision (2013); Diamond & Rajan (2001) |
| Loan to Deposit Ratio (LDR)                   | $\frac{\text{Total loans}}{\text{Total deposits}}$                                  | Bordeleau & Graham (2010); Berger & Bouwman (2009)                    |
| Cash Flow from Operations to Net Income (OIR) | $\frac{\text{Operating cash flow}}{\text{Net income}}$                              | Dechow & Dichev (2002); Schipper & Vincent (2003)                     |

**Source:** Compiled by the Author

### 3.4. Method of Data Collection

The study uses secondary data sourced from the financial statements and annual reports of listed commercial banks in Sri Lanka. These documents are accessed through the official websites of the banks, regulatory disclosures, or financial databases, such as the Colombo Stock Exchange.

### 3.5. Data Analysis using Panel Data Regression

The analysis employs panel data techniques to investigate the relationship between cash flow risk management practices and financial performance. By incorporating both cross-sectional and time-series data, panel regression models are utilised to identify patterns and effects. Statistical software, such as STATA, is used for data processing and regression analysis.

Panel data regression techniques are employed to examine the relationship between cash flow risk management practices and the sustainable financial performance of listed banks. The study first estimates an Ordinary Least Squares (OLS) model, which assumes no individual differences across banks. To address potential biases from unobserved heterogeneity, fixed effects (FE) and random effects (RE) models are employed.

**Fixed Effects Model (FE):** This model accounts for time-invariant, bank-specific characteristics by assigning each bank its own intercept. It controls for unobserved variables that remain constant over time. An F-test determines whether the FE model is a better fit than the OLS model.

**Random Effects Model (RE):** This model assumes that individual-specific effects are random and uncorrelated with the explanatory variables, thereby offering greater efficiency in generalising results. A Breusch-Pagan LM test compares the RE model against OLS to verify its suitability.

To choose between FE and RE models, the Hausman test is used. A significant result favours the FE model, while a non-significant result supports the RE model for efficiency (Sheytanova, 2015; Amini et al., 2012).

### Model

$$SGR_{it} = \beta_0 + \beta_1 TAR_{it} + \beta_2 LCR_{it} + \beta_3 LDR_{it} + \beta_4 OIR_{it} + \varepsilon_{it} \quad (1)$$

Where,

SGR = Sustainable growth rate

TAR = Operating cash flow to total assets ratio

LCR = Liquidity coverage ratio

LDR = Loan to deposit ratio

OIR = Cash flow from operations to net income ratio

$\varepsilon$  = Error term

## 4. Results and Discussion

### 4.1. Descriptive Statistics

**Table 4.1:** Descriptive Statistics

| Variable | Mean  | Std. dev. | Minimum | Maximum |
|----------|-------|-----------|---------|---------|
| SGR      | 0.378 | 0.202     | 0.003   | 1.030   |
| TAR      | 0.045 | 0.638     | 0.000   | 0.607   |
| LCR      | 2.238 | 1.995     | 0.539   | 13.144  |
| LDR      | 0.928 | 0.199     | 0.074   | 1.862   |
| OIR      | 1.235 | 1.614     | 0.005   | 13.067  |

**Source:** STATA output

Table 4.1 presents the descriptive statistics for several financial ratios, including the sustainable growth rate (SGR), operating cash flow to total assets ratio (TAR), liquidity coverage ratio (LCR), and loan-to-deposit ratio (LDR), Cash Flow from Operations to Net



Income Ratio (OIR), based on 130 observations from selected listed commercial banks in Sri Lanka between 2014 and 2023.

The Sustainable Growth Rate (SGR) has a low mean value (0.378) with a low standard deviation (0.2), indicating that most banks in the sample struggle with achieving sustainable growth, as they are unable to grow at a rate that can support their liabilities, which could lead to significant risks. The Operating Cash Flow to Total Assets Ratio (TAR) also has a low mean (0.045), suggesting that these banks are not efficiently utilising their assets to generate income, which may negatively impact their operations. The Liquidity Coverage Ratio (LCR) has a mean value of 2.238 with a standard deviation of 1.995, indicating that banks have sufficient liquidity to meet their short-term liabilities, which is essential for solvency, particularly during economic downturns. The Loan-to-Deposit Ratio (LDR) also has a mean of 0.928, implying that banks may not be effectively utilising deposits for lending, which suggests an imbalance with more deposits than loans. The Cash Flow from Operations to Net Income Ratio (1.235) has a positive value, indicating that the banks are generating income from operations that exceeds their overall operating income, which supports their solvency and future investments. The standard deviations for all these variables reveal considerable variability in financial performance across the banks. Positive scores across the ratios indicate significant fluctuations, while the minimum values highlight that some banks are facing challenges in growth and asset utilisation. Conversely, the maximum values show that some banks are performing exceptionally well, especially in terms of liquidity.

## 4.2. OLS Regression

The OLS regression (Table 4.2) provides a preliminary understanding of the data, which includes 130 observations and coefficients for variables such as LDR, OIR, LCR, and TAR. The R-squared in the OLS model (0.094) indicates a modest explanation of variability by the model. However, OLS regressions do not account for unobserved heterogeneity, which is often crucial in panel data, particularly financial data involving banks, where unobservable intrinsic characteristics significantly influence outcomes.

**Table 4.2:** Summary of OLS Regression results

| <b>R- Squared</b> | <b>Adj R- Squared</b> | <b>F-Statistics</b> | <b>Prob (F-Statistics)</b> |                    |
|-------------------|-----------------------|---------------------|----------------------------|--------------------|
| 0.094             | 0.065                 | 3.270               | 0.013                      |                    |
| <b>Variable</b>   | <b>Coefficient</b>    | <b>Std. Err.</b>    | <b>t-Statistic</b>         | <b>Probability</b> |
| TAR               | 1.199                 | 0.802               | 1.49                       | 0.138              |
| LCR               | 0.011                 | 0.009               | 1.21                       | 0.227              |
| OIR               | -0.073                | 0.031               | -2.33                      | 0.021              |
| LDR               | -0.049                | 0.095               | -0.52                      | 0.604              |
| _cons             | 0.434                 | 0.097               | 4.45                       | 0.000              |

**Source:** STATA output

### 4.3. Fixed Effects (FE) and Random Effects (RE) Models

The FE model controls for all time-invariant characteristics within each bank, allowing for the assessment of the effects of variables that vary over time. This model is preferred when significant individual differences that do not change over time could bias the estimators.

**Table 4.3:** Fixed Effect & Random Effect Regression Results

| <b>Fixed-effects Regression</b>  |              |                  |          |                   |                             |        |
|----------------------------------|--------------|------------------|----------|-------------------|-----------------------------|--------|
| <b>F (4,113) = 4.46</b>          |              |                  |          |                   |                             |        |
| <b>Prob &gt; F = 0.002</b>       |              |                  |          |                   |                             |        |
| <b>Variable</b>                  | <b>Coef.</b> | <b>Std. Err.</b> | <b>t</b> | <b>P &gt; (t)</b> | <b>(95% Conf. Interval)</b> |        |
| TAR                              | 1.558        | 0.527            | 2.96     | 0.004             | 0.514                       | 2.603  |
| LCR                              | -0.002       | 0.007            | -0.23    | 0.815             | -0.016                      | 0.013  |
| OIR                              | -0.077       | 0.021            | -3.69    | 0.000             | -0.118                      | -0.036 |
| LDR                              | 0.073        | 0.066            | 1.11     | 0.268             | -0.057                      | 0.203  |
| _cons                            | 0.338        | 0.067            | 5.06     | 0.000             | 0.206                       | 0.470  |
| <b>Random-effects Regression</b> |              |                  |          |                   |                             |        |
| <b>Wald chi2 (4) = 17.93</b>     |              |                  |          |                   |                             |        |
| <b>Prob &gt; chi2 = 0.001</b>    |              |                  |          |                   |                             |        |
| <b>Variable</b>                  | <b>Coef.</b> | <b>Std. Err.</b> | <b>z</b> | <b>P &gt; (z)</b> | <b>(95% Conf. Interval)</b> |        |
| TAR                              | 1.546        | 0.522            | 2.96     | 0.003             | 0.521                       | 2.571  |
| LCR                              | -0.001       | 0.007            | -0.07    | 0.924             | -0.014                      | 0.013  |
| OIR                              | -0.077       | 0.020            | -3.73    | 0.000             | -0.117                      | -0.036 |
| LDR                              | 0.064        | 0.064            | 1.00     | 0.320             | -0.062                      | 0.191  |
| _cons                            | 0.344        | 0.081            | 4.21     | 0.000             | 0.183                       | 0.504  |

Source: STATA output

#### F-Test for FE Model

The F-test result ( $F(12, 113) = 19.33$  with  $\text{Prob} > F = 0.0000$ ) strongly rejects the null hypothesis that all  $u_i = 0$ , indicating significant entity-specific effects. This test confirms the presence of substantial within-entity variations that justify the use of the FE model.

#### Random Effects (RE) Model

The RE model considers both within- and between-entity variations, assuming that the individual effects are random and uncorrelated with the regressors. This model is generally more efficient than the FE model if the random effects assumption holds, as it uses more of the data by considering the average effect across entities.

### Breusch-Pagan LM Test for RE Model

The LM test, providing a chi-square statistic of 197.682 with a p-value of 0.0000, suggests that the variance attributed to the entities is significantly different from zero, indicating potential suitability of the RE model for the data.

### Hausman Test: Deciding Between FE and RE

The Hausman test is a critical tool in panel data analysis used to determine the appropriateness of Fixed Effects (FE) versus Random Effects (RE) models. In this test,

Null Hypothesis –  $H_0$ : Random effect model is consistent

Alternative Hypothesis –  $H_a$ : Fixed effect model is consistent

It tests the null hypothesis that the difference in coefficients between the FE and RE models is not systematic, which means the unique errors (individual-specific effects) are not correlated with the regressors. P-value of 0.7619: A p-value greater than 0.05 (typically the threshold for significance) indicates that there is no significant evidence against the null hypothesis. This suggests that the coefficients estimated by the RE model are consistent and not significantly different from those calculated by the FE model.

### 4.4. Interpretation and Implications of Model

The high p-value supports the conclusion that the Random Effects model is suitable for the analysis. This model assumes that the individual-specific effects are uncorrelated with the regressors across all banks. Given the p-value of 0.7619, this assumption is upheld, making the RE model more efficient for the study.

$$SGR_{it} = 0.3440 + 1.5462 TAR_{it} + 0.0005 LCR_{it} + 0.0770 OIR_{it} + 0.0646 LDR_{it} + \varepsilon_{it}$$

This study extends prior research on the relationship between cash flow risk management practices and sustainable financial performance (SFP) by analysing listed commercial banks. Using the Random Effects (RE) model, it identifies specific cash flow ratios as determinants of SFP, contributing to the literature on banking sector sustainability. The findings highlight both corroborations and deviations from earlier studies.

The study confirms a positive and significant impact of TAR on SFP. This finding aligns with Dechow's (1994) emphasis on the importance of generating sustainable operating cash flows to ensure long-term financial stability. TAR's high coefficient underscores its pivotal role in fostering sustainable operations and financial endurance for banks.

A negative relationship between OIR and SFP (-0.0770) suggests that the inefficient conversion of cash flows to net income has an adverse impact on financial sustainability. This

observation is consistent with earlier research by DeFond and Hung (2003) and Barth et al. (2001), which found that poor operational efficiency and excessive reinvestment reduce profitability and increase financial risks, ultimately harming long-term performance.

The study identifies a negative, albeit small, effect of LCR on SFP. This aligns with Diamond and Rajan (2001), who proposed that high liquidity levels constrain investment opportunities and profitability. However, the result contrasts with Berger and Bouwman (2009), who argued that liquidity enhances risk mitigation and sustainability. The findings suggest a tradeoff between maintaining liquidity and achieving profitability for commercial banks.

LDR demonstrates a positive relationship with SFP, indicating that increased lending relative to deposits boosts financial performance. This finding aligns with studies by Ahmad et al. (2019) and Trujillo-Ponce (2013), which observed that efficient capital utilisation through lending enhances revenue generation and long-term sustainability in banks.

These results highlight the complex dynamics of cash flow risk management and its implications for achieving sustainable financial performance in the banking sector. The findings reveal that the effectiveness of cash flow risk management practices on sustainable financial performance varies significantly depending on the banking environment. In developed economies, studies such as Pasiouras and Kosmidou (2007) demonstrate that regulatory impacts partially mediate the relationship between liquidity, capital coefficients, and financial performance. However, in low- and middle-income countries, including Sri Lanka, research such as Perera and Weerasinghe (2016) highlights the importance of risk management and operational efficiency as critical determinants of long-term sustainability.

This study contributes to the literature on the Asian context by demonstrating the pivotal role of cash flow risk management practices in determining the financial sustainability of banks, particularly in emerging markets. The empirical findings align with previous research, confirming that effective cash flow risk management has a significant impact on sustainable financial performance in the banking sector.

## **5. Conclusion**

This study examined the impact of managing cash flow risk on the sustainable financial performance of listed commercial banks in Sri Lanka, focusing on four cash flow ratios: operating cash flow to total assets (TAR), cash flow from operations to net income (OIR), liquidity coverage ratio (LCR), and loan-to-deposit ratio (LDR).

The findings emphasise the critical role of effective cash flow risk management in achieving financial sustainability, particularly in Sri Lanka's volatile economic environment. As key agents of financial intermediation, credit granting, and economic growth, banks must

prioritise sustainable financial performance to ensure overall financial system stability. Through an extensive review of the literature and econometric analysis using OLS, FE, and RE models, the study revealed that cash management activities have a significant influence on bank performance, with TAR emerging as a major contributor to sustainability. The research emphasises the importance of balanced management of funds and credit in achieving sustainable financial outcomes within the banking sector.

This research provides valuable insights into the relationship between cash flow risk management practices and sustainable financial performance (SFP) among Sri Lankan banks. A strong positive correlation between the operating cash flow to total assets ratio (TAR) and SFP highlights that higher operating cash flows relative to total assets enhance financial sustainability, consistent with prior empirical studies. The inverse relationship between cash flow from operations to net income ratio (OIR) and SFP suggests operational inefficiencies negatively affect financial sustainability, aligning with earlier research on operational challenges in banks. While the liquidity coverage ratio (LCR) has a slight negative impact on SFP, the findings affirm that excessive liquidity can constrain profitability, reflecting the well-documented tradeoff between liquidity and profitability. The loan-to-deposit ratio (LDR) has a positive influence on SFP, indicating that efficient lending practices relative to deposits enhance financial performance, which supports existing studies on the profitability of effective capital allocation in banks. Overall, the study reinforces the importance of sustainable cash flow risk management practices in shaping the financial performance of banks, contributing to the growing body of literature on this topic.

## Reference

- Ahmad, N., Naveed, A., Ahmad, S., & Butt, I. (2019). 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>
- Aktas, C., Cortuk, O., Teker, S., & Yildirim, B. D. (2012). Measurement of Liquidity-Adjusted Market Risk by VaR and Expected Shortfall: Evidence from Turkish Banks. *Journal of Applied Finance & Banking*, 2(5), 1–8.
- Almeida, H., Campello, M., & Weisbach, M. S. (2004). The Cash Flow Sensitivity of Cash. *The Journal of Finance*, 59(4), 1777–1804. <https://doi.org/10.1111/j.1540-6261.2004.00679.x>
- Amini, S., Delgado, M. S., Henderson, D. J., & Parmeter, C. F. (2012). Fixed vs random: The Hausman test four decades later in *Essays in honour of Jerry Hausman* (pp. 479–513). Emerald Group Publishing Limited.

- Arojo, A., Cabug-os, L., Cumba, R., Sumicad, E., & Naparan, G. (2024). A Correlational Study on the Cash Flow Management Utilization and Financial Performance of Specialty Beverage Businesses. *International Journal of Research Publication and Reviews*, 5, 2382–2390.
- Astuti, P., & Gunarsih, T. (2021). Value-at-Risk Analysis in Risk Measurement and Formation of Optimal Portfolio in Banking Shares. *JBTI : Jurnal Bisnis : Teori Dan Implementasi*, 12. <https://doi.org/10.18196/jbti.v12i2.12263>
- Barth, M. E., Cram, D. P., & Nelson, K. K. (2001). Accruals and the prediction of future cash flows. *The accounting review*, 76(1), 27–58. <https://doi.org/10.2308/accr.2001.76.1.27>
- Berger, A. N., & Bouwman, C. H. (2009). Bank liquidity creation. *The Review of Financial Studies*, 22(9), 3779-3837. <https://doi.org/10.14293/S2199-1006.1.SOR-PPYPW68.v1>
- Blancher, N. R., Appendino, M., Bibolov, A., Fouejieu, A., Li, J., Ndoeye, A., Panagiotakopoulou, A., Shi, W., & Sydorenko, T. (2019). Financial Inclusion of Small and Medium-Sized Enterprises in the Middle East and Central Asia. Retrieved from <https://www.elibrary.imf.org/view/journals/087/2019/002/article-A001-en.xml>
- Bordeleau, É., & Graham, C. (2010). *The impact of liquidity on bank profitability* (No. 2010-38). Bank of Canada.
- Central Bank of Sri Lanka. (2018). Banking Sector. Retrieved from <https://www.cbsl.gov.lk/en/financial-system/financial-system-stability/banking-sector>
- Central Bank of Sri Lanka. (2020). Central Bank of Sri Lanka [Annual Report].
- Chernobai, A., Ozdagli, A., & Wang, J. (2021). Business complexity and risk management: Evidence from operational risk events in U.S. bank holding companies. *Journal of Monetary Economics*, 117, 418–440. <https://doi.org/10.1016/j.jmoneco.2020.02.004>
- Diamond, D. W., & Rajan, R. G. (2001). Liquidity risk, liquidity creation, and financial fragility: A theory of banking. *Journal of Political Economy*, 109(2), 287-327. <http://www.nber.org/papers/w7430>
- Dechow, P. M. (1994). Accounting Earnings and Cash Flows as Measures of Firm Performance: The Role of Accounting Accruals. *The Accounting Review*. [https://doi.org/10.1016/0165-4101\(94\)90016-7](https://doi.org/10.1016/0165-4101(94)90016-7)
- Dechow, P. M., & Dichev, I. D. (2002). The quality of accruals and earnings: The role of accrual estimation errors. *The accounting review*, 77(s-1), 35–59.

- DeFond, M. & M. Hung. (2003). An Empirical Analysis of Analysts' Cash Flow Forecasts. *Journal of Accounting and Economics*, 35, 73–100.
- Eyisi, A. S., & Okpe, I. I. (2014). The Impact of Cash Flow Ratio on Corporate Performance. *Research Journal of Finance and Accounting*, 5(6).
- Fernando, J., & Basnayake, D. (2022). Banks' risk management: An analysis of risk management practices of the Sri Lankan banking sector. In the *International Conference on Business and Information*.
- Freeman, R., & McVeagh, J. (2001). A Stakeholder Approach to Strategic Management. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.263511>
- Gemzik-Salwach, A. (2012). The Use of a Value-at-Risk Measure for Analysing Bank Interest Margins. *E-Finanse*, 8. Retrieved from <https://bibliotekanauki.pl/articles/599468.pdf>
- Gowthaman, J. (2022). The Impact of Banking Sector Stability on Economic Growth: Evidence from Sri Lanka for the Post-War Period. 4, 945–950. <https://doi.org/10.56726/IRJMETs32275>
- Gunawardene, N. (2017). Digital Transformation in Sri Lanka: Opportunities and Challenges in Pursuit of Liberal Policies. Friedrich Naumann Foundation (FNF) Sri Lanka. Retrieved from <https://www.rticommission.lk/web/images/pdf/DigitalTransformationinSriLankareport-FINAL-30Nov2017.pdf>
- Guliyev, T., & Muzaffarov, M. (2024). Deciphering Sustainable Growth: The Influence of Corporate Financial Metrics on SGR and Stock Returns. *WSB Journal of Business and Finance*, 58(1), 114–121.
- Habeeb, F., & Wcikramasinghe, C. (2019). Innovation and Development of Digital Finance: A Review on Digital Transformation in Banking & Financial Sector of Sri Lanka. Retrieved from <https://www.empyrealpublishinghouse.com/pdf/edited-book-of-dr-vijay-prakash-gupta.pdf#page=140>
- Ho, T., Abbott, M., & Abrahamson, A. (1999). Value at risk of a bank's balance sheet. *International Journal of Theoretical and Applied Finance*, 1. <https://doi.org/10.1142/S0219024999000042>
- Jayamaha, R. (2008). The Impact of IT in the Banking Sector. Retrieved from <https://www.bis.org/review/r080201d.pdf>
- Jensen, M. C. & Meckling, W. H. (1976). Theory of the Firm: Managerial Behaviour, Agency Costs, and Ownership Structure. *Journal of Financial Economics* 3, 305–60.

- Kedarya, T., Elalouf, A., & Cohen, R. S. (2023). Calculating Strategic Risk in Financial Institutions. *Global Journal of Flexible Systems Management*, 1–12. <https://doi.org/10.1007/s40171-023-00342-3>
- Kimani, J., & Kibera, M. (2023). Evolution of Risks Facing Commercial Banks in Kenya and Associated Strategic Responses. *International Journal of Modern Risk Management*, 1, 56–65. <https://doi.org/10.47604/ijmrm.2245>
- KPMG Sri Lanka. (2021). KPMG Sri Lanka Issue 7 June 2021 Banking Report. Retrieved from <https://assets.kpmg.com/content/dam/kpmg/lk/pdf/kpmg-sri-lanka-banking-report-june-2021.pdf>
- Lins, K. V., Servaes, H., & Tamayo, A. (2017). Social capital, trust, and firm performance: The value of corporate social responsibility during the financial crisis. *the Journal of Finance*, 72(4), 1785-1824.
- Madushika, W. A. D., & Wijesinghe, B. A. C. H. (2022, October). Cash flows and firm performance: Evidence from Colombo Stock Exchange. In the *5th Annual Research Symposium in Management* (p. 221).
- Mashamba, T. (2021). Liquidity regulations and bank behaviour: an emerging markets perspective. *Journal of Governance and Regulation*, 10(4).
- Nandalal, P. (2021). Sri Lanka's macro-financial. Central Bank of Sri Lanka. Retrieved from [https://unctad.org/system/files/official-document/BRI-Project\\_RP13\\_en.pdf](https://unctad.org/system/files/official-document/BRI-Project_RP13_en.pdf)
- Nasimiyu, A. (2024). Cash-flow Management Practices and Financial Performance of Small and Medium Business Enterprises in Kenya. *African Journal of Commercial Studies*, 4, 252–263. <https://doi.org/10.59413/ajocs/v4.i3.7>
- Oral, C., & CenkAkkaya, G. (2015). Cash Flow at Risk: A Tool for Financial Planning. *Procedia Economics and Finance*, 23, 262–266. [https://doi.org/10.1016/S2212-5671\(15\)00358-5](https://doi.org/10.1016/S2212-5671(15)00358-5)
- Perera, E. A. Y. D., & Weerasinghe, T. D. (2016). Gender Imbalance in Sri Lankan Labour Markets and Concerns of Human Resource Management. *academia.edu*
- Pasiouras, F., & Kosmidou, K. (2007). Factors influencing the profitability of domestic and foreign commercial banks in the European Union. *Research in International Business and Finance*, 21(2), 222–237. <https://doi.org/10.1016/j.ribaf.2006.03.007>
- Sheytanova, T. (2015). The accuracy of the Hausman Test in panel data: A Monte Carlo study.



- Shabir, M., Jiang, P., Wang, W., & Işık, Ö. (2023). COVID-19 pandemic impact on banking sector: A cross-country analysis. *Journal of Multinational Financial Management*, 67, 100784. <https://doi.org/10.1016/j.mulfin.2023.100784>
- Schipper, K., & Vincent, L. (2003). Earnings quality. *Accounting Horizons*, 17.
- Tashakkori, A., & Teddlie, C. (2010). *SAGE Handbook of Mixed Methods in Social Behavioural Research*. SAGE Publications, Inc. <https://doi.org/10.4135/9781506335193>
- Trujillo-Ponce, A. (2013). What determines the profitability of banks? Evidence from Spain. *Accounting & Finance*, 53(2), 561–586. <https://doi.org/10.1111/j.1467-629X.2011.00466.x>
- Vural, O. (2004). Cash Flow-At-Risk in Publicly Traded Non-Financial Firms in Turkey: An Application in Defence Companies, The Institute of Economics and Social Sciences, Master of Business Administration, Bilkent University, Turkey.
- Wickramasinghe, M. B., & Gunawardane, K. (2017). Cash Flow Risk Management Practices on Sustainable Financial Performance in Sri Lanka. *dr.lib.sjp.ac.lk* 6(8).
- Wijesinghe, J., & Pallearachchi, D. (2022). Banking Sector Development and Economic Growth in Sri Lanka: An Econometric Analysis. *South Asian Journal of Finance*, 2 (1). <https://doi.org/10.4038/sajf.v2i1.42>
- Wijesinghe, C., Hansson, H., & Colomboge, R. (2018). University-Industry Collaboration for ICT Innovation in Sri Lanka. *Proceedings of E-Learn: World Conference on E-Learning in Corporate, Government, Healthcare, and Higher Education 2018*, 407–412. <https://www.learntechlib.org/p/185008>.

## CHAPTER TWO

### Impact of Macroeconomic Determinants on Carbon Emission in Developing Countries

Pieris M.H.D. & Dayaratne D.A.I.

Department of Accountancy and Finance, Faculty of Management Studies  
Sabaragamuwa University of Sri Lanka  
[hirushidilhari@gmail.com](mailto:hirushidilhari@gmail.com)

#### Abstract

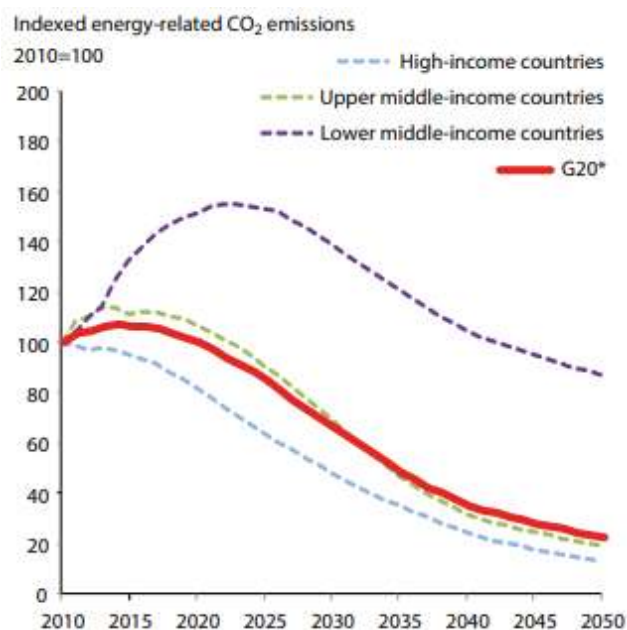
*The primary purpose of the research is to examine the macroeconomic variables that influence environmental quality in developing countries. First, this study employs a dynamic panel data model to address the endogeneity problem and utilises a system-generalised method of moments estimator to examine the impact of macroeconomic determinants on environmental quality, using panel data from 113 developing countries from 2013 to 2022. Based on the income level, the sample is categorised into four groups. The analysis focuses on seven macroeconomic determinants: foreign direct investment, renewable energy consumption, economic growth, trade openness, natural resources, information and communication technology, and financial development. Robustness tests were conducted using the general term of the lagged independent variable approach, while the primary data analysis employed econometric estimation methods, including ordinary least squares, fixed effects, and the dynamic generalised methods of moments approach, to select the model for the dynamic panel. The results show that foreign direct investment, financial development, and economic growth have a significantly positive impact on carbon emissions. On the other hand, information and communication technology, as well as renewable energy consumption, have an insignificant negative impact. All other remaining variables showed an insignificant positive effect. This study's findings suggest green macroeconomic initiatives as an eco-friendly approach to achieving both environmental and economic sustainability.*

**Keywords:** Carbon Emission, Developing Countries, Environmental Quality, Generalised Methods of Moments (GMM), Macroeconomic Variables.

## 1. Introduction

Global warming and climate change have become urgent environmental concerns that are causing alarm among economists, legislators, and academics everywhere. The primary cause of these issues is the excessive release of greenhouse gas emissions, particularly carbon dioxide (CO<sub>2</sub>), which accelerates environmental degradation and disrupts climate stability (Onuonga, 2020). By promoting energy consumption and trade, rapid industrialisation and globalisation have exacerbated these consequences and increased ecological stress in emerging nations (Ahmed & Long, 2013). Since the start of industrialisation in the 1970s, energy consumption has risen steadily, contributing to the growth of international trade while also leading to significant environmental concerns. Globalisation has benefited developing countries by lowering investment and trade obstacles, facilitating the flow of technology, labour, and mobilising capital. However, it has also contributed to rising environmental degradation, partly due to increased energy consumption. The ongoing industrialisation process in developing countries remains highly vulnerable to the adverse impact of global climate change.

Developing countries frequently struggle to strike a balance between economic growth and emissions, which are widely recognised as a major contributor to climate change, as they utilise their advantages and resources to achieve economic parity. Developing countries face significant challenges in reducing carbon emissions and meeting global reduction objectives at various stages of development. Additionally, it is noteworthy that around 80% of the world's carbon dioxide (CO<sub>2</sub>) emissions come from the top 20 emitting nations (UN trade & development, 2021). On a worldwide scale, global warming currently poses a serious threat to environmental health. Thus, by implementing various policies, all nations are attempting to reduce CO<sub>2</sub> emissions. This is supported by Figure 1.1. The CO<sub>2</sub> emission pathway is displayed by income category. The majority of countries are implementing net-zero emission targets, which is encouraging because they aim to reduce around 63% of global emissions (IEA, 2021). However, to remain viable and credible, these goals must be quickly integrated into both short-term policies and considerably more ambitious Nationally Determined Contributions (NDCs) for the period up to 2030. Severe weather events and other climatic phenomena that show signs of human-caused climate change have been reported in 2021. Interestingly, extreme heat in North America and widespread flooding in Western Europe have been recognised as important examples of this phenomenon (United Nations Climate Change, 2021).



**Figure 1.1:** Emissions pathway by income group

**Source:** IEA (2017) and OECD calculations

Global economies are increasingly adopting sustainable energy sources and exploring strategies to mitigate CO<sub>2</sub> emissions in response to the escalating environmental challenges associated with climate change. Existing empirical data suggest that rapid economic expansion and rising energy consumption in developing nations account for a substantial portion of global carbon emissions (Ahmed & Long, 2013).

One aspect of the relationship between economic activity and carbon emissions that has been examined extensively and whose data is no longer controversial is the association between economic growth and carbon emissions. The list of factors influencing carbon emissions has not yet been determined. Therefore, by investigating the factors that influence carbon emissions in emerging nations, the author aims to contribute to the existing body of literature. To the best of the researcher's knowledge, no study has examined the factors that influence carbon emissions in developing nations both across income levels and as a whole. The current research examines how macroeconomic parameters affect carbon emissions in the developing world, both overall and by socioeconomic class, with the goal of addressing this gap.

This study's primary concern is the growing harm to the environment caused by carbon emissions worldwide, primarily due to the exponential increase since the Industrial Revolution. Environmental pollution is increasing due to greenhouse gas emissions (Pelickis, 2016). One of the primary causes of environmental deterioration, climate change, and global warming has been identified as the release of greenhouse gases, specifically carbon dioxide (CO<sub>2</sub>) (Onuonga, 2020). All such environmental harms have led to a worsening of ecological

quality and pose a significant risk to achieving high levels of sustainability. The relationship between macroeconomic indicators and ecological quality, particularly CO<sub>2</sub> emissions, is multifaceted and complex. Although economic growth and industrialisation increase emissions, the implementation of efficient environmental policies, innovation, and sustainable practices can decouple environmental degradation from economic growth. Building successful international plans to lower CO<sub>2</sub> emissions requires addressing these problems.

According to this research, several factors, including population, trade, energy usage, and economic development, influence CO<sub>2</sub> emissions (Kwakwa et al., 2020). Most studies have investigated individual factors affecting CO<sub>2</sub> emissions, as well as combinations of two or three factors. However, an agreed-upon list of macroeconomic factors influencing a decrease in environmental quality still needs to be fully discovered (Tsaurai, 2020). Therefore, by conducting a thorough investigation into the factors affecting carbon emissions in developing nations, this study aims to bridge the existing gap in the literature.

Industrialised nations have increasingly directed their investments to developing countries or established production facilities in resource-rich regions, leveraging skilled human capital, raw materials, vast land resources, and financial resources. This development has resulted in pollution-intensive industries transferring from developed to developing economies, while developing countries pursue economic advancement through such industrialisation. As a result, the increased carbon emissions and environmental pollution in the developing world have become a significant factor contributing to global warming. Climate change is becoming a major worry as a result of the phenomenon of industry transferring from developed to developing nations due to cheap labour, an abundance of natural resources, and lax environmental rules (Nawaz et al., 2021; Apergis et al., 2023; Nyeadi, 2023; Song et al., 2021; Aghasafari et al., 2021).

According to the Intergovernmental Panel on Climate Change (IPCC) reports, all economies must adopt steps to help keep global temperatures below 2°C (Gunarto, 2020). According to Rukikaire & Nullis (2021), the occurrence and severity of various weather and climate extremes are being amplified in all geographical regions worldwide due to global climate change. Developing countries have generally emphasised efforts to promote and enhance their industrial activity, substantially expanding their energy consumption to generate more goods and services. The economic growth of developing countries drives extensive energy use, and as a result, waste is often disposed of in the environment, leading to environmental degradation. Hence, the level of environmental contamination in developing countries has increased significantly in the 21<sup>st</sup> century.

### **1.1. Research Objectives**

1. To determine the relationship between macroeconomic variables and carbon emissions in developing countries.
2. To examine the impact of macroeconomic determinants on carbon emissions in developing countries.
3. To explore the impact of macroeconomic determinants on carbon emissions based on the developing countries' income levels.

## **2. Literature Review**

### **2.1. Theoretical Review**

In the theoretical review, the researcher outlines the fundamental theories employed in the research. The theoretical review section encompasses the examination of the EKC model hypothesis and the Pollutant Haven Hypothesis. The researcher used these theories to develop the proposed study by defining the variables and providing supporting arguments.

The Environmental Kuznets Curve (EKC) theory was initially proposed by Simeon Kuznets in 1955. The term "inverted-U relationship" is derived from the research conducted by Kuznets (1955), who proposed a comparable association between income disparity and economic development. The concept of the Environmental Kuznets Curve (EKC) was first introduced in the early 1990s through the influential research conducted by Grossman and Krueger (1991) on the potential effects of NAFTA, as well as the background study conducted by Shafik and Bandyopadhyay (1992) for the 1992 World Development Report. Nevertheless, the notion that the preservation or enhancement of environmental quality is contingent upon economic growth constitutes a fundamental component of the sustainable development discourse advocated by the World Commission on Environment and Development (1987) in their seminal publication, "Our Common Future" (Ekins, 1997)

Two alternative theories associate FDI and the environment, namely, the "pollution-haven" and "pollution-halo" theories. The pollution-halo hypothesis posits that foreign companies, particularly those originating from developed economies, bring with them advanced and environmentally friendly technologies, as well as superior management techniques, that have the potential to enhance the host country's environmental quality. The pollution-halo concept gains particular significance when examining the pollution intensity of local businesses in relation to foreign standards.

The concept of the Pollution Haven Hypothesis (PHH) was initially proposed by Copeland and Taylor (1994) within the framework of North-South trade facilitated by NAFTA. Under the North American Free Trade Agreement (NAFTA), companies based in heavily regulated countries, such as the United States and Canada, found themselves in direct competition with companies operating in economically disadvantaged countries like Mexico, which had less stringent environmental regulations. According to the predictions made by Copeland and Taylor (1994), NAFTA was anticipated to have detrimental environmental consequences for Mexico and result in a significant loss of jobs for the United States. Within the context of trade liberalisation, companies producing environmentally harmful items would relocate from affluent nations with stringent environmental regulations to developing countries with relatively weak environmental regulations. Hence, under the context of free and liberalised commerce, it is plausible that developing countries may assume the role of pollution havens, accommodating the environmentally detrimental businesses of developed countries.

## **2.2. Empirical Review**

Many studies have examined the causal relationships between various environmental deterioration and economic variables, as well as pollution in terms of carbon emissions. Various empirical studies have yielded different results due to methodological contrasts and study contexts (Khan & Ahmad, 2021). The literature has extensively modelled the connection between economic growth and environmental quality using the emissions–income link.

Based on the factors highlighted, it is evident that Asian economies have exhibited a more commendable performance in terms of carbon emissions compared to developed countries on a global scale (Gunarto, 2020). The majority of developing countries are located in Asian regions. Currently, many developing countries are implementing innovative strategies to mitigate environmental degradation and reduce carbon emissions associated with their developmental activities (Gunarto, 2020).

To determine long-term correlations between variables, Onuonga (2020) employed the ARDL bounds testing approach to examine the relationship between environmental quality, financial development, and economic growth in Kenya. The study, which utilised time series data from 1970 to 2019, confirmed that environmental quality is negatively impacted by trade openness, population growth, energy consumption, financial development, and foreign direct investment. In Kenya, it was also discovered that the use of natural resources increased air pollution. Regarding the relationship between income and air pollution, the study questioned the EKC hypothesis but concluded that it was more pertinent when considering financial development.

Fitriyah (2019) used the EKC model for Indonesia to investigate the relationship between energy consumption, financial development, economic growth, and carbon emissions. A long-term and statistically significant association between these factors was empirically demonstrated using the ARDL bounds testing technique. Research has shown that financial development, energy consumption, and economic expansion all have a positive and statistically significant impact on CO<sub>2</sub> emissions over the long and short terms.

(2021) pointed out that because developing countries have more lax environmental regulations, they are pollution havens; hence, FDI inflows from developed to developing countries are likely to raise emissions. FDI can, however, also be beneficial in enhancing managerial efficiency and introducing new technologies, both of which may lead to a reduction in emissions. GDP per capita, energy consumption, trade openness, urban population, and renewable energy utilisation were their control variables. Recent research on the Pollution Halo Effect (PHE) and the Pollution Haven Hypothesis (PHH) suggests that the impact of foreign direct investment (FDI) on CO<sub>2</sub> emissions may not be uniform across all Chinese regions. PHH or PHE has been proven in numerous regions of China, confirming the prevalence of aggregation bias (Apergis et al., 2023), as cited in Ahmad et al.. The empirical data, as cited in Apergis et al. (2023) and Cai et al. (2018), hypothesise that China serves as a pollution refuge for 22 industrialised countries and 19 developing countries, confirming the PHH in the case of China.

Similarly, Nyeadi investigated how FDI inflows and financial growth affected the use of clean energy and carbon dioxide emissions in Sub-Saharan Africa (SSA). FDI did not significantly affect the use of clean energy in SSA, according to the study, which also controlled for economic growth. However, when the sample was divided according to income, a strong correlation was found: FDI had a negative impact on middle-income economies but a positive impact on clean energy use in low-income nations. FDI has a positive correlation with CO<sub>2</sub> emissions across the board, especially in low-income economies.

On a global scale, countries are achieving sustainable development by obtaining environmentally friendly FDI as well as strengthening technology capabilities. However, this is not always the case with South Asia and other emerging nations, where record CO<sub>2</sub> emissions have been reached. This is partly due to the fact that a significant number of growing economies are located in Asia, where excessive expansion, foreign investment, and lax environmental regulations all contribute to environmental degradation. Nawaz et al. (2021) present empirical results that contradict the conventional EKC hypothesis, which posits an inverse U-shaped relationship between CO<sub>2</sub> emissions and per capita GDP. Instead,



a U-shaped relationship is observed between FDI and CO<sub>2</sub> emissions, suggesting that further FDI inflows may lower emissions beyond a certain point. However, most South Asian nations face a dire challenge in attaining sustainable economic development, as FDI remains a key driver of environmental deterioration (Nawaz et al., 2021).

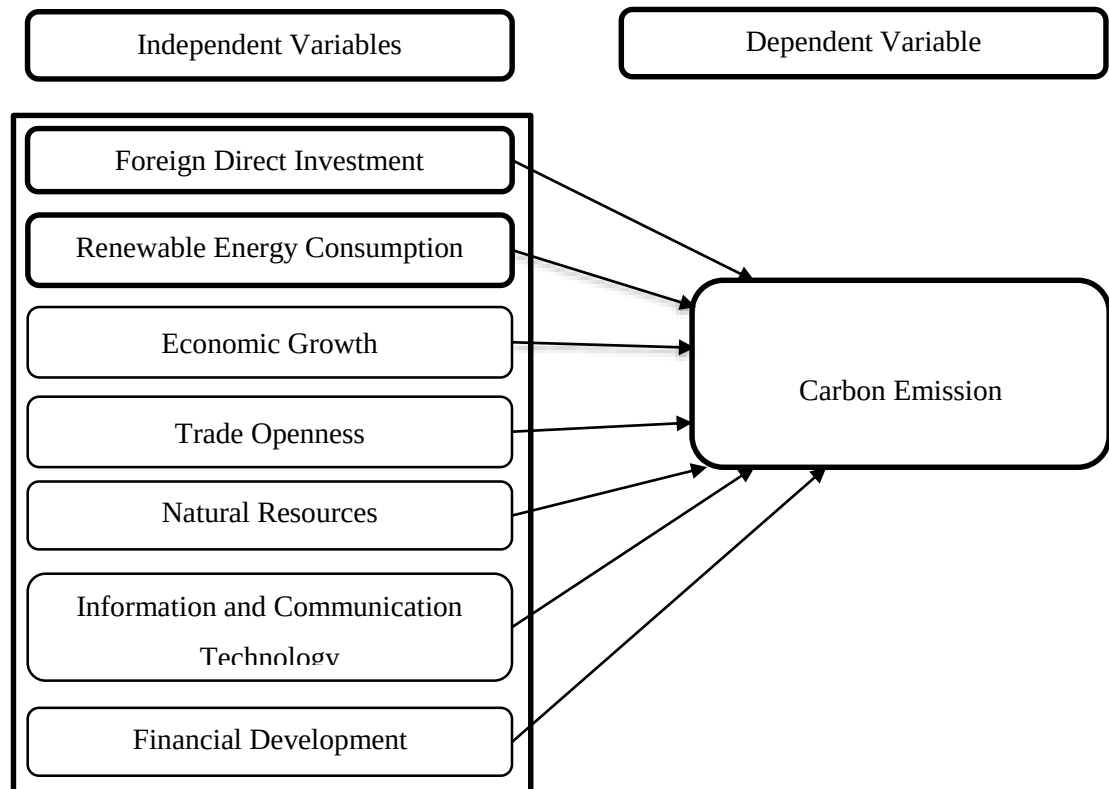
A considerable number of empirical studies have examined the impact of different variables on CO<sub>2</sub> emissions, both individually and in combination with two or three variables. There is a considerable body of literature that investigates factors such as renewable energy consumption, FDI, and economic growth as determinants of CO<sub>2</sub> emissions pollution. However, those studies investigated each factor separately. Therefore, the present study aims to examine the impact of seven macroeconomic determinants on CO<sub>2</sub> emissions in a single study, thereby filling this gap.

In addition, most empirical studies have centred on single countries or regions. This study, in contrast, encompasses all available developing countries and aggregates them into four income groups to see how the effect of macroeconomic determinants on carbon emissions varies across different income levels. Several methodological limitations have been identified in existing empirical studies, including the failure to capture the dynamic characteristics of CO<sub>2</sub> emissions data, the inability to address issues of endogeneity, autocorrelation, and heteroskedasticity, which results in biased and inconsistent results. The present study addresses all these issues using a system-generalised method of moments (GMM) estimator. Ultimately, this study fills a gap in the literature by providing unique insights to the global community.

### **3. Methodology**

#### **3.1. Conceptual Framework**

The study developed the conceptual model using evidence from previous researchers to address the research objectives. The independent variables of the study are foreign direct investment, Renewable energy consumption, economic growth, Trade openness, Natural resources, Information and Communication Technology, and Financial development. The study examined how these independent variables impact carbon emissions.



**Figure 3.1:** Conceptual Framework

**Source:** Developed by the researcher

The following hypotheses are developed based on the conceptual framework.

- H<sub>1</sub>: There is a significant impact of foreign direct investments on carbon emissions in developing countries.
- H<sub>2</sub>: There is a significant impact of renewable energy consumption on carbon emissions in developing countries.
- H<sub>3</sub>: There is a significant impact of economic growth on carbon emissions in developing countries.
- H<sub>4</sub>: There is a significant impact of trade openness on carbon emissions in developing countries.
- H<sub>5</sub>: There is a significant impact of natural resources on carbon emissions in developing countries.
- H<sub>6</sub>: There is a significant impact of information and communication technology on carbon emissions in developing countries.
- H<sub>7</sub>: There is a significant impact of financial development on carbon emissions in developing countries.

### 3.2. Operationalisation of the study

**Table 3.1:** Measurement of Variables

| Variables                                      | Indicator                                                          | Reference                 | Source                |
|------------------------------------------------|--------------------------------------------------------------------|---------------------------|-----------------------|
| Carbon Dioxide Emission                        | Carbon emissions (metric tons per capita)                          | (Khan & Ahmad, 2021)      | World Bank Indicators |
| Foreign Direct Investment (FDI)                | Net inflows as a percentage of GDP                                 | (Khan & Ahmad, 2021)      |                       |
| Renewable energy consumption (REC)             | Renewable energy consumption (% of total final energy consumption) | (Khan & Ahmad, 2021)      |                       |
| Economic growth (EG)                           | Gross Domestic Product Growth (annual %)                           | (Nyeadi, 2023)            |                       |
| Trade openness (TO)                            | Total trade (% of GDP)                                             | (Marques & Caetano, 2020) |                       |
| Natural Resources (NR)                         | Total natural resources rents (% of GDP)                           | (Adjei et al., 2018)      |                       |
| Information and communication technology (ICT) | Individuals using the Internet (% of the population)               | (Tsaurai, 2020)           |                       |
| Financial Development (FD)                     | Domestic credit issued to the private sector (% of GDP)            | (Nyeadi, 2023)            |                       |

**Source:** Previous Literature

### 3.3. The Data and Sample

This study adopts a quantitative research approach and aims to address the research questions through the analysis of data collected from secondary sources. The study used the following sampling criteria. Considering the availability of the data, the researcher chose 113 developing countries. The data was collected for 10 years, from 2013 to 2022. The 113 developing countries were categorised into four categories according to income level: high-income, upper-middle-income, lower-middle-income, and low-income developing countries.

**Table 3.2:** Sample Size

| <b>Income Level</b>                                                                                                                                                                                                                                                                                                                                                                                                                 | <b>Number of Countries</b> |
|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|----------------------------|
| <u>High-Income</u>                                                                                                                                                                                                                                                                                                                                                                                                                  |                            |
| Antigua and Barbuda, Bahamas, Bahrain, Barbados, Chile, Kuwait, Oman, Panama, Poland, Qatar, Romania, Saudi Arabia, Seychelles, Uruguay                                                                                                                                                                                                                                                                                             | 14                         |
| <u>Upper-middle Income</u>                                                                                                                                                                                                                                                                                                                                                                                                          |                            |
| Albania, Argentina, Armenia, Azerbaijan, Belarus, Belize, Bosnia and Herzegovina, Botswana, Brazil, Bulgaria, China, Colombia, Costa Rica, Dominica, Ecuador, El Salvador, Equatorial Guinea, Fiji, Gabon, Georgia, Guatemala, Indonesia, Iraq, Jamaica, Kazakhstan, Malaysia, Maldives, Mauritius, Mexico, Moldova, Montenegro, Namibia, North Macedonia, Paraguay, Peru, Russia, Serbia, South Africa, Thailand, Tonga,           | 40                         |
| <u>Lower-middle Income</u>                                                                                                                                                                                                                                                                                                                                                                                                          |                            |
| Algeria, Angola, Bangladesh, Benin, Bhutan, Bolivia, Cambodia, Cameroon, Comoros, Djibouti, Egypt, Eswatini, Ghana, Guinea, Haiti, Honduras, India, Iran, Jordan, Kenya, Kyrgyzstan, Lebanon, Lesotho, Mauritania, Mongolia, Morocco, Myanmar, Nepal, Nicaragua, Nigeria, Pakistan, Philippines, Samoa, Senegal, Solomon Islands, Sri Lanka, Tajikistan, Tanzania, Tunisia, Ukraine, Uzbekistan, Vanuatu, Vietnam, Zambia, Zimbabwe | 45                         |
| <u>Low-Income</u>                                                                                                                                                                                                                                                                                                                                                                                                                   |                            |
| Burkina Faso, Burundi, Central African Republic, Chad, Gambia, Guinea-Bissau, Madagascar, Mali, Mozambique, Niger, Rwanda, Sudan, Togo, Uganda                                                                                                                                                                                                                                                                                      | 14                         |

**Source:** World Bank Classification

### 3.4. Data analysis

The study used a two-step system GMM to address the research objectives and obtain precise conclusions. Several previous studies failed to address the potential issue of endogeneity. This study employs a system-generalised method of moments (GMM) estimator to investigate the impact of macroeconomic variables on environmental quality, utilising panel data from various developing countries. The present research has extensively explored the study of dynamic specification with a lagged dependent variable. Researchers used CO<sub>2</sub> emissions as a proxy for assessing the dependent variable. Given the cumulative nature of CO<sub>2</sub> emissions

over time, it is essential to incorporate a dynamic panel data model that includes the lagged dependent variable, as this allows for an analysis of the relationship between current emissions and those of the previous year. Moreover, the GMM is a more suitable approach for estimating a dynamic panel data model. This is because GMM is well-suited for addressing issues such as endogeneity, heteroskedasticity, and autocorrelation that may arise in the variables being examined.

#### 4. Results and Discussion

The two-step system GMM is the most suitable estimating method for this investigation, as indicated by the data in Table 4.1. When using traditional panel estimating techniques, the endogeneity of right-hand side regressors may result in biased and inconsistent estimation, primarily because the error term and the lagged effect of CO<sub>2</sub> emissions are correlated. An alternative approach is provided by Arellano & Bond (1991), who use the first-difference GMM estimator. The first-difference GMM employs moment conditions as tools to deal with the endogeneity issue, assuming that there is no serial correlation in the error terms and that the exogenous explanatory factors are weak. Furthermore, fixed effects are eliminated by the model's first differencing, and theoretically, the two-step GMM estimator produces more accurate estimates.

**Table 4.1:** Model selection

|                                                                                                                                                               | <b>Pool OLS</b> | <b>Fixed Effect</b> | <b>1<sup>st</sup> Difference GMM</b> |
|---------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------------|---------------------|--------------------------------------|
| <b>L.CO<sub>2</sub>E</b>                                                                                                                                      | 0.9730          | 0.6852              | 0.4659                               |
| Conclusion: The value of $\delta$ in the Difference GMM (0.4659) is lower than that of the FE model (0.6852); hence, System GMM is appropriate for this data. |                 |                     |                                      |
| pval in parentheses                                                                                                                                           |                 |                     |                                      |
| *** p<0.01, ** p<0.05, * p<0.1                                                                                                                                |                 |                     |                                      |

**Source:** STATA Output

However, as mentioned in Arellano & Bover (1995) and Blundell & Bond, the lagged levels are not good tools for the two-step GMM estimator when the autoregressive process is sufficiently persistent. Blundell & Bond (2023) proposed the system-GMM estimator, which combines moment conditions for the level and differenced equations, as a way to circumvent this restriction. Therefore, the primary estimate method used in this study is the two-step system-GMM estimator. The Arellano-Bond GMM estimator might be a better choice if the coefficient on lagged levels is highly persistent. Post-estimation diagnostics such as the Sargan test and the Arellano-Bond serial correlation tests are used to assess the validity of the instruments and any serial correlation in the residuals.

#### 4.1. Dynamic panel-data Estimation, Two-step System GMM

**Table 4.2:** Model selection

| Prob > chi2 = 0.000                                                         |         |           |
|-----------------------------------------------------------------------------|---------|-----------|
| Variable                                                                    | Coef.   | P> z      |
| COE L1.                                                                     | 0.9361  | 0.0000*** |
| FDI                                                                         | 0.0227  | 0.0220**  |
| REC                                                                         | -0.0012 | 0.2080    |
| EG                                                                          | 0.0246  | 0.0000*** |
| TO                                                                          | 0.0013  | 0.4400    |
| NR                                                                          | 0.0090  | 0.1020    |
| ICT                                                                         | -0.0038 | 0.1010    |
| FD                                                                          | 0.0012  | 0.0490**  |
| _cons                                                                       | -0.1556 | 0.1760    |
| Arellano-Bond test for AR(1) in first differences: z = -2.88 Pr > z = 0.004 |         |           |
| Arellano-Bond test for AR(2) in first differences: z = -0.62 Pr > z = 0.532 |         |           |
| Sargan test = Prob > chi2 = 0.084                                           |         |           |
| Hansen test = Prob > chi2 = 0.388                                           |         |           |
| pval in parentheses                                                         |         |           |
| *** p<0.01, ** p<0.05, * p<0.1                                              |         |           |

**Source:** STATA Output

Here, the number of instruments is lower than the number of groups, as  $15 < 117$ ; the researcher has met the reasonable requirement. Although the chi-square value is 0.000, the model is correctly specified due to its significant p-value. The lag value of the dependent variable is crucial, as it impacts the current value of CO<sub>2</sub>.

The AB test for AR (1) in the first difference says that the p-value ( $0.004 < 0.05$ ) is less than the significance level, so there is first-order serial correlation since it needs the dynamic panel data modelling. However, second-order serial correlation says by the AB test AR(2) results ( $0.532 > 0.05$ ), so due to the use of L for instrumental variables, we do not need to reject the null hypothesis.

To meet the over-identification restrictions, the researcher used a set of instruments that are valid if the p-value is greater than the results. According to the result, Hansen is robust, as the p-value (0.084) is greater than 0.05. The difference in Sargan tests of exogeneity of the instrument subset ( $0.388 > 0.05$ ) meets the required threshold for exogenous instruments, as it is greater than 0.05.

The results also show that CO<sub>2</sub> emissions in the previous year, FDI, EG and FD significantly impacted the environmental quality at the 95% confidence level. The results indicate that the increase in these three variables, including LCOE, is associated with an increase in CO<sub>2</sub> emissions. On the other hand, REC, TO, NR, and ICT do not have a significant impact on

environmental quality. The increase in the REC and ICT leads to a decrease in CO<sub>2</sub> emissions. These results demonstrate that high-income developing countries employed some sustainable methods while engaging in REC and ICT-related activities. The rise of the TO and NR leads to an increase in CO<sub>2</sub> emissions.

Two-step system GMM can be written as follows;

$$\text{COE}_t = -0.1556 + 0.9361\text{COE}_{t-1} + 0.0227\text{FDI}_t + 0.0246\text{EG}_t + 0.0012\text{FD}_t + \varepsilon_t$$

According to Table 4.2, economic growth had a significant positive impact on carbon emissions. This finding aligns with that of Tsaurai (2020), Aye & Edoja (2017), and Ye et al. (2021), who argue that economic growth is associated with a high level of economic activity, resulting in significant energy usage and increased pollution and carbon emissions. Additionally, this result is inconsistent with those of Sepehrdoust et al. (2023) and Aye & Edoja (2017). Natural resources had an insignificant positive effect on carbon emissions. The results do not align with those of Tsaurai (2020) and Kwakwa et al. (2020). The study noted that the extraction of natural resources is done using heavy equipment and machinery, which emit CO<sub>2</sub>. Trade openness had an insignificant positive effect on CO<sub>2</sub> emissions. This result is similar to those of Tsaurai (2020) and Ali et al. (2021), but differs from Huo et al. (2022). FDI was found to have a significant negative impact on carbon emissions, with results in line with those of Jijian et al. (2021) and Cheng & Yang (2016). However, this result differs from that of Nyeadi (2023). A significant positive relationship exists between financial development and carbon emissions across developing countries, as observed by Aye & Edoja (2017), Fitriyah (2019), and Ye et al. (2021). This finding is consistent with the work of Aye & Edoja (2017), Fitriyah (2019), and Ye et al. (2021). In contrast, Nyeadi (2023) and Ali et al. (2021) report inconsistent results. ICT had an insignificant negative influence on carbon emissions, in line with Lee & Brahmasrene (2014) and not in line with Lee & Brahmasrene (2014), Tsaurai (2020) and Nyeadi (2023). REC had an insignificant positive influence on carbon emissions, in line with Tsaurai (2020), but not in line with Ali et al. (2021) and Sepehrdoust et al. (2023).

This research examines the impact of selected macroeconomic variables on carbon emissions in developing countries. In addition to the above, this study analyses how those macroeconomic variables impact CO<sub>2</sub> emissions based on the income levels of developing countries.

## 4.2. Dynamic Panel-Data Estimation, Two-Step System GMM for High-Income Developing Countries

**Table 4.3:** Dynamic panel-data Estimation, Two-step System GMM for High-Income Developing Countries

| Prob > chi2 = 0.000                                                         |         |           |
|-----------------------------------------------------------------------------|---------|-----------|
| Variable                                                                    | Coef.   | P> z      |
| COE L1.                                                                     | 0.8950  | 0.0000*** |
| FDI                                                                         | -0.4068 | 0.0670*   |
| REC                                                                         | 0.0017  | 0.8630    |
| EG                                                                          | 0.1499  | 0.0920*   |
| TO                                                                          | 0.0158  | 0.0910*   |
| NR                                                                          | -0.0211 | 0.5060    |
| ICT                                                                         | 0.0037  | 0.9360    |
| FD                                                                          | 0.0195  | 0.0600*   |
| _cons                                                                       | -0.7125 | 0.8350    |
| Arellano-Bond test for AR(1) in first differences: z = -1.31 Pr > z = 0.192 |         |           |
| Arellano-Bond test for AR(2) in first differences: z = 0.98 Pr > z = 0.327  |         |           |
| Sargan test = Prob > chi2 = 0.738                                           |         |           |
| Hansen test = Prob > chi2 = 0.599                                           |         |           |
| pval in parentheses                                                         |         |           |
| *** p<0.01, ** p<0.05, * p<0.1                                              |         |           |

**Source:** STATA Output

According to the results, the number of instruments is the same as the number of groups, which is 14=14. Although the Chi-square value is 0.000, the model is correctly specified due to its significant p-value. The lag value of the dependent variable is crucial, as it impacts the current value of COE.

AB test AR (1) for first-order serial correlation (0.192 > 0.05) accepts the null hypothesis; this is not significant. So, there is no first-order serial correlation with residual values. In the AB test, AR (2) second-order correlation (0.327 > 0.05), as set by the fact that there is no second-order serial correlation, the researcher has used L2 as an instrument, and the results showed estimation to be correct.

To meet the over-identification restrictions, the researcher used the set instruments, which are valid if the p-value is greater than the reported results. According to the result, Hansen is robust as the p-value (0.599) is greater than 0.05. The results of the Sargan tests for the difference in exogeneity of the instrument subset (0.738 > 0.05) meet the requirement for exogenous instruments, as they exceed the 0.05 threshold.

The results also indicate that CO2 emissions in the previous year had a significant impact on environmental quality at the 95% confidence level. The results suggest that an increase in



LCOE leads to an increase in CO2 emissions. On the other hand, FDI, REC, EG, TO, NR, ICT and FD do not significantly impact environmental quality. The increase in FDI and REC leads to a decrease in CO2 emissions. These results demonstrate that high-income developing countries employed some sustainable methods while engaging in FDI and REC-related activities. However, the rise of EG, TO, NR, FD, and ICT leads to increased CO2 emissions.

#### 4.3. Dynamic Panel-Data Estimation, Two-Step System GMM for Upper-Middle Income Developing Countries

**Table 4.4:** Dynamic panel-data estimation, two-step system GMM for upper-middle-income developing countries

| Prob > chi2 = 0.000                                                         |          |           |
|-----------------------------------------------------------------------------|----------|-----------|
| Variable                                                                    | Coef.    | P> z      |
| COE L1.                                                                     | 0.83095  | 0.0000*** |
| FDI                                                                         | -0.02467 | 0.2230    |
| REC                                                                         | -0.00510 | 0.0520*   |
| EG                                                                          | 0.06196  | 0.0000*** |
| TO                                                                          | 0.00124  | 0.3400    |
| NR                                                                          | 0.01689  | 0.0040*** |
| ICT                                                                         | 0.01502  | 0.0010*** |
| FD                                                                          | 0.00319  | 0.1280    |
| _cons                                                                       | -0.56877 | 0.0040    |
| Arellano-Bond test for AR(1) in first differences: z = -3.23 Pr > z = 0.001 |          |           |
| Arellano-Bond test for AR(2) in first differences: z = -0.03 Pr > z = 0.977 |          |           |
| Sargan test = Prob > chi2 = 0.000                                           |          |           |
| Hansen test = Prob > chi2 = 0.200                                           |          |           |
| pval in parentheses                                                         |          |           |
| *** p<0.01, ** p<0.05, * p<0.1                                              |          |           |

**Source:** STATA Output

Here, the number of instruments is lower than the number of groups, as  $16 < 41$ ; the researcher has met the requirement. That is good. Although the Chi-square value is 0.000, the model is correctly specified due to its significant p-value. The lag value of the dependent variable is crucial, as it impacts the current value of COE.

AB test for AR (1) in the first difference says that the p-value ( $0.001 < 0.05$ ) is less than the significance level, so there is first-order serial correlation since it needs the dynamic panel data modelling. However, second-order serial correlation says by the AB test AR (2) results, ( $0.977 > 0.05$ ), so due to the use of lag 2 for instrumental variables, the study does not need to reject the null hypothesis.

To meet the over-identification restrictions, the researcher used the set instruments, which are valid if the p-value is greater than the reported results. According to the Hansen result,  $0.200 > 0.05$ . The results of the Sargan tests for the difference in exogeneity of the instrument subset ( $0.000 < 0.05$ ) do not meet the required threshold, as they should be greater than 0.05.

The results also show that CO2 emissions in the previous year, as well as EG, NR, and ICT, have a significant impact on environmental quality at the 95% confidence level. The results indicate that the increase in LCOE, EG, NR, and ICT leads to an increase in CO2 emissions. On the other hand, FDI, REC, TO, and FD do not have a significant impact on environmental quality. The increase in FDI and REC leads to a decrease in CO2 emissions. These results prove that upper-middle-income developing countries used some sustainable methods while engaging in FDI and REC-related activities. However, the rise in TO and FD leads to increased CO2 emissions.

#### 4.4. Dynamic Panel-Data Estimation, Two-Step System GMM for Lower-Middle Income Developing Countries

**Table 4.5:** Dynamic Panel-Data Estimation, Two-Step System GMM for Upper-Middle Income Developing Countries

| Prob > chi2 = 0.0000                                                        |         |           |
|-----------------------------------------------------------------------------|---------|-----------|
| Variable                                                                    | Coef.   | P> z      |
| COE L1.                                                                     | 0.8025  | 0.0000*** |
| FDI                                                                         | -0.0073 | 0.8170    |
| REC                                                                         | -0.0043 | 0.4260    |
| EG                                                                          | 0.0160  | 0.0098*** |
| TO                                                                          | -0.0009 | 0.4470    |
| NR                                                                          | 0.0175  | 0.2380    |
| ICT                                                                         | 0.0025  | 0.2090    |
| FD                                                                          | 0.0030  | 0.0760*   |
| _cons                                                                       | 0.1791  | 0.6250    |
| Arellano-Bond test for AR(1) in first differences: z = -1.36 Pr > z = 0.175 |         |           |
| Arellano-Bond test for AR(2) in first differences: z = 0.66 Pr > z = 0.511  |         |           |
| Sargan test = Prob > chi2 = 0.000                                           |         |           |
| Hansen test = Prob > chi2 = 0.098                                           |         |           |
| pval in parentheses                                                         |         |           |
| *** p<0.01, ** p<0.05, * p<0.1                                              |         |           |

**Source:** STATA Output

Here, the number of instruments is lower than the number of groups, as  $15 < 45$ ; the researcher has met the requirement. Although the Chi-square value is 0.000, the model is correctly specified due to its significant p-value. The lag value of the dependent variable is crucial, as it impacts the current value of COE.

AB test AR (1) for first-order serial correlation ( $0.175 > 0.05$ ) accepts the null hypothesis; this is not significant. So, there is no first-order serial correlation with residual values. In the AB test AR (2) second-order correlation ( $0.511 > 0.05$ ), as set by the fact that there is no second-order serial correlation, the researcher has used L as an instrument, and the results showed that the estimation was correct.

To meet the over-identification restrictions, the researcher used the set instruments, which are valid if the p-value is greater than the reported results. According to the Hansen result,  $0.098 > 0.05$ . The results of the Sargan tests for the difference in exogeneity of the instrument subset ( $0.000 < 0.05$ ) do not meet the required threshold, as they should be greater than 0.05.

The results shown in Table 4.5 also indicate that CO<sub>2</sub> emissions in the previous year and EG have a significant impact on environmental quality at the 95% confidence level. The results indicate that the increase in LCOE and EG leads to an increase in CO<sub>2</sub> emissions. On the other hand, FDI, REC, TO, NR, ICT and FD do not significantly impact environmental quality. The increase in FDI, REC, and TO leads to a decrease in CO<sub>2</sub> emissions. These results demonstrate that lower-middle-income developing countries employed sustainable methods when engaging in FDI, REC, and TO-related activities. However, raising the NR, ICT, and FD leads to increased CO<sub>2</sub> emissions.

#### 4.5. Dynamic panel-data estimation, two-step system GMM for lower-income developing countries

**Table 4.6:** Dynamic panel-data estimation, two-step system GMM for lower-income developing countries

| Prob > chi2 = 0.0000                                                        |         |        |
|-----------------------------------------------------------------------------|---------|--------|
| Variable                                                                    | Coef.   | P> z   |
| COE L1.                                                                     | 0.5164  | 0.3030 |
| FDI                                                                         | 0.0011  | 0.3300 |
| REC                                                                         | -0.0022 | 0.2260 |
| EG                                                                          | 0.0022  | 0.3580 |
| TO                                                                          | 0.0000  | 0.9450 |
| NR                                                                          | 0.0000  | 0.9860 |
| ICT                                                                         | 0.0001  | 0.9390 |
| FD                                                                          | 0.0018  | 0.4090 |
| _cons                                                                       | 0.2010  | 0.1790 |
| Arellano-Bond test for AR(1) in first differences: z = -1.06 Pr > z = 0.289 |         |        |
| Arellano-Bond test for AR(2) in first differences: z = 0.45 Pr > z = 0.650  |         |        |
| Sargan test Prob > chi2 = 0.051                                             |         |        |
| Hansen test Prob > chi2 = 0.700                                             |         |        |
| pval in parentheses                                                         |         |        |
| *** p<0.01, ** p<0.05, * p<0.1                                              |         |        |

Source: STATA Output

According to the results, the number of instruments is lower than the number of groups ( $15 < 16$ ), so the researcher has met the requirement. Although the Chi-square value is 0.000, the model is correctly specified due to its significant p-value. The lag value of the dependent variable is crucial, as it impacts the current value of COE.

AB test AR (1) for first-order serial correlation ( $0.289 > 0.05$ ) accepts the null hypothesis; this is not significant. So, there is no first-order serial correlation with residual values. In the AB test AR (2) second-order correlation ( $0.650 > 0.05$ ), as set by the fact that there is no second-order serial correlation, the researcher has used L2 as an instrument, and the results showed estimation was correct.

To meet the over-identification restrictions, the researcher used the set instruments, which are valid if the p-value is greater than the reported results. According to the result, Hansen is robust as the p-value (0.700) is greater than 0.05. In the results of the Sargan tests for the difference in exogeneity of the instrument subset, the p-value (0.051) is greater than 0.05, meeting the requirement for exogenous instruments.

The results in Table 4.5 indicate that no macroeconomic variables have a significant impact on environmental quality at the 95% confidence level. The results indicate that FDI, REC, EG, TO, NR, ICT, and FD do not have a significant impact on environmental quality. These results demonstrate that lower-income developing countries employed some sustainable methods while engaging in related activities. Increases in selected macroeconomic variables, except for REC, result in higher CO2 emissions.

## 5. Conclusion

The growing global concern over climate change stems from the enduring detrimental effects of greenhouse gas emissions on the ecosystem. The impact of global warming is evident through the manifestation of rising sea levels, increasing ocean temperatures, glacial melting, changing rainfall patterns, a significant decline in biodiversity, reduced agricultural yields, and declining labour force productivity worldwide. There is a pressing need for empirical research on the macroeconomic variables that influence environmental quality, which is crucial for promptly implementing environmental protection policies essential for ensuring a sustainable future in developing countries.

This study demonstrated that economic growth cannot consistently improve environmental quality. Therefore, it is imperative for policymakers to carefully formulate and implement measures that promote economic growth while enhancing environmental quality, thereby achieving sustainable development. Given the evidence suggesting that foreign direct

investment, renewable energy consumption, economic growth, trade openness, natural resources, information and communication technology, and financial development may potentially contribute to economic activities that generate environmental pollution as an unintended consequence, it is recommended that regulatory bodies prioritise the provision of credit for investments in the utilisation and advancement of environmentally friendly technology. This can be achieved by implementing lower interest rates on agreements about environmental protection.

To address the issue of heightened CO<sub>2</sub> emissions in countries with significant industrial sectors, it is essential to implement policies that encourage greater engagement in the tertiary industry, such as the service and finance sectors, or incentivise the adoption of environmentally sustainable technologies and economic practices within the secondary industry. Green macroeconomic activities refer to environmentally friendly methods that can contribute to economic and environmental sustainability.

Governments in high-income developing countries can invest in carbon capture systems and technologies to mitigate climate change. Given the positive effect of the lag-dependent variable, allocate resources and financing to develop and implement sophisticated carbon capture technology to offset last year's emissions. These countries can also initiate green financing programs. They can encourage financial institutions to consider environmental factors when making investment decisions and to promote sustainable projects and businesses. Green technological innovation can be introduced in upper-middle-income developing countries. Researchers can enhance green technology research and development to promote economic growth while minimising environmental impacts. Not only that, but these governments must improve environmental monitoring. The government needs to invest in information and communication technology to enhance environmental monitoring and management, enabling data-driven decision-making for sustainable long-term growth. As natural resource extraction activities weaken the environment in these countries, responsible authorities and departments should not only guide companies that extract natural resources on the importance of afforestation and encourage them to practice land reclamation and afforestation, but also establish laws governing such practices in the country to ensure a safe environment.

The findings from lower-middle-income countries suggest that a comprehensive policy framework is necessary to protect the environment while promoting economic growth. Policymakers can utilise sustainable economic policies to develop and implement measures that support industries with low carbon footprints and sustainable practices, while fostering economic growth. In addition, the study suggests some renewable energy promotions. As a

result, governments can incentivise the use of renewable energy sources to minimise reliance on carbon-intensive energy sources and promote cleaner alternatives. Lower-income developing countries can prioritise projects that provide access to renewable energy sources, particularly in remote areas, to enhance energy access and reduce their reliance on fossil fuels. Additionally, relevant authorities can invest in education and training programs to enhance community knowledge and capacity for sustainable practices. Furthermore, these countries can concentrate on environmentally sustainable agriculture, resource management, and Energy conservation.

The growing global concern over climate change stems from the enduring detrimental effects of greenhouse gas emissions on the ecosystem. The impact of global warming is evident through the manifestation of rising sea levels, increasing ocean temperatures, glacial melting, changing rainfall patterns, a significant decline in biodiversity, reduced agricultural yields, and declining labour force productivity worldwide. There is a pressing need for empirical research on the macroeconomic variables that influence environmental quality, which is crucial for promptly implementing environmental protection policies essential for ensuring a sustainable future in developing countries.

The present study examined the impact of macroeconomic variables on environmental quality in developing countries. Therefore, future research may focus on examining the impact of macroeconomic variables on sectors that significantly contribute to environmental degradation, such as energy, transportation, agriculture, and manufacturing. The analysis of sector-specific data provides valuable insights into the varying impacts of different industries on environmental quality, thereby enabling the identification of appropriate policy actions. The variables included in this study were chosen based on data availability. Future research may consider additional factors, such as infrastructural development, solar radiation, overall biocapacity, and air temperature, to further enhance understanding of the relationship between these variables.

## Reference

- Adjei, P., Adjei Kwakwa, P., Alhassan, H., & Adu, G. (2018). Effect of natural resources extraction on energy consumption and carbon dioxide emission in Ghana Effect of natural resources extraction on energy consumption and carbon dioxide emission in Ghana. *Munich Personal RePEc Archive*, 1(1), 1–19.
- Aghasafari, H., Aminizadeh, M., Karbasi, A., & Calisti, R. (2021). CO<sub>2</sub> emissions, export and foreign direct investment: Empirical evidence from the Middle East and North

- Africa Region. *Journal of International Trade and Economic Development*, 30(7), 1054–1076. <https://doi.org/10.1080/09638199.2021.1934087>
- Ahmed, K., & Long, W. (2013). An empirical analysis of CO<sub>2</sub> emission in Pakistan using the EKC hypothesis. *Journal of International Trade Law and Policy*, 12(2), 188–200. <https://doi.org/10.1108/JITLP-10-2012-0015>
- Ali, R., Hussain, R. I., & Hussain, S. (2021). The Impact of Macroeconomic Factors on Carbon Dioxide Emission in South Asia : a Panel Analysis. *Pakistan Economic and Social Review*, 59(1), 51–84.
- Apergis, N., Pinar, M., & Unlu, E. (2023). How do foreign direct investment flows affect carbon emissions in BRICS countries? Revisiting the pollution haven hypothesis using bilateral FDI flows from OECD to BRICS countries. *Environmental Science and Pollution Research*, 30(6), 14680–14692. <https://doi.org/10.1007/s11356-022-23185-4>
- Arellano, M., & Bond, S. (1991). *Arellanobond91.pdf*. In *The Review of Economic Studies* (Vol. 58, Issue 2, pp. 277–297).
- Arellano, M., & Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. *Journal of Econometrics*, 68(1), 29–51. [https://doi.org/10.1016/0304-4076\(94\)01642-D](https://doi.org/10.1016/0304-4076(94)01642-D)
- Aye, G. C., & Edoja, P. E. (2017). Effect of economic growth on CO<sub>2</sub> emission in developing countries: Evidence from a dynamic panel threshold model. *Cogent Economics and Finance*, 5(1). <https://doi.org/10.1080/23322039.2017.1379239>
- Behera, S. R., & Dash, D. P. (2017). The effect of urbanisation, energy consumption, and foreign direct investment on the carbon dioxide emission in the SSEA (South and Southeast Asian) region. *Renewable and Sustainable Energy Reviews*, 70(November 2015), 96–106. <https://doi.org/10.1016/j.rser.2016.11.201>
- Blundell, R., & Bond, S. (2023). Reprint of: Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, 234, 38–55. <https://doi.org/10.1016/j.jeconom.2023.03.001>
- Cheng, S., & Yang, Z. (2016). The effects of FDI on Carbon Emissions in China: Based on a Spatial Econometric Model. *Revista de la Facultad de Ingeniería*, 31(1998), 137–149. <https://doi.org/10.21311/002.31.6.15>
- Fitriyah, N. (2019). Financial development and environmental degradation in Indonesia: Evidence from the autoregressive distributed lag bound testing method. *International*

Journal of Energy Economics and Policy, 9(5), 394–400.  
<https://doi.org/10.32479/ijeep.8286>

Gökmenoğlu, K., & Taspınar, N. (2016). The relationship between CO2 emissions, energy consumption, economic growth and FDI: the case of Turkey. *Journal of International Trade and Economic Development*, 25(5), 706–723.  
<https://doi.org/10.1080/09638199.2015.1119876>

Gunarto, T. (2020). Effect of Economic Growth and Foreign Direct Investment on Carbon Emissions in Asian States. *International Journal of Energy Economics and Policy*, 10(5), 563–569. <https://doi.org/10.32479/ijeep.10218>

Hadi, S., Retno, S., & Yuliani, S. (2018). The Impact of Foreign Direct Investment on the Quality of the Environment in Indonesia. *E3S Web of Conferences*, 73, 1–5.  
<https://doi.org/10.1051/e3sconf/20187310025>

Hanif, I., Faraz Raza, S. M., Gago-de-Santos, P., & Abbas, Q. (2019). Fossil fuels, foreign direct investment, and economic growth have triggered CO2 emissions in emerging Asian economies: Some empirical evidence. *Energy*, 171, 493–501.  
<https://doi.org/10.1016/j.energy.2019.01.011>

Huo, W., Ullah, M. R., Zulfiqar, M., Parveen, S., & Kibria, U. (2022). Financial Development, Trade Openness, and Foreign Direct Investment: A Battle Between the Measures of Environmental Sustainability. *Frontiers in Environmental Science*, 10(February), 1–10. <https://doi.org/10.3389/fenvs.2022.851290>

Jijian, Z., Twum, A. K., Agyemang, A. O., Edziah, B. K., & Ayamba, E. C. (2021). Empirical study on the impact of international trade and foreign direct investment on carbon emission for Belt and Road countries. *Energy Reports*, 7, 7591–7600.  
<https://doi.org/10.1016/j.egyr.2021.09.122>

Khan, Y. A., & Ahmad, M. (2021). Investigating the impact of renewable energy, international trade, tourism, and foreign direct investment on carbon emissions in developing as well as developed countries. *Environmental Science and Pollution Research*, 28(24), 31246–31255. <https://doi.org/10.1007/s11356-021-12937-3>

Kwakwa, P. A., Alhassan, H., & Adu, G. (2020). The Effect of Natural Resource Extraction on Energy Consumption and Carbon Dioxide Emissions in Ghana. *International Journal of Energy Sector Management*, 14(1), 20–39. <https://doi.org/10.1108/IJESM-09-2018-0003>



- Lee, J. W., & Brahmasrene, T. (2014). ICT, CO2 Emissions and Economic Growth: Evidence from a Panel of ASEAN. *Global Economic Review*, 43(2), 93–109. <https://doi.org/10.1080/1226508X.2014.917803>
- Mahadevan, R., & Sun, Y. (2020). Effects of foreign direct investment on carbon emissions: Evidence from China and its Belt and Road countries. *Journal of Environmental Management*, 276 (September), 111321. <https://doi.org/10.1016/j.jenvman.2020.111321>
- Marques, A. C., & Caetano, R. (2020). The impact of foreign direct investment on emission reduction targets: Evidence from high- and middle-income countries. *Structural Change and Economic Dynamics*, 55, 107–118. <https://doi.org/10.1016/j.strueco.2020.08.005>
- Nawaz, S. M. N., Alvi, S., & Akmal, T. (2021). The Impasse of Energy Consumption Coupling with Pollution Haven Hypothesis and Environmental Kuznets Curve: A Case Study of South Asian Economies. *Environmental Science and Pollution Research*, 28(35), 48799–48807. <https://doi.org/10.1007/s11356-021-14164-2>
- Nyeadi, J. D. (2023). The impact of financial development and foreign direct investment on environmental sustainability in Sub-Saharan Africa: using the PMG-ARDL approach. *Economic Research-Ekonomika Istrazivanja*, 36(1), 2796–2818. <https://doi.org/10.1080/1331677X.2022.2106270>
- Odugbesan, J. A., & Adebayo, T. S. (2020). The Symmetrical and Asymmetrical Effects of Foreign Direct Investment and Financial Development on Carbon Emissions: Evidence from Nigeria. *SN Applied Sciences*, 2(12), 1–15. <https://doi.org/10.1007/s42452-020-03817-5>
- Onuonga, S. M. (2020). The Impact of Financial Development and Economic Growth on Environmental Quality of Kenya. *Journal of Economics and Sustainable Development*, 11(12), 15–26. <https://doi.org/10.7176/jesd/11-12-03>
- Rozendal, C. (2020). The Influence of GDP, FDI, and Energy Consumption on CO2 Emissions: An Econometric Analysis Using a Panel ARDL Model. February.
- Sepehrdoust, H., Tartar, M., & Mohtashami, S. (2023). Impact of Determinant Macro Economic Variables on Environmental Changes in Iran. *Environmental Health Insights*, 17. <https://doi.org/10.1177/11786302221149855>
- Shahidan Shaari, M., Masnan, F., Hidayah Harun, N., & Fadzilah Zainal, N. (2020). Macroeconomic Factors Affecting CO2 Emissions in Malaysia: An ARDL Approach.

IOP Conference Series: Materials Science and Engineering, 864(1).  
<https://doi.org/10.1088/1757-899X/864/1/012050>

- Song, W., Mao, H., & Han, X. (2021). The two-sided effects of foreign direct investment on carbon emissions performance in China. *Science of the Total Environment*, 791, 148331. <https://doi.org/10.1016/j.scitotenv.2021.148331>
- Tsaurai, K. (2020). Exploring the macroeconomic determinants of carbon emissions in transitional economies: A panel data analysis approach. *International Journal of Energy Economics and Policy*, 10(6), 536–544. <https://doi.org/10.32479/ijeep.9362>
- Wang, Y., Liao, M., Xu, L., & Malik, A. (2021). The Impact of Foreign Direct Investment on China's Carbon Emissions through Energy Intensity and Emissions Trading Systems. *Energy Economics*, 97, 105212. <https://doi.org/10.1016/j.eneco.2021.105212>
- Ye, Y., Khan, Y. A., Wu, C., Shah, E. A., & Abbas, S. Z. (2021). The Impact of Financial Development on Environmental Quality: Evidence from Malaysia. *Air Quality, Atmosphere and Health*, 14(8), 1233–1246. <https://doi.org/10.1007/s11869-021-01013-x>
- .

## CHAPTER THREE

### Stock Price Reactions to Scrip Dividend Announcements: An Event Study in the Colombo Stock Exchange (CSE)

Tharushi A.S. & Dharmarathna D.G.

Department of Accountancy and Finance, Faculty of Management Studies  
Sabaragamuwa University of Sri Lanka  
[astharushi@gmail.com](mailto:astharushi@gmail.com)

#### Abstract

*This study investigates the stock price reaction to scrip dividend announcements and assesses market efficiency in the CSE from 2012 to 2022. Scrip dividends, which are increasingly utilised as a means of profit distribution, offer a relevant context for evaluating the informational efficiency of emerging markets. Based on the event study methodology, the 22 scrip dividend announcements of 15 listed companies are analysed, using an event window of 31 days and an estimation period of 120 days. Abnormal returns were evaluated using two modelling methods: the market model, which factored in volatility clustering, and a time series model. The findings also demonstrate varying abnormal returns during the event period, with a significant negative announcement-day abnormal return. However, the Average Abnormal Returns (AAR) and Cumulative Average Abnormal Returns (CAAR) were statistically insignificant, indicating that the scrip dividend announcements had no significant influence on stock prices. The findings invalidate the semi-strong form of market efficiency in the Sri Lankan context, raising concerns about the potential for insider trading and speculative market activity. The paper highlights that regulatory reforms are necessary to increase transparency and efficiency in the CSE.*

**Keywords:** Abnormal Returns, Event Study Methodology, Market Efficiency, Scrip Dividends.

#### 1. Introduction

One of the most contentious and extensively researched areas of corporate finance is dividend policy. A company declares a dividend within the financial year, typically on a quarterly or biannual basis, to fulfil investor expectations while assessing the company's capacity and strategy (Campanella et al., 2016). In addition to cash dividends, companies declare scrip dividends, where shareholders receive the dividend as an extra share rather than in cash. This form of dividend has gained popularity in markets with liquidity limitations or where the

company wants to retain the dividend to reinvest in the business. Although scrip dividends may indicate financial strength and potential for future growth, their real significance for shareholder value and stock prices is unclear.

In developed markets, the impact of various forms of dividend announcements on investor behaviour and market efficiency has been investigated in numerous studies. The efficiency of the market is determined by how well the information is reflected in the prices of capital assets. The Efficient Market Hypothesis (EMH), developed by Eugene Fama (1970), posits that in an efficient market, new information is rapidly incorporated into stock prices. Consequently, it suggests that there are no persistent opportunities for investors to consistently achieve abnormal returns.

Such evidence, however, is limited in emerging markets such as Sri Lanka. The Colombo Stock Exchange (CSE), a relatively small and illiquid market, offers a unique environment for exploring how investors respond to information-based events, such as the announcement of scrip dividends. Since it may be subject to information asymmetry, speculative trading, and less stringent regulatory enforcement, it is of particular interest to determine whether the CSE exhibits features implied by the semi-strong form of market efficiency, which posits that all publicly available information is already reflected in the stock prices.

The existing body of literature presents differing outcomes regarding the impact of dividend announcements on market reactions at the Colombo Stock Exchange (CSE). Dissabandara and Perera (2011) and Dharmarathna (2013) conducted studies that reveal findings that exhibit some divergence from each other. Subsequently, Dharmarathna (2020) has examined how stock returns in CSE positively react to stock dividend announcements.

Although scrip dividends are becoming increasingly common as a tool for profit distribution within companies listed on the CSE, there remains a paucity of empirical research on the effect of scrip dividend announcements on stock prices and investor actions. Hypothetically, scrip-dividend announcements should convey value-relevant information to the market, which should prompt an immediate response in stock prices if the market is informationally efficient. However, it remains underexplored to what degree the CSE indicates this responsiveness, with concerns being raised about market inefficiency, low investor awareness, and the potential for insider trading.

This paper aims to fill that gap by investigating the response of stock prices to the scrip dividend announcements in the CSE. The fulfilment of this gap will not just be added to the academic literature. Still, it will also be helpful to investors, policymakers, and regulators who need to increase the level of transparency and fairness in the capital market. The study

employs an event study methodology, which examines whether such announcements convey new, value-relevant information or if price movements are reduced by market inefficiencies or pre-disclosure insider trading. This research has implications for the broader debate on the development of capital markets and the impact of corporate disclosures on investor decisions in emerging economies.

### **1.1. Research Objectives**

The primary objective of this research is to analyse the stock price response to scrip dividend announcements and assess the degree of market efficiency in the CSE. To do this, the study is conducted by the following specific objectives:

1. To analyse abnormal stock returns surrounding scrip dividend announcements using the event study methodology.
2. To determine whether scrip dividend announcements have a statistically significant impact on stock prices in the short term.
3. To assess the extent to which the Colombo Stock Exchange reflects semi-strong form market efficiency.
4. To explore potential implications of insider trading or speculative activity in relation to scrip-dividend announcements.

### **1.2. Hypotheses**

In line with the research objectives, the study tests the following hypotheses:

H<sub>0</sub>: Scrip dividend announcements do not lead to statistically significant abnormal stock returns on the Colombo Stock Exchange.

H<sub>1</sub>: Scrip dividend announcements lead to statistically significant abnormal stock returns on the Colombo Stock Exchange.

These hypotheses will be tested by analysing Average Abnormal Returns (AAR) and Cumulative Average Abnormal Returns (CAAR) over a specified event window surrounding the announcement date. The statistical significance of these returns will determine whether the market reacts efficiently to the announcements, in line with the semi-strong form of the Efficient Market Hypothesis (EMH).

This study holds both academic and practical significance. From an academic standpoint, it contributes to the limited body of empirical literature on scrip dividend announcements in emerging markets, particularly within the Sri Lankan context. While dividend policy has been

extensively studied in developed economies, research specifically focusing on the price effects of scrip dividends in South Asian markets remains scarce. This research fills that gap by applying event study methodology to assess whether these announcements carry new, value-relevant information that is reflected in share prices.

Practically, the findings of this study provide valuable insights for various stakeholders in the capital market. Investors can better understand the informational value of scrip dividend announcements and adjust their strategies accordingly. Company managers can gain insight into how the market perceives such announcements, which guides them in shaping their dividend policy. Regulators and policymakers, meanwhile, can use the findings to evaluate the effectiveness of disclosure regulations and detect potential inefficiencies or insider trading activities. Ultimately, the study informs initiatives aimed at improving transparency, market efficiency, and investor confidence in the Colombo Stock Exchange

## **2. Literature Review**

### **2.1. Theoretical Review**

The Efficient Market Hypothesis (EMH) is a key theory in financial economics, suggesting that financial markets are highly efficient in incorporating all available information quickly and accurately. Fama (1970) introduced three forms of EMH, namely, Weak Form Efficiency, Semi-Strong Form Efficiency and Strong Form Efficiency. Weak Form Efficiency states that all information contained in past stock prices and trading volumes is already reflected in current stock prices. Semi-Strong Form Efficiency suggested that not only historical stock prices and trading volumes but also all publicly accessible information are already reflected in stock prices, and the strongest version of the EMH states that all information, whether it is available to the public or known only to insiders, is already taken into account in the prices of assets. This theory sets the foundation for the current study, which aims to investigate the level of efficiency in the CSE's response to scrip dividend announcements.

Theories related to dividend policy offer various perspectives on the relevance of dividends in determining a firm's value. Miller and Modigliani (1958) introduced the dividend irrelevance theory, which asserts that a company's dividend policy should not affect its stock price. Modigliani and Miller made several critical assumptions on perfect capital markets, including the absence of taxes, no transaction costs, and ideal information. If a company offers higher dividends, investors can reinvest dividends to buy more shares if they prefer to receive cash. Conversely, if the company's dividend is too small, investors can create their own desired cash flows by selling a portion of their shares. While the dividend irrelevance theory

challenges the conventional wisdom about dividend policy, its practical applicability is subject to real-world considerations.

On the other hand, the Dividend Signalling Theory, a significant concept in corporate finance, posits that a company's dividend policy serves as a means of conveying valuable information to investors about its financial health and prospects (Bhattacharya, 1979). Changes in dividend payouts or the initiation of dividend payments can send distinct signals to the market. When a company increases its dividend, it is often interpreted as a positive signal, indicating management's confidence in the company's profitability and growth potential and vice versa. Thus, the dividend signalling theory provides an appropriate theoretical framework for developing the hypothesis on the share price reaction to scrip announcements on the CSE.

## **2.2. Empirical Review**

Dividend announcements and stock price action have been a topic of financial research that dates to the early days of finance, when the historic theories of dividend irrelevance were established by Modigliani and Miller (1961). Their model assumes that dividend policy does not influence firm value in an ideal capital market; however, further empirical studies have contradicted this assumption, particularly in emerging and imperfect markets.

In the Sri Lankan context, Dissa Bandara (2001) conducted a study on the CSE to explore the type of information conveyed through dividend announcements, finding that alterations in annual cash dividends provided insights into how managers perceived the prospects of their companies. In essence, these dividend changes were seen as signals of managers' assessments of the firm's future performance. Furthering the findings, Dissabandara and Samarakoon (2002) carried out a thorough investigation into the relationship between dividend announcements, firm size, and dividend growth within the context of the Sri Lankan stock market. The study yielded significant discoveries. Initially, it was discovered that dividend announcements contain substantial informational value within the context of the Sri Lankan stock market. Upon the release of these announcements, the market exhibited a favourable response.

In contrast, Dharmarathna and Amarasekara (2016) examined the market reactions to 35 stock split announcements made by 35 companies in the Sri Lankan Share Market during the period from 2009 to 2014. They observed that a statistically significant adverse market reaction occurred both before and after the public announcement, suggesting that market participants had anticipated and responded unfavourably to the information regarding stock splits. Further, Dedunu (2018) analysed 60 dividend announcements, explicitly focusing on the initial and

final dividend announcements made within the time frame of 2016 to 2017, and found that the disclosure of dividend announcements did not generate any visible positive or negative responses in the form of market price fluctuations within the context of the CSE.

Even more complicated is the scrip dividend, a type of non-cash distribution that allows shareholders to take an additional equity stake. They can indicate prospective earnings, capital maintenance or demonstrate a lack of liquidity. Experimental studies of developed markets, such as those by Dyl and Weigand (1998) and Abeyratna and Power (2002), have yielded inconclusive results on whether scrip dividends have a positive or negative impact on stock prices. Scholarly work suggests that investors perceive scrip dividends as an indicator of growth potential and financial soundness. In contrast, others argue that the dilutive impact or apparent poor value leads to neutral or adverse responses.

The event study methodology has become a standard tool to analyse market reactions to corporate events. Studies such as Ball and Brown (1968) and Fama et al. (1969) established the foundation for measuring abnormal returns surrounding event windows. In the context of dividend announcements, researchers have used event studies to test the semi-strong form of market efficiency, which states that stock prices reflect all publicly available information. If markets are efficient, any new information, such as a scrip dividend announcement, should be quickly and accurately incorporated into stock prices.

In emerging markets, the evidence is less conclusive. Gunasekarage and Power (2001) examined the Sri Lankan market and noted deviations from semi-strong efficiency, particularly in the presence of insider trading and low investor awareness. Similarly, Samarakoon (1997) and Nimalathasan and Pratheepkanth (2012) found that market reactions to earnings and dividend-related news in Sri Lanka are inconsistent and often delayed, raising concerns about transparency, regulatory oversight, and investor sophistication.

Despite this, there remains a lack of focused empirical research on scrip dividend announcements within the Sri Lankan context. Most existing literature in the region tends to aggregate all dividend types or focus primarily on cash dividends. This discrepancy suggests that more specific research should be conducted to examine the effects of information content and the price of scrip dividends, especially in markets such as the CSE, where responses may be distorted by information asymmetry and speculative behaviour.

The study is significant to the literature by employing an event study design to test the impact of script dividend announcements on the Colombo Stock Exchange, measuring abnormal returns and cumulative returns to estimate the level of market efficiency. In this way, it



contributes to the overall knowledge of dividend signalling in emerging markets and the operational process of capital markets in Sri Lanka.

### 3. Methodology

In this study, the author employs an event study design to examine stock price responses to the scrip dividend announcement on the CSE. The event study design is a popular research method in finance that examines the impact of specific events on stock prices, aiming to gain insight into market efficiency through the speed and accuracy of stock price movements in response to new information. The methodology is based on comparing the actual stock returns within the event window with the expected returns, which are counterfactual (i.e., the returns the stock would have had if the event had not occurred).

#### 3.1. Sample Selection

The sample in this study comprises 22 scrip dividend announcements from 15 companies listed on the Colombo Stock Exchange between 2012 and 2022. The companies chosen were those that paid scrip dividends during this time frame and had an adequate trading history and data to conduct the event study. The final sample was restricted to those companies that consistently adhered to regulatory requirements for public announcements, ensuring that the data used was reliable and transparent.

The event window is defined as 31 days, consisting of a 15-day pre-announcement window, announcement date, and a 15-day post-announcement window. This window is chosen to capture both the market reaction to the announcement and any potential pre-disclosure information leakage. The estimation period is set to 120 days before the event window. This period is used to estimate the normal (expected) returns of the stock, based on the assumption that stock price behaviour during this period is not affected by the dividend announcement.

#### 3.2. Models Used for Analysis

To calculate abnormal returns, the study employs two models:

**Market Model with Volatility Clustering:** The values of the normal returns of the stocks in the sample are estimated by the market model. The model assumes a linear relationship between the returns of the stock and the returns of the market index (e.g., the All-Share price index of the CSE). Since there is a likelihood of volatility clustering in stock returns, the market model analyses volatility clustering to explain the presence of autocorrelations in the error terms. This allows for more accurate estimation of expected returns.

The market model is specified as follows:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \epsilon_{it} \quad (1)$$

Where:

$R_{it}$  = return of stock  $i$  at time  $t$ .

$R_{mt}$  = return of the market index at time  $t$ .

$\alpha_i$  and  $\beta_i$  = parameters to be estimated.

$\epsilon_{it}$  = error term.

**Time Series Model:** A time series model is also used to capture any potential serial correlation in the data that may affect the calculation of abnormal returns. This model accounts for any patterns in stock returns that could be driven by factors unrelated to the scrip dividend announcement, ensuring that only the impact of the announcement itself is measured.

#### Calculation of Abnormal Returns (AR)

The difference between the actual returns and the forecasted returns, as suggested by market and time series models, is referred to as abnormal returns. Specifically:

$$AR_{it} = R_{it} - R_{it}^e$$

Where:

$AR_{it}$  = abnormal return of stock  $i$  on day  $t$

$R_{it}$  = actual return of stock  $i$  on day  $t$

$R_{it}^e$  = expected return of stock  $i$  on day  $t$ , as estimated from the market or time series model

#### Cumulative Abnormal Returns (CAAR)

To analyse the aggregate effect of scrip dividend announcements, Cumulative Average Abnormal Returns (CAAR) are computed over different sub-periods within the event window. CAAR is the sum of the abnormal returns over a specified period

### 3.3. Statistical Testing

To determine the statistical significance, t-tests were used for the abnormal returns. The t-test is used to test whether the average abnormal returns (AAR) are significantly different from zero.

Null Hypothesis ( $H_0$ ): Abnormal returns are not significantly different from zero, indicating no market reaction to the scrip dividend announcement.

Alternative Hypothesis ( $H_1$ ): Abnormal returns are significantly different from zero, suggesting a market reaction to the scrip dividend announcement.

### 3.4. Data Sources

Data for stock prices, scrip dividend announcements, and market indices were collected from publicly available sources, including the Colombo Stock Exchange database, company financial reports, and third-party financial data providers. The stock price data used for analysis was adjusted for dividends, stock splits, and other corporate actions to ensure accuracy in the measurement of returns.

## 4. Results and Discussion

The results from the event study methodology are presented in Table 4.1, which shows the daily Average Abnormal Returns (AAR) and Cumulative Average Abnormal Returns (CAAR) for the 31-day event window surrounding the scrip dividend announcements from the Market Model and Time series Models.

**Table 4.1:** AARs and CAARs around the scrip dividend announcement day and corresponding t-state during the event period

| Date | Market Model |        |        |        | Time Series |        |        |        |
|------|--------------|--------|--------|--------|-------------|--------|--------|--------|
|      | AAR          | Tvalue | CAAR   | Tvalue | AAR         | Tvalue | CAAR   | Tvalue |
| -15  | 0.002        | 1.122  | 0.002  | 1.122  | 0.009       | 1.009  | 0.009  | 1.009  |
| -14  | -0.001       | -0.938 | 0.001  | 0.258  | -0.006      | -1.259 | 0.003  | 0.309  |
| -13  | 0.001        | 0.447  | 0.001  | 0.690  | 0.007       | 0.894  | 0.010  | 1.027  |
| -12  | -0.002       | -0.866 | 0.000  | -0.022 | 0.002       | 0.540  | 0.012  | 0.980  |
| -11  | -0.002       | -1.032 | -0.002 | -0.475 | -0.011      | -1.669 | 0.002  | 0.139  |
| -10  | -0.003       | -1.726 | -0.005 | -0.893 | -0.005      | -1.409 | -0.003 | -0.210 |
| -9   | 0.003        | 1.266  | -0.002 | -0.483 | 0.004       | 0.609  | 0.002  | 0.106  |
| -8   | 0.001        | 0.417  | -0.001 | -0.294 | -0.004      | -0.788 | -0.003 | -0.164 |
| -7   | 0.000        | -0.139 | -0.002 | -0.260 | 0.002       | 0.401  | -0.001 | -0.063 |
| -6   | 0.001        | 0.401  | -0.001 | -0.136 | -0.001      | -0.275 | -0.002 | -0.143 |
| -5   | 0.001        | 0.379  | 0.000  | 0.037  | -0.013      | -1.167 | -0.016 | -0.742 |
| -4   | 0.001        | -0.297 | -0.001 | -0.080 | 0.002       | 0.279  | -0.014 | -0.692 |
| -3   | -0.003       | -0.981 | -0.004 | -0.311 | -0.013      | -1.513 | -0.027 | -1.327 |
| -2   | -0.002       | -0.818 | -0.005 | -0.017 | 0.007       | 0.762  | -0.020 | -0.863 |
| -1   | -0.002       | -1.024 | -0.007 | -0.509 | -0.004      | -0.594 | -0.024 | -1.074 |
| 0    | -0.013       | -1.193 | -0.020 | -1.026 | -0.006      | -0.551 | -0.029 | -1.191 |
| 1    | 0.012        | 1.023  | -0.007 | -0.475 | 0.014       | 1.535  | -0.016 | -0.168 |
| 2    | 0.011        | 0.575  | -0.007 | -0.372 | -0.002      | -0.425 | -0.018 | -0.686 |

|    |        |        |        |        |        |        |        |        |
|----|--------|--------|--------|--------|--------|--------|--------|--------|
| 3  | -0.002 | -0.286 | -0.007 | -0.389 | 0.006  | 1.064  | -0.011 | -0.443 |
| 4  | -0.002 | -0.808 | -0.009 | -0.405 | -0.005 | -0.778 | -0.016 | -0.650 |
| 5  | 0.001  | 1.676  | -0.008 | -0.347 | 0.017  | 1.787  | 0.001  | 0.034  |
| 6  | 0.001  | 0.506  | -0.007 | -0.348 | 0.000  | 0.016  | 0.001  | 0.037  |
| 7  | -0.001 | -0.564 | -0.008 | -0.421 | 0.006  | 1.430  | 0.007  | 0.226  |
| 8  | -0.002 | -0.730 | -0.009 | -0.461 | 0.011  | 1.340  | 0.018  | 0.628  |
| 9  | 0.002  | 1.706  | -0.003 | -0.421 | -0.006 | -0.888 | 0.012  | 0.416  |
| 10 | -0.002 | -0.311 | -0.004 | -0.421 | 0.003  | 0.743  | 0.015  | 0.490  |
| 11 | 0.001  | 1.113  | -0.004 | -0.176 | 0.009  | 0.774  | 0.024  | 0.773  |
| 12 | -0.001 | -0.611 | -0.006 | -0.004 | -0.004 | -0.647 | 0.020  | 0.615  |
| 13 | -0.001 | -0.440 | -0.006 | -0.004 | -0.004 | -0.349 | 0.017  | 0.484  |
| 14 | -0.001 | -0.386 | -0.004 | -0.005 | 0.004  | -0.440 | 0.021  | 0.603  |
| 15 | 0.001  | 0.615  | -0.004 | -0.004 | 0.000  | 0.053  | 0.021  | 0.606  |

Critical Value 5% is 2.074

**Source:** Analysis Output

Abnormal Returns (AAR) Analysis, as presented in Table 4.1, reveals that the AAR values for the event window exhibit both positive and negative fluctuations. However, a few notable trends emerge.

The average abnormal returns in this pre-announcement period (Day -15 to Day -1) are generally small, with values oscillating between positive and negative figures. For instance, on Day -15, the AAR was positive at 0.0019, followed by negative returns on several subsequent days, including Day -10 with a return of -0.0030 and Day -3 with a return of -0.0028. The average returns during this period do not show significant evidence of price movement in anticipation of the announcement. On the announcement day (Day 0), the AAR was -0.0126, reflecting a significant negative abnormal return. This suggests that the market responded unfavorably to the scrip dividend announcement, possibly due to the perceived dilutive effect or the non-cash nature of the dividend.

The abnormal return post-announcement (Day +1 to Day +15) continues to exhibit volatility. For example, Day 1 shows a positive AAR of 0.0118, but by Day 2, this is followed by a small negative return of -0.0018, and the fluctuations continue. Despite the volatility, there is no clear pattern of significant positive or negative price movements following the announcement, which suggests that the market did not exhibit a strong reaction to the news once it was incorporated into the price.

The CAAR values show the cumulative effect of abnormal returns over the event window. During the pre-announcement period, CARR remains close to zero, with only minor fluctuations in the cumulative abnormal return, indicating no significant price movement leading up to the announcement.

The CAAR on the announcement day reached -0.0197, a sizable negative cumulative abnormal return. This confirms that the market reacted negatively to the scrip dividend announcement, consistent with the AAR for this day. The post-announcement CAAR remains negative, and there has been no significant recovery in cumulative abnormal returns, which currently stand at -0.0051 by Day 14. This implies that the market was initially unresponsive to the scrip dividend and then responded positively to the event thereafter.

The T-values on AAR and CAAR show that the majority of the abnormal returns and cumulative abnormal returns are statistically insignificant. As an example, though abnormal returns are bigger on some days (e.g. Day -15 and T-value -1.1224 and Day 0 and T-value -1.1932), the general tendency is not statistically significant abnormal returns over the period of the event. The statistical significance of the T-values is not always the same, which also supports the conclusion that scrip dividend announcements had no substantial impact on stock prices.

The results of this paper are significant in understanding how the market responds to scrip-dividend announcements on the CSE and will add to the overall literature on market efficiency in these types of markets. This is discussed below as the key points based on the results and available literature.

#### **4.1. Market Efficiency**

The absence of any significant abnormal returns in the scrip-dividend announcement dates indicates inefficiency in the CSE. The Efficient Market Hypothesis (EMH) states that the prices of stocks are expected to be influenced by all publicly available information, such as corporate activities and scrip dividends. The adverse price reaction on Day 0 and the fact that no further recovery was recorded regarding the abnormal returns suggest, however, that the market was not efficient in adjusting to the new information.

This finding aligns with the results of the literature on emerging markets, including those by Gunasekarage and Power (2001) and Samarakoon (1997), which have documented inefficiencies in the Sri Lankan stock market. Such inefficiencies are typically attributed to factors such as poor information dissemination, speculative trading behaviours, and weak regulations, which may slow down or distort market responses to news.

#### **4.2. The Dilution Effect of Scrip Dividends**

The fact that the negative abnormal return on the announcement day (Day 0) is positive suggests that investors may view scrip dividends as dilutive. The issuance of new shares by a company may result in the dilution of existing shareholder equity if the firm does not

distribute the cash. This is why the stock price responded negatively to the announcement, as investors may perceive the issuance of additional stocks as an indicator of financial distress or failure to generate sufficient cash flow.

The available literature, such as Dyl and Weigand (1998), suggests that scrip dividends may be viewed as a last resort dividend policy, which exacerbates negative market responses even further in cases where companies are financially strained. This view might also explain the volatility witnessed in the post-announcement period, where it failed to stabilise and had significant positive abnormal returns.

### **4.3. Comparison with Developed Markets**

In developed markets, the market reaction to scrip dividends is often more immediate and may reflect a more informed investor base and greater market efficiency. For instance, Fama (1970) and Michaely et al. (1995) found that stock prices in developed markets generally adjust quickly to dividend announcements, with the market efficiently incorporating the implications of scrip dividends. However, in emerging markets like Sri Lanka, the market is often characterised by lower levels of transparency, less sophisticated investors, and regulatory challenges, which could explain the delayed or muted market response observed in this study.

The analysis highlights the limitations of the Market model, especially when the R-squared values remain consistently low (below 0.50) throughout the period. As noted, the model's explanatory power in capturing variations in abnormal returns is weak, which undermines its effectiveness in predicting stock price movements, particularly within the context of event-study methodology. Given the findings from Dhamarthana and Peiris (2017) regarding the inadequacy of the Market model for capturing stock market responses to events (such as dividend announcements), your decision to turn to volatility time series models is a reasonable one. Volatility models, such as GARCH (Generalised Autoregressive Conditional Heteroskedasticity) and its variations, can account for time-varying volatility and provide more accurate predictions for expected returns in event studies. This approach has shown promise in similar contexts (as in Dharmarathna's 2020 study). To defend the switch, it will be sufficient to state that these models are able to reflect the dynamics of financial markets, the variation of volatility over time, and enhance the precision of abnormal returns forecasts.

### **4.4. Comparison of Models**

The comparison of the market model and the results of the volatility model provides a better understanding of the extent to which volatility-based models are more robust and accurate in explaining stock market responses to news and events. The results of applying different time

series models to the same sample sets are presented in this section. Adapted to the nature of each specific event, these models encompass, in some cases, Autoregressive Moving Average (ARMA) models and, in other cases, Generalised Autoregressive Conditional Heteroskedasticity (GARCH) models. The time series approach provides a deeper understanding of the dynamics of abnormal returns (AAR) and cumulative abnormal returns (CAAR), which account for time-varying volatility and the autocorrelation structure of abnormal returns.

The AAR values exhibit considerable variability throughout the event window, indicating that stock prices respond to the event in different ways at various points in time. It is worth noting that the values of AAR to some extent are positive, indicating a short-term market reaction to the event. In contrast, other values are negative, indicating market adjustments or reactions to market noise. An example of this is the AAR of 0.0136 (t-value: 1.5355) on day -1, indicating a positive response, and the AAR of -0.0108 (t-value: -1.6686) on day 1, suggesting a decline in the abnormal return.

The t-values indicate the statistical significance of the abnormal returns for each day within the event window. Several t-values (e.g., -11 with a t-value of -1.6686) indicate statistically significant abnormal returns, suggesting that market reactions to the event are not purely random. However, many days also feature t-values that are not significant (e.g., 0.0001 on day 6), reinforcing the notion that the event's impact varies over time.

CAARs provide a cumulative perspective, offering a broader view of the market's overall response to the event over time. CAAR values initially show a declining trend leading up to the event day (e.g., -0.0240 on day -1), followed by slight increases post-event, as seen on days 1 (0.0136) and 5 (0.0168). This suggests a partial recovery of the abnormal returns in the days following the event.

### **ARMA Models**

The ARMA models were applied to capture the linear relationship between past values and current abnormal returns. These models help account for serial correlation in the data, providing a refined estimate of expected returns during periods when past behaviours influence market trends. However, the ARMA models may not fully capture the volatility clustering observed in the market, particularly during periods of heightened market uncertainty.

## **GARCH Models**

The GARCH models are implemented to model the conditional volatility of the returns, and it is understood that the volatility of a stock's returns changes over time, around significant events. The GARCH models fit in better, as they capture the periods of increased volatility that tend to follow or precede major market announcements or economic events. These models isolate abnormal returns with time-varying volatility, aiming to provide more precise predictions of anticipated returns.

The findings indicate that complex series models are required in understanding the dynamics of stock market reactions. The volatility and serial correlation in the data, which vary with time, highlight the shortcomings of more basic models such as the Market model. With the use of ARMA and GARCH models, we can better determine the influence of events on the market, as these two models are able to consider volatility clustering and autocorrelation that the Market model does not address.

To sum up, the volatility-adjusted method based on ARMA and GARCH is more efficient, as it enables the obtaining of more precise estimates of abnormal returns and their cumulative impact. Such a strategy aligns with the methodology employed by Dharmarathna (2020) and represents a more effective approach than the Market model, particularly in addressing complex market dynamics during such events.

This result contrasts with that of Adow (2013), who found positive abnormal returns and increased trading activity following scrip dividend announcements in the Kenyan market. The variation in outcomes can be attributed to market-specific factors, including differences in investor behaviour, the regulatory framework, and the level of market maturity. Additionally, the difference in sample size and the frequency of occurrence of a given event can contribute to the mixed results. These aspects demonstrate the necessity of considering local market factors when extrapolating results from an international setting.

The findings of this work also have significant implications for the Efficient Market Hypothesis (EMH), particularly the semi-strong version, which posits that all publicly disclosed information is entirely and instantly reflected in stock prices. This assumption is challenged by the fact that there are no significant abnormal returns in response to scrip dividend announcements in the case of Sri Lanka. The results can be traced back to previous studies by Bandara (2001), Bandara and Perera (2011), and Dharmarathna (2013), who have also observed indicators of market inefficiency in response to different dividend-related events on the Colombo Stock Exchange (CSE).



It should be noted, however, that these findings contradict those of Dharmarathna (2013), whose data suggested a certain degree of market efficiency in relation to an equivalent form of corporate actions. This deviation points to the fact that market reaction to the announcement of dividends in Sri Lanka may not be the same depending on the nature of the event (e.g., final, interim, and stock dividend) and in addition to that, it depends on the nature of the market, investor sentiment and informational transparency during the announcement.

The total evidence from this research is that scrip dividend announcements in the Sri Lankan market do not convey price-sensitive information to investors, and they are not considered an indicator of firm performance or value. As a result, the Colombo Stock Exchange does not seem to conform to the semi-strong version of market efficiency. This result has important consequences for both investors and policymakers: investors may need to pursue options beyond what the market announces to seek abnormal returns, and regulators and market developers may want to prioritise better transparency and information flow as a means of enhancing market efficiency.

## **5. Conclusion**

This research primarily aimed to investigate the stock price response to scrip dividend announcements in the Sri Lankan equity market, using an event study approach. According to the analysis of 22 announcements, the results indicate that the market reaction is statistically insignificant, in terms of both Average Abnormal Returns (AAR) and Cumulative Average Abnormal Returns (CAAR). These findings indicate that scrip dividend announcements do not convey price-sensitive information to investors on the CSE.

The existence of insignificant abnormal returns contradicts the implications of the semi-strong form of the Efficient Market Hypothesis (EMH), which posits that all publicly available information is instantly reflected in stock prices. The results are consistent with previous studies by Bandara (2001), Bandara and Perera (2011), and Dharmarathna (2013), which have identified inefficiency in the Sri Lankan market. The findings, however, vary from the international literature, such as Adow (2013), which recorded a positive market response to scrip dividend announcements in the Kenyan setting. They are the opposite results, which serve to emphasise the role of country-specific factors and market structures in explaining event study results. Generally, the evidence provided herein suggests that the Sri Lankan market is not a semi-strong-form efficient market in relation to scrip dividend announcements.

## Reference

- Abeyratna, G., & Power, D. M. (2002). The post-announcement performance of scrip and cash dividend issues in the UK. *European Journal of Finance*, 8(1), 31–52. <https://doi.org/10.1080/13518470110051374>
- Adow, A. I. (2013). The effect of scrip dividend on the returns of securities listed at the Nairobi Securities Exchange (Master's thesis, University of Nairobi). Retrieved from <https://erepository.uonbi.ac.ke/handle/11295/63353>
- Ball, R., & Brown, P. (1968). An empirical evaluation of accounting income numbers. *Journal of Accounting Research*, 6(2), 159–178. <https://doi.org/10.2307/2490232>
- Bandara, D. B. P. H. (2001). Stock price reaction to dividend announcements: Evidence from the Colombo Stock Exchange [Unpublished master's thesis]. University of Sri Jayewardenepura. Academia+1Journals of USJ University+1
- Bandara, D. B. P. H., & Perera, K. D. I. (2011). The impact of dividend announcements: Reconciliation of Sri Lankan evidence over the last two decades. In *Proceedings of the 8th International Conference on Business Management (Vol. 8)*. University of Sri Jayewardenepura. <https://journals.sjp.ac.lk/index.php/icbm/article/view/220>
- Bhattacharya, S. (1979). Imperfect Information, Dividend Policy, and "The Bird in the Hand" Fallacy. *The Bell Journal of Economics*, 10(1), 259. <https://doi.org/10.2307/3003330>
- Campanella, F., Mustilli, M., & D'Agnele, E. (2016). Efficient Market Hypothesis and Fundamental Analysis: An Empirical Test in the European Securities Market. *Review of Economics and Finance*, 6(1), 27–42.
- Dedunu, H. H. (2018). Impact of dividend announcement on share price: Evidence from Colombo Stock Exchange. *International Journal of Management Sciences and Business Research*, 7(12), 1–7.
- Dharmarathna, D. G. (2013). Stock Price Reaction to Dividend Announcements and Information Efficiency in the Sri Lankan Share Market. *International Journal of Research in Social Sciences*, 3(2), 100–111.
- Dharmarathna, D. G. (2020). Stock Price Reaction to Stock Dividend Announcements and Information Efficiency in the Sri Lankan Stock Market. *International Journal of Research in Social Sciences*, 38(1), 1–15.
- Dharmarathna, D. G., & Amarasekera, C. (2016). Stock Price Reactions to Stock Split Announcements and Information Efficiency in the Sri Lankan Capital Market. *Journal of Wayamba Management*, 7(1), 40–60.

- Dharmarathna, D.G. Peiris T.U.I (2017). Validity of market model in the event-study methodology: Evidence from dividend announcements in Colombo Stock Exchange (CSE). Conference proceedings in the 10th Tourism Outlook Conference in collaboration with the 2nd Interdisciplinary Conference of Management Researchers and the 1st International Environmental Sustainability Conference (IESC-2017).
- Dissa Bandara, P. H., & Samarakoon, L. P. (2002). Dividend announcements, firm size and dividend growth in the Sri Lankan Stock Market. *Sri Lankan Journal of Management*, 7, 228–245.
- Dyl, E. A., & Weigand, R. A. (1998). The Information Content of Dividend Alternatives: Cash and Stock Dividends. *Journal of Financial Research*, 21(2), 179–190. <https://doi.org/10.1111/j.1475-6803.1998.tb00269.x>
- Fama, E. F., Fisher, L., Jensen, M. C., & Roll, R. (1969). The adjustment of stock prices to new information. *International Economic Review*, 10(1), 1–21. <https://doi.org/10.2307/2525569>
- Fama, E. F. (1970). Efficient Capital Markets: A Review of Theory And Empirical Work. *The Journal of Finance*, 25(2), 383–417. <https://doi.org/10.1111/j.1540-6261.1970.tb00518>
- Gunasekarage, A., & Power, D. M. (2001). The post-announcement performance of dividend-changing companies: The case of Sri Lanka. *Accounting Research Journal*, 14(2), 28–49. <https://doi.org/10.1108/10309610108229458>
- Modigliani, F., & Miller, M. H. (1961). Dividend policy, growth, and the valuation of shares. *Journal of Business*, 34(4), 411–433. <https://doi.org/10.1086/294442>
- Modigliani, F., & M. H. M. (1958). The Cost of Capital, Corporation Finance and the Theory of Investment. *The American Economic Review*, 48(3), 261–297. <https://www.jstor.org/stable/1809766>
- Nimalathasan, B., & Pratheepkanth, P. (2012). Dividend policy and stock price volatility: Evidence from listed manufacturing companies in Sri Lanka. *Global Journal of Management and Business Research*, 12(14), 1–7.
- Samarakoon, L. P. (1997). Efficiency of the stock market in Sri Lanka: Some empirical evidence. *Sri Lankan Journal of Management*, 2(3), 187–201.

## CHAPTER FOUR

### Accuracy of Bankruptcy Prediction Models in Forecasting Company Delisting During an Economic Crisis: Evidence from Sri Lanka

Tharushika H. & Edirisinghe U.C.

Department of Accountancy and Finance, Faculty of Management Studies  
Sabaragamuwa University of Sri Lanka, Belihuloya, Sri Lanka  
[chathurika@mgt.sab.ac.lk](mailto:chathurika@mgt.sab.ac.lk)

#### Abstract

*This study aims to investigate the validity of Altman's Z-score model and Zmijewski's X-score model as a tool for predicting the delisting risk of Sri Lankan companies. Although the two models have been frequently tested for assessing financial distress, their effectiveness in predicting delisting remains under-researched, particularly in terms of their predictive capability during economic crisis conditions. Sri Lanka has been experiencing a severe economic and political crisis since 2019, and listed companies have been constantly threatened with survival during this period. Considering the data availability, 18 delisted companies were selected as the sample of delisted companies, and data were collected two years prior to the company's delisting. For comparison purposes, 18 non-listed companies were also selected based on their highest market capitalisation, considering their unlikelihood of delisting in the near future. The results showed that the revised Altman's Z-score model has a higher accuracy rate of 69.45% compared to the Zmijewski X-score model, which has an accuracy rate of 63.89%. The Chi-square model's results indicate a relationship between Altman's Z-score model and the delisting status of the companies, but no relationship between the Zmijewski X-score model and delisting. Additionally, Altman's Z-score model is more accurate in predicting delisting than the Zmijewski X-model. The study contributes to validating the bankruptcy prediction models as a tool for delisting prediction and recommends the revised Altman's Z'-score model as a predictor of delisting companies in the Sri Lankan context..*

**Keywords:** Altman's Z-score model, Bankruptcy, Delisting, Financial distress, Zmijewski X-score model

.

## 1. Introduction

The delisting of companies from stock exchanges is a pivotal event in financial markets, signifying the removal of a publicly traded entity and its subsequent exemption from the regulatory frameworks and reporting obligations that govern listed firms (Martinez & Serve, 2017). Several reasons may cause a company to become delisted: voluntary delisting, mergers or acquisitions, and failure to meet the listing requirements set by the stock exchange (Bortolon & Silva, 2015). These requirements typically include maintaining minimum levels of financial performance, adhering to reporting and disclosure obligations, and meeting corporate governance standards. Another reason is financial distress (Croci & Giudice, 2014). If a company experiences financial difficulties, such as bankruptcy or insolvency, it may be delisted from the exchange. In such cases, the company's shares may be removed from the exchange as part of a restructuring process or liquidation (Chan, 2016). Accordingly, the majority of reasons for a company's delisting indicate financial distress and failure to meet listing requirements (Martinez & Serve, 2017; Wang & Campbell, 2010). Understanding the factors that contribute to a company's delisting and accurately predicting its likelihood can provide valuable insights into market dynamics, economic conditions, and managerial effectiveness.

As of May 31, 2023, the Colombo Stock Exchange (CSE) comprises 289 firms across 20 GICS industry categories, with a total market capitalisation of Rs. 3,598.30 billion (CSE, 2023). According to the information published by CSE, 100 companies were delisted from the CSE as of June 30, 2021, and by May 31, 2022, this number had increased to 106. Moreover, the number of companies going delisted is increasing day by day. The accurate prediction of financial distress and potential delisting of companies holds significant importance for investors, creditors, regulators, and other stakeholders. The ability to identify and forecast companies at risk of delisting provides valuable insights for making informed investment decisions, managing credit risk, and implementing proactive measures to mitigate financial distress.

Altman's Z-score model and Zmijewski's X-score model are two prominent models developed primarily to predict financial distress, including bankruptcy. The Altman Z-score model and Zmijewski X-score model have historical significance in assessing financial health and have also been applied to predict delisting events. However, while both models have proven their worth in bankruptcy prediction, their application in predicting delisting events necessitates further investigation. Delisting does not necessarily equate to bankruptcy, and companies may exit public trading for reasons unrelated to financial distress (Celli, 2015; Grice Jr & Dugan, 2003; Gunathilaka, 2014; Kpodoh, 2010; Nanayakkara & Azeez, 2015; Pavlović et al., 2012;

Radivojac et al., 2021). However, Previous studies (Benny & Hutagaol, 2013; Bortolon & Silva, 2015) show that profitability and liquidity are determining factors for most delisting and are also commonly associated with bankruptcy. Thus, it is reasonable to assume that bankruptcy models can be used for predicting delisting; however, very few studies have tested the validity of these models for such predictions, particularly in a country facing an economic crisis, such as Sri Lanka.

This research aims to contribute to the existing body of knowledge by evaluating the accuracy of the Altman Z-score model and the Zmijewski model in predicting delisting. By examining the model's performance against real-world delisting outcomes, this study aims to illuminate the model's strengths, limitations, and potential areas for improvement. While numerous researchers have attempted to develop these models and validate their effectiveness (Hari et al., 2019; Nenengsih, 2018), findings have often varied across different countries and time periods. This inconsistency raises questions about the reliability and applicability of established models in diverse market environments. Thus, this study addresses a significant gap in the existing literature on delisting prediction models, particularly in emerging economies, where such research is rare. Notably, selecting Sri Lanka as the context for this study contributes to the literature by enabling the investigation of the delisting prediction capabilities of these models in an economic crisis setting. Given these perspectives, it is crucial to investigate delisting within the Sri Lankan context while understanding delisting dynamics and enhancing the predictive frameworks in a region where such insights are sorely needed.

The organisation of the study is as follows: Following the introduction, a review of the literature on bankruptcy theories and prediction models will be presented. The methodology section will succeed this. The subsequent section presents the results and their discussion. Finally, the concluding remarks will be provided, along with suggestions for future research.

## **2. Literature Review**

Delisting a company from a stock exchange is a complex process influenced by various factors. Several financial and economic theories and concepts are relevant to understanding the reasons and implications of delisting. These theories affect the predictability of delisting possibilities.

### **Signalling Theory**

Signalling Theory, as articulated by Ross (1977), stated that "company management benefits from the information they possess and share with investors." The information is primarily

related to the company's financial and operational performance, which in turn influences expectations about prospects and, consequently, impacts the company's stock price. Information serves as a crucial asset for investors, encompassing insights into a company's current status, historical performance, and even its prospects. The information should be valuable if it meets criteria such as relevance, accuracy, timeliness, and completeness. Investors use this information as a tool for analysis when making financial market decisions. Through the publication of information announced in the media, investors may receive a positive or negative signal that affects their investment decision (Endri et al., 2020). The level of trading activity in stocks serves as a reflection of the market's response to economic conditions. When the information provided contains a positive signal, the company has more favourable expectations for the future. According to Endri et al. (2020), market efficiency will reveal the connection between publicly disclosed information, including financial, political, environmental, and social reports, and its impact on fluctuations in stock trading volume. According to signalling theory, companies exhibit early signs of financial distress.

### **Early Warning System Theory**

An early warning system (EWS) is another theory that detects and anticipates potential risks or threats, enabling timely intervention and mitigation. EWS is employed in various domains, including financial crises. Duwipa (2013) defined the EWS as a series of systems that function to notify the occurrence of an event, which can be natural or social in nature. Early warning activities provide information in a clear and easily understood language. Since signal models can also be viewed as a type of trend analysis, the Early Warning System (EWS) can be considered a 'development of the form of signal theory'. Mainly, the EWS model was developed to anticipate economic crises (Berg et al., 2005; Kaminsky & Reinhart, 1999)

Both of these theories are grounded in the fact that reliable, accurate information on company performance signals potential distress, such as the possibility of delisting. However, the usefulness of the data for its user depends on the predictive model used to analyse the relevant data. Bankruptcy prediction models, such as the revised Altman Z-score model and Zmijewski X-score model, which utilise a range of financial ratios to predict financial distress, have the potential to be used to predict delisting possibilities due to financial distress. However, their suitability for predicting delisted companies should be further ascertained.

### **Altman's Model and Zmijewski Model for Delisting Prediction**

The prediction of a firm's delisting, financial distress, or bankruptcy is significant for many parties, including investors, creditors, suppliers, and customers. Companies often end up in bankruptcy due to economic distress stemming from a decline in industry operating income

and poor management, resulting from consistently negative operating income over five years (Whitaker, 1999). Delisting and bankruptcy are two significant events that, although distinct in nature, share certain similarities in the corporate world. Both processes often signify a company's financial distress.

Many studies have examined the ability of Altman's Z-score model and the Zmijewski model to predict bankruptcy, while few researchers have investigated whether these models can also be used to predict delisting (Anugrah, 2019; Fatmawati, 2012; Husein & Pambekti, 2014; Nenengsih, 2018). Fatmawati (2012) investigated the empirical evidence that the Zmijewski model, the Altman model, and the Springate models could be used as predictors of a company's delisting. He collected samples randomly during the same timeframe when the company was delisted and used the logistic regression method for analysis. The results showed that among the three predictor models for delisting, only the Zmijewski model could effectively predict companies delisted during the observation period. Neither the Altman model nor the Springate models could be used effectively as predictive models for delisting (Fatmawati, 2012). Confirming the results of his study, Husein and Pambekti (2014) and Nenengsih (2018) pointed out that the Zmijewski model can be used to predict bankruptcy. Apart from Fatmawati (2012), they tested one additional bankruptcy model (the Grover model) in their study. According to their results, the Zmijewski model stands out as the most suitable model for predicting delisting due to its high level of significance compared to the other models (Husein & Pambekti, 2015). Additionally, the Zmijewski X-score model is used to emphasise the leverage ratio as an indicator of financial distress in companies. The greater the amount of debt, the more accurate the prediction of the company's delisting (Fatmawati, 2012). According to Fatmawati's (2012) opinion, the Altman Z-model and the Springate X-score model are also less suitable for predicting delisting because these models emphasise profitability measures more than the Zmijewski model.

In contrast, some researchers pointed out that the Zmijewski X-score model is not suitable for predicting delisting, and Altman's Z-score model is more suitable (Anugrah, 2019; Hadi & Anggraeni, 2008; Rachmania, 2016). Rachmania (2016) demonstrated that, among the modified Altman Z-score model, the Springate model, and the Zmijewski model, only the modified Altman Z-score model (3rd version) and the Springate model could be used to predict delisting companies. As a reason for this, he mentioned that the modified Altman Z-score model and the Springate model showed a completeness ratio when compared to the Zmijewski model. Additionally, a similar study was conducted by Hadi & Anggraeni (2008), who concluded that, among bankruptcy prediction models, the Altman Z-score model is the most effective predictor, while the Zmijewski model does not predict delisting. Additionally, research conducted by Anugrah (2019) showed that both the Altman X-score and Taffler



models are significantly better compared to the Zmijewski X-score model. According to the literature reviews, various researchers offer differing opinions regarding the prediction model for delisting. Therefore, it is essential to assess the accuracy of Altman's Z-score model in identifying companies for delisting in the Sri Lankan context.

Several studies have attempted to develop an early warning system model to predict delisting (Endri et al., 2020; Hari et al., 2019; Hwang et al., 2014). Endri et al. (2020) developed an early warning system model for detecting the potential delisting of the Indonesian Sharia Stock Index. They utilised Support Vector Machines (SVM) to develop this model, incorporating several financial ratios, including debt-to-equity, return on invested capital, quick ratio, asset turnover ratio, current ratio, return on assets, return on equity, leverage, long-term debt, and interest coverage. Most of these ratios are also contained in Altman's Z-score model. Similarly, Hari et al. (2019) developed a delisting prediction model employing logistic regression. In this study, the same financial ratios and sample were used to develop the model, as done by Endri et al. (2020). However, they developed the prediction model with a higher level of accuracy, 93.85%. In 2014, Hwang et al. (2014) developed a delisting prediction model based on non-financial information. The use of non-financial information in the delisting model holds greater significance, as it can provide a broader range of stakeholders with advanced indicators for anticipating delisting events. Their results suggested that shareholders should closely consider many qualitative factors not reflected in financial statements to forecast delisting and thereby reduce the social drawbacks associated with delisting companies. Siripokakit (2005) attempted to develop an early warning sign to predict the probability of mandatory delisting from the stock exchange, examine the price and trading volume reactions to delisting, and investigate the macroeconomic conditions surrounding delisting.

Several previous studies conducted by different countries have tested the validity of bankruptcy models, including Altman's Z-score and Zmijewski's X-score model, in predicting the delisting status of companies. According to the literature reviews, different researchers offer various opinions regarding the prediction model for delisting. Existing research contradicts the idea that Altman's Z'-score model and Zmijewski's X-score model can be used to predict delisting companies. Notably, the accuracy of these models in predicting the delisting of companies operating during a national economic crisis has not been assessed yet, which is a significant research gap that this study aims to fill.

### 3. Methodology

This research is conducted using a predictive research design approach. The study aims to evaluate the effectiveness of Altman's Z-score model and Zmijewski X-score model in predicting outcomes related to delisting in a new context. A predictive research design is a type of research design that aims to predict future occurrences by identifying patterns and relationships in existing data. This type of research design is commonly employed in various fields, including economics, finance, healthcare, and social sciences. This research will use a quantitative research approach.

#### 3.1. Model Explanation

##### Altman's Z'-Score Model

Altman's Z-score model is predictive (a linear combination of several financial ratios) developed by Altman (1968) to predict the near-term likelihood of companies failing into bankruptcy or insolvency. He estimated the model using multiple discriminant analysis to derive a linear equation that combined multiple financial ratios, such as liquidity, leverage, and solvency. This Z-score value helps investors, creditors, and analysts make informed decisions about the company's financial health. The original model, developed in 1968, was for public manufacturing companies as follows:

$$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 0.99X_5 \quad (1)$$

Where:

- $X_1$  = Working Capital/ Total Assets
- $X_2$  = Retained Earnings/ Total Assets
- $X_3$  = Earnings before Interest and Taxes/ Total Assets
- $X_4$  = Market Capitalisation/ Total Liabilities
- $X_5$  = Total Sales/ Total Assets

Altman later revised the Z-score model for private firms (1982), non-manufacturing firms, and emerging markets in 2006.

For private manufacturing firms:

$$Z' = 0.717X_1 + 0.847X_2 + 3.107X_3 + 0.42X_4 + 0.998X_5 \quad (2)$$

For non-manufacturing firms:

$$Z'' = 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4 \quad (3)$$

For emerging markets:

$$Z'' = 3.25 + 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4 \quad (4)$$

This study evaluates the revised Altman's Z-score model for non-manufacturing companies in Sri Lanka to predict the delisting of companies, as most delisted companies in the country are non-manufacturing companies.

**Table 3.1:** Revised Altman's Z-score cut-off points

| Classification Zones | Z-Score Models |            |           |
|----------------------|----------------|------------|-----------|
|                      | Z              | Z'         | Z''       |
| Safe                 | > 2.99         | > 2.90     | > 2.60    |
| Grey                 | 1.81 - 2.99    | 1.23 - 2.9 | 1.1 - 2.6 |
| Distress             | < 1.8          | < 1.23     | < 1.10    |

**Source:** Altman (2006)

### Zmijewski X-Score Model

Zmijewski employs ratio analysis to measure a company's performance, leverage, and liquidity in predicting bankruptcy (Zmijewski, 1984). Using the financial ratios formulated by Zmijewski, the status of a company can be predicted using two classifications, namely, distress and non-distress. Zmijewski estimated the model using probit analysis, which weights the log-likelihood function by the ratio of the population frequency rate to the sample frequency rate of the individual groups, bankrupt and non-bankrupt (Belyaeva, 2014). The formula used is:

$$X\text{-Score} = -4.3 - 4.5X_1 + 5.7X_2 - 0.004X_3 \quad (5)$$

X1 = Net Income/ Total Assets

X2 = Total Liabilities / Total Assets

X3 = Current Assets/ Current Liabilities

**Table 3.2:** Zmijewski X-score Cut-off Points

| Classification Zones | X-Score |
|----------------------|---------|
| Distress             | $X > 0$ |
| Non-Distress         | $X < 0$ |

**Source:** Zmijewski (1984)

### 3.2. Variables Calculations

#### Variables Calculation of revised Altman's Z''- score model

Revised Altman's Z''-score model (2006) is based on four variables, each one representing a financial ratio. The following table shows how each variable is measured and the sources that will collect data for the study.

**Table 1.3:** Variables Calculation- Altman's Z''-score model

| Variables | Sign           | Measurement/ Reference                                                | Source                                        |
|-----------|----------------|-----------------------------------------------------------------------|-----------------------------------------------|
| WCTA      | X <sub>1</sub> | $\frac{\text{Working capital}}{\text{Total assets}}$                  | Annual reports of delisted & listed companies |
| RETA      | X <sub>2</sub> | $\frac{\text{Retained earnings}}{\text{Total assets}}$                | Annual reports of delisted & listed companies |
| EBITA     | X <sub>3</sub> | $\frac{\text{Earnings before interest and tax}}{\text{Total assets}}$ | Annual reports of delisted & listed companies |
| MVETL     | X <sub>4</sub> | $\frac{\text{Market value of equity}}{\text{Total liabilities}}$      | Annual reports of delisted & listed companies |

**Source:** Altman (2006)

#### Variables Calculation of the Zmijewski X-score Model

The Zmijewski X-Score model (1984) is based on three variables, each representing a financial ratio. The following table shows how each variable is measured and the sources that will collect data for the study.

**Table 3.2:** Variables Calculation- Zmijewski X-Score model

| Variables | Sign           | Measurement                                                | Source                                        |
|-----------|----------------|------------------------------------------------------------|-----------------------------------------------|
| ROA       | X <sub>1</sub> | $\frac{\text{Net income}}{\text{Total assets}}$            | Annual reports of delisted & listed companies |
| TLTA      | X <sub>2</sub> | $\frac{\text{Total liabilities}}{\text{Total assets}}$     | Annual reports of delisted & listed companies |
| WC        | X <sub>3</sub> | $\frac{\text{Current assets}}{\text{Current liabilities}}$ | Annual reports of delisted & listed companies |

**Source:** Zmijewski (1984)

### 3.3. Data Collection Method

Secondary data were mainly collected using the financial statements of delisted and listed companies in Sri Lanka. Secondary data sources (data from delisted companies) do not provide data to data collectors directly because, after companies are delisted, the Colombo Stock Exchange removes the financial statements of those delisted companies from its official website (the CSE library). Therefore, the data used in this study were collected from the websites of delisted companies, as well as some other websites, such as 'investing.com'. The data of the listed companies were collected from the CSE website.

### 3.4. Population and Sampling

The study population comprises all delisted and listed companies in Sri Lanka as of May 31, 2023. As of May 31, 2022, the number of delisted companies is 106. This study uses a purposive sampling technique as a sampling approach. Specific considerations or criteria guide the selection of the sample. The criteria used to select the delisted company sample in this study are as follows:

- a) Should be a company which have been delisted from the Colombo Stock Exchange as of 31<sup>st</sup> May 2023.
- b) Should be a company whose financial data for three consecutive years prior to the stated delisted date by the Colombo Stock Exchange (CSE) is publicly available.

Only 18 companies met the above criteria out of the delisted companies as of May 31, 2023. Data were collected from the annual report of the 3 years preceding the company's delisting. Therefore, the sample size of this study consists of 72 observations drawn from the company's financial statements. To further maintain the accuracy of the study and for comparison purposes, the study collected data from 18 listed companies (which have managed to maintain their listing continuously). These companies were selected based on the highest market capitalisation criteria. Eighteen non-manufacturing listed companies that recorded the highest market capitalisation as of October 5, 2023, were selected, considering their likelihood of not being subject to delisting in the near future due to their higher market capitalisation. Additionally, non-manufacturing companies were selected because this study evaluates the revised Altman's Z-score model, which is typically used for non-manufacturing companies.

### 3.5. Data Analysis Methods

Secondary data collected via the financial statements of both listed and delisted companies were analysed using Excel. Furthermore, test the accuracy of Altman's Z'-score model and Zmijewski's X-score model to answer the hypothesis that is proposed in this study. The

hypothesis was checked by using the Chi-square test. The prediction results' distress or not distress' were determined by looking at the cut-off point of both models. Then, the accuracy level of the model is calculated by comparing the number of correct predictions with the number of samples.

### **Accuracy Level Model**

The method used by Najib & Cahyaningdyah (2020) to calculate the accuracy level is employed in this study to assess the accuracy of Altman's Z-score model in predicting delisting.

$$\text{Model's Accuracy} = \frac{\text{Prediction's Correct}}{\text{Number of Samples}} * 100\%$$

### **3.6. Hypothesis Development**

This research aimed to check the accuracy level of Altman's Z'-score and Zmijewski's X-score model in predicting delisting companies in Sri Lanka. The model achieves the highest level of accuracy, enabling it to predict the delisting experienced by the company. Therefore, the proposed hypothesis is as follows:

H<sub>0</sub>: Altman's Z"-score model and Zmijewski's X-score model do not have predictive ability in accurately identifying the likelihood of company delisting in Sri Lanka..

H<sub>1</sub>: Altman's Z"-score model and Zmijewski's X-score model have predictive ability in accurately identifying the likelihood of company delisting in Sri Lanka.

The hypothesis is tested by comparing the calculated chi-square value to the critical value (tabular value). The critical value depends on the significance level and the degrees of freedom of the data set. If the calculated chi-square value is greater than the critical value, then the null hypothesis is rejected, and the alternative hypothesis is accepted.

## **4. Results and Discussion**

The data were analysed using Altman's Z-score model and Zmijewski X-score model for 36 companies, including delisted and listed companies. This section of the study provides an overview of the study variables, Altman's Z-score model, and Zmijewski X-score model. Finally, a detailed examination of the analysis's outcomes is presented.

#### 4.1. Altman's Z''-Score Values for Delisted Companies

Table 4.1 is the result of the calculation of Altman's Z''-score values for delisted companies from the Colombo Stock Exchange. According to the calculated Z-scores for the past 3 years, out of 54 results, 21 results fall within the safe zone, and 33 results fall within the moderate and distress zones. This means Altman's Z-score model gave 33 correct predictions and 21 incorrect predictions for delisted companies.

**Table 4.1:** Calculated Altman's Z''-score values for Delisted Companies

| No.  | Company                              | Company Code | Altman Z-Score |        |        |
|------|--------------------------------------|--------------|----------------|--------|--------|
|      |                                      |              | t-1            | t-2    | t-3    |
| DL1  | AIA Insurance Lanka PLC              | CTCE         | 1.01           | 1.80   | 0.65   |
| DL2  | Arpico Finance Company PLC           | ARPI         | 4.90           | 4.74   | 2.79   |
| DL3  | Commercial Leasing Company PLC       | COML         | 0.44           | -0.52  | 0.09   |
| DL4  | Hotel Developers (Lanka) PLC         | HDEV         | 13.49          | 15.16  | 15.47  |
| DL5  | Huejay International Investments PLC | HUEJ         | -10.84         | -9.50  | -8.18  |
| DL6  | Morison PLC                          | MORI-N       | 1.04           | 3.34   | 4.80   |
| DL7  | MTD Walkers PLC                      | KAPI         | -43.66         | -1.60  | -1.68  |
| DL8  | Orient Finance PLC                   | ORIN         | 0.67           | 4.81   | 4.59   |
| DL9  | Prime Finance PLC                    | GSF          | 2.46           | 1.59   | -1.07  |
| DL10 | Property Development PLC             | PDL          | 6.90           | 6.26   | 6.88   |
| DL11 | Trade Finance and Investments PLC    | TFIL         | 0.18           | -0.06  | 0.07   |
| DL12 | Beruwala Walk Inn PLC                | BINN         | -5.22          | -5.14  | 0.43   |
| DL13 | Ceylon Leather Product PLC           | CLPL         | 6.64           | 4.86   | 2.46   |
| DL14 | Entrust Securities PLC               | ESL          | -15.69         | -15.51 | -29.87 |
| DL15 | Finlays Colombo PLC                  | JFIN         | 16.62          | 10.30  | 8.95   |
| DL16 | Kalpitiya Beach Resort PLC           | CITK         | -1.21          | -0.72  | -1.38  |
| DL17 | Kuruwita Textile Mills PLC           | KURU         | -0.53          | -0.82  | -0.51  |
| DL18 | Metropolitan Resource Holding PLC    | MPRH         | 20.59          | 29.54  | 13.70  |

Source: Author Calculations

#### 4.2. Test Altman's Z''-score Values for Listed Companies

Table 4.2 is the result of the calculation of Altman's Z''-score values for listed companies from the Colombo stock exchange. Here, listed companies were selected based on the highest market capitalisation criteria, as those companies are unlikely to delist in the near future due to their higher market capitalisation. According to the calculated Z-scores for the past 3 years, out of 54 results, 41 results fall within the safe zone, and 13 results fall within the moderate and distress zones. This means that Altman's Z-score model made 41 correct predictions and 13 incorrect predictions for the listed companies.

**Table 4.2:** Calculated Altman's Z''-score values for listed companies

| No. | Company                        | Symbol     | Altman Z-Score |       |       |
|-----|--------------------------------|------------|----------------|-------|-------|
|     |                                |            | t-1            | t-2   | t-3   |
| L1  | John Keells Holdings PLC       | JKH.N0000  | 7.48           | 7.64  | 56.45 |
| L2  | Expolanka Holdings PLC         | EXPO.N0000 | 3.63           | 3.02  | 1.34  |
| L3  | LOLC Holdings PLC              | LOLC.N0000 | 4.05           | 3.34  | 1.24  |
| L4  | Sri Lanka Telecom PLC          | SLTL.N0000 | 53.70          | 39.08 | 37.44 |
| L5  | LOLC Finance PLC               | LOFC.N0000 | 0.85           | 0.98  | 0.60  |
| L6  | Commercial Bank of Ceylon PLC  | COMB.N0000 | 3.06           | 4.18  | 2.64  |
| L7  | Melstacorp PLC                 | MELS.N0000 | 1.98           | 3.03  | 7.54  |
| L8  | Browns investments PLC         | BIL.N0000  | -0.68          | 4.08  | 0.78  |
| L9  | Sampath Bank PLC               | SAMP.N0000 | 3.77           | 5.53  | 3.32  |
| L10 | Hatton National Bank PLC       | HNB.N0000  | 1.52           | 1.49  | 1.39  |
| L11 | Lanka IOC PLC                  | LIOC.N0000 | 2.97           | 1.14  | 2.82  |
| L12 | Aitken Spence PLC              | SPEN.N0000 | 7.81           | 7.59  | 5.63  |
| L13 | Carson Cumberbatch PLC         | CARS.N0000 | 22.66          | 20.99 | 14.51 |
| L14 | Valibel One PLC                | VONE.N0000 | 20.70          | 34.88 | 8.42  |
| L15 | Ceylinco Insurance PLC         | CINS.N0000 | 9.81           | 3.29  | 3.09  |
| L16 | C T Holdings PLC               | CTHR.N0000 | 11.61          | 58.72 | 56.41 |
| L17 | Hemas Holdings PLC             | HHL.N0000  | 14.31          | 61.02 | 25.37 |
| L18 | Richard Pieris and Company PLC | RICH.N0000 | 2.28           | 3.91  | 1.30  |

**Source:** Author Calculations

In Table 3.1, based on Altman's Z''-score model cut-off points, a Z'' greater than 2.6 is a safe zone (companies that are not bankrupt), and less than 1.1 is a distressed zone (companies that go bankrupt). The value between 2.6 and 1.1 is a grey zone (cannot determine whether the company will go bankrupt or not). When applying this model to predict delisted companies, if the value of Z'' > 2.6 means 'listed', Z'' < 1.1 'delist' and 1.1 < Z'' < 2.6 means 'can't be determined whether the company will go delisted or not'. Here, Altman's z-score value is calculated for three years because Altman's model has the ability to predict bankruptcy three years prior to the company's bankruptcy.

#### 4.3. Zmijewski X-Score values for Delisted Companies

Table 4.3 is the result of the calculation of Zmijewski X-score values for delisted companies from the Colombo Stock Exchange. According to the calculated X-scores for 2 years, out of 36 results, 18 results were distress and 18 results were non-distress. This means the Zmijewski X-score model gave 18 correct predictions and 18 incorrect predictions for delisted companies.



**Table 4.3:** Calculated Zmijewski X-score values for delisted companies

| No.  | Company                              | Company Code | Zmijewski x-score results |              |
|------|--------------------------------------|--------------|---------------------------|--------------|
|      |                                      |              | t-1                       | t-2          |
| DL1  | AIA Insurance Lanka PLC              | CTCE         | Non-Distress              | Non-Distress |
| DL2  | Arpico Finance Company PLC           | ARPI         | Non-Distress              | Non-Distress |
| DL3  | Commercial Leasing Company PLC       | COML         | Distress                  | Distress     |
| DL4  | Hotel Developers (Lanka) PLC         | HDEV         | Distress                  | Distress     |
| DL5  | Huejay International Investments PLC | HUEJ         | Distress                  | Distress     |
| DL6  | Morison PLC                          | MORI-N       | Non-Distress              | Non-Distress |
| DL7  | MTD Walkers PLC                      | KAPI         | Distress                  | Distress     |
| DL8  | Orient Finance PLC                   | ORIN         | Non-Distress              | Non-Distress |
| DL9  | Prime Finance PLC                    | GSF          | Non-Distress              | Non-Distress |
| DL10 | Property Development PLC             | PDL          | Non-Distress              | Non-Distress |
| DL11 | Trade Finance and Investments PLC    | TFIL         | Distress                  | Distress     |
| DL12 | Beruwala Walk Inn PLC                | BINN         | Distress                  | Distress     |
| DL13 | Ceylon Leather Product PLC           | CLPL         | Non-Distress              | Non-Distress |
| DL14 | Entrust Securities PLC               | ESL          | Distress                  | Distress     |
| DL15 | Finlays Colombo PLC                  | JFIN         | Non-Distress              | Non-Distress |
| DL16 | Kalpitiya Beach Resort PLC           | CITK         | Distress                  | Distress     |
| DL17 | Kuruwita Textile Mills PLC           | KURU         | Distress                  | Distress     |
| DL18 | Metropolitan Resource Holding PLC    | MPRH         | Non-Distress              | Non-Distress |

Source: Author Calculations

#### 4.4. Test Zmijewski X-Score Values for Listed Companies

Table 4.4 shows the calculation of Zmijewski X-score values for listed companies on the Colombo Stock Exchange. For two years, 36 X-scores were calculated: 11 were distressing, and 25 were non-distressing. This means the Zmijewski X-score model gave 5 correct predictions and 11 incorrect predictions for delisted companies.

**Table 4.4:** Calculated Zmijewski X-score values for listed companies

| No. | Company                       | Symbol     | Zmijewski X-score results |              |
|-----|-------------------------------|------------|---------------------------|--------------|
|     |                               |            | t-1                       | t-2          |
| L1  | John Keells Holdings PLC      | JKH.N0000  | Non-Distress              | Non-Distress |
| L2  | Expolanka Holdings PLC        | EXPO.N0000 | Non-Distress              | Non-Distress |
| L3  | LOLC Holdings PLC             | LOLC.N0000 | Non-Distress              | Non-Distress |
| L4  | Sri Lanka Telecom PLC         | SLTL.N0000 | Distress                  | Distress     |
| L5  | LOLC Finance PLC              | LOFC.N0000 | Non-Distress              | Non-Distress |
| L6  | Commercial Bank of Ceylon PLC | COMB.N0000 | Non-Distress              | Non-Distress |
| L7  | Melstacorp PLC                | MELS.N0000 | Distress                  | Non-Distress |
| L8  | Browns Investments PLC        | BIL.N0000  | Distress                  | Non-Distress |
| L9  | Sampath Bank PLC              | SAMP.N0000 | Non-Distress              | Non-Distress |
| L10 | Hatton National Bank PLC      | HNB.N0000  | Non-Distress              | Non-Distress |
| L11 | Lanka IOC PLC                 | LIOC.N0000 | Non-Distress              | Non-Distress |

|     |                                |            |              |              |
|-----|--------------------------------|------------|--------------|--------------|
| L12 | Aitken Spence PLC              | SPEN.N0000 | Non-Distress | Distress     |
| L13 | Carson Cumberbatch PLC         | CARS.N0000 | Distress     | Distress     |
| L14 | Valibel One PLC                | VONE.N0000 | Non-Distress | Non-Distress |
| L15 | Ceylinco Insurance PLC         | CINS.N0000 | Non-Distress | Non-Distress |
| L16 | C T Holdings PLC               | CTHR.N0000 | Distress     | Non-Distress |
| L17 | Hemas Holdings PLC             | HHL.N0000  | Distress     | Non-Distress |
| L18 | Richard Pieris and Company PLC | RICH.N0000 | Distress     | Distress     |

**Source:** Author Calculations

The primary function of bankruptcy prediction models is to predict future business failures. This study tries to evaluate the effectiveness of bankruptcy prediction models to predict delisting status. According to the results, there are two types of errors that are,

Type 1 error: if the model predicts the samples did not experience delist when, in fact, experiencing distress.

Type 2 error: if the model predicts a sample experiencing delist when it is not experiencing delist.

According to that, error rates are calculated as follows:

$$\text{Type I Error} = \frac{\text{Number of Type I Errors}}{\text{Number of Sample}} * 100\%$$

$$\text{Type 2 Error} = \frac{\text{Number of Type 2 Errors}}{\text{Number of Sample}} * 100\%$$

#### 4.5. Model Comparison

**Table 4.5:** Model Comparison: Prediction Power One Year Prior to Delisting

|                                | <b>Result:<br/>Listed<br/>predict:<br/>Listed</b> | <b>Result:<br/>Delisted<br/>predicted:<br/>Delisted</b> | <b>Result:<br/>Delisted<br/>predicted:<br/>Listed</b> | <b>Result:<br/>Listed<br/>predicted:<br/>Delisted</b> | <b>Overall<br/>accuracy</b> | <b>Type 1<br/>error</b> | <b>Type<br/>2<br/>error</b> |
|--------------------------------|---------------------------------------------------|---------------------------------------------------------|-------------------------------------------------------|-------------------------------------------------------|-----------------------------|-------------------------|-----------------------------|
| Altman's<br>Z''-score<br>model | 13                                                | 12                                                      | 6                                                     | 5                                                     | 69.44%                      | 16.67%                  | 3.89%                       |
| Zmijewski<br>X-score<br>model  | 11                                                | 9                                                       | 9                                                     | 7                                                     | 55.56%                      | 25.00%                  | 9.44%                       |

**Source:** Author Calculations

The results are based on the 18 listed companies and 18 delisted companies one year prior to delisting. The revised Altman's Z-score model has the highest accuracy rate of 69.44%, while the Zmijewski X-score model has a lower accuracy than the listed category with a type 1 error

rate of 25%. One year prior to the rate of 55.56%. Zmijewski X-score model has a tendency to misclassify delisted firms into delisting- Revised Altman's Z''-score model.

**Table 4.6:** Chi-square test: One year prior to delisting - Altman's Z''-score Model

| <b>Altman's (2006) Z''-score Model</b> |                 |               |              |
|----------------------------------------|-----------------|---------------|--------------|
|                                        | <b>Delisted</b> | <b>Listed</b> | <b>Total</b> |
| Z < 2.6                                | 12              | 5             | 17           |
| Z > 2.6                                | 6               | 13            | 19           |
| Total                                  | 18              | 18            | 36           |
| $X^2 = 5.46$                           |                 |               |              |

**Source:** Output Results

According to the significance level (0.05) and degree of freedom, the critical value (tabular value) is 3.841, and the calculated chi-square is 5.46. Therefore, the chi-square test rejects the null hypothesis and accepts the alternative hypothesis; there is an association between delisting and Altman's Z''-score model. Table 4.6 above shows the chi-square statistics.

**Table 4.7:** Chi-square test: One year prior to delisting- Zmijewski X-score Model

| <b>Zmijewski (1983) X-score Model</b> |                 |               |              |
|---------------------------------------|-----------------|---------------|--------------|
|                                       | <b>Delisted</b> | <b>Listed</b> | <b>Total</b> |
| Z < 0                                 | 9               | 11            | 20           |
| Z > 0                                 | 9               | 7             | 16           |
| Total                                 | 18              | 18            | 36           |
| $X^2 = 0.45$                          |                 |               |              |

**Source:** Output Results

According to the significance level (0.05) and degree of freedom, the critical value (tabular value) is 3.841, and the calculated chi-square is 0.45. Therefore, the chi-square test accepts the null hypothesis that there is no association between delisting and the Zmijewski X-score model. Table 4.7 above, shows the chi-square statistics.

**Table 4.8:** Model Comparison: Prediction Power Two Years Prior to Delisting

|                               | <b>Result:<br/>Listed<br/>predict:<br/>Listed</b> | <b>Result:<br/>Delisted<br/>predicted:<br/>Delisted</b> | <b>Result:<br/>Delisted<br/>predicted:<br/>Listed</b> | <b>Result:<br/>Listed<br/>predicted:<br/>Delisted</b> | <b>Overall<br/>accuracy</b> | <b>Type 1<br/>error</b> | <b>Type 2<br/>error</b> |
|-------------------------------|---------------------------------------------------|---------------------------------------------------------|-------------------------------------------------------|-------------------------------------------------------|-----------------------------|-------------------------|-------------------------|
| Alman's<br>Z''-score<br>model | 15                                                | 10                                                      | 8                                                     | 3                                                     | 69.45%                      | 22.22%                  | 8.33%                   |
| Zmijewski<br>X-score<br>model | 14                                                | 9                                                       | 9                                                     | 4                                                     | 63.89%                      | 25.00%                  | 11.11%                  |

**Source:** Output Results

The results show that the revised Altman's Z''-score model has the highest accuracy rate of 69.45%, while the Zmijewski X-score model has a lower accuracy rate of 63.89%. The Zmijewski X-score model tends to misclassify delisted firms as listed, with a Type 1 error rate of 25%.

**Table 4.9:** Chi-square test: Two years prior to delisting- Revised Altman's Z''-score model

| <b>Altman's (2006) Z''-score Model</b> |                 |               |              |
|----------------------------------------|-----------------|---------------|--------------|
|                                        | <b>Delisted</b> | <b>Listed</b> | <b>Total</b> |
| Z < 2.6                                | 10              | 3             | 13           |
| Z > 2.6                                | 8               | 15            | 23           |
| Total                                  | 18              | 18            | 36           |
| $X^2 = 5.90$                           |                 |               |              |

**Source:** Output Results

According to the significance level (0.05) and degree of freedom, the critical value (tabular value) is 3.841, and the calculated chi-square is 5.90. Therefore, the chi-square test rejects the null hypothesis and accepts the alternative hypothesis that there is an association between delisting and Altman's Z''-score model.

**Table 4.10:** Chi-square test: Two years prior to delisting- Zmijewski X-score Model

| <b>Zmijewski (1983) X-score Model</b> |                 |               |              |
|---------------------------------------|-----------------|---------------|--------------|
|                                       | <b>Delisted</b> | <b>Listed</b> | <b>Total</b> |
| Z < 0                                 | 9               | 14            | 23           |
| Z > 0                                 | 9               | 4             | 13           |
| Total                                 | 18              | 18            | 36           |
| $X^2 = 3.01$                          |                 |               |              |

**Source:** Output Results

According to the significance level (0.05) and degree of freedom, the critical value (tabular value) is 3.841, and the calculated chi-square is 3.01. Therefore, the chi-square test accepts the null hypothesis that there is no association between delisting and the Zmijewski X-score model.

The findings are further discussed in light of the conclusions drawn from the present study. The results of the study are consistent with those of previous studies by Hadi & Anggraeni (2008), Rachmania (2016), Anugrah (2019), and Supitriyani et al. (2022). Rachmania (2016) shows that among the modified Altman Z''-score model, Springate model, and Zmijewski model, only the modified Altman Z-score model (3<sup>rd</sup> version) and the Springate model can be used to predict delisting companies. The results of this study confirmed his findings again. Additionally, Hadi & Anggraeni (2008) concluded that, among bankruptcy prediction models, the Altman Z-score model is the most effective predictor, while the Zmijewski model does

not predict delisting. Additionally, research conducted by Anugrah (2019) showed that both the Altman X-score and Taffler models are significantly better compared to the Zmijewski X-score model. Additionally, Supitriyani et al. (2022) noted that the Altman model is the most accurate prediction model for predicting bankruptcy, achieving the highest degree of accuracy compared to other bankruptcy prediction models.

However, the results of the study are inconsistent with several previous studies (Fatmawati, 2012; Nenengsih, 2018; Winaya et al., 2020). Fatmawati (2012) demonstrated that only the Zmijewski model could effectively predict companies delisted during the observation period; neither the Altman model nor the Springate model could be used as predictive models for delisting. Confirming the results of his study, Husein & Pambekti (2014) and Nenengsih (2018) pointed out that the Zmijewski model can be used to predict bankruptcy. In the study by Husein & Pambekti (2014), the Zmijewski X-model stands out as the most appropriate model for predicting delisting due to its high level of significance compared to other models, such as the Altman Z-score model and the Grover model. Overall, they demonstrated that the Altman Z-score model is less suitable for predicting delisting, especially in the context of companies operating during an economic crisis.

## **5. Conclusion**

The primary objective of the researcher was to assess the predictive capabilities of Altman's Z''-score model and Zmijewski's X-score model as tools for predicting companies with delisting potential. The research was conducted based on a sample of 18 delisted companies and 18 listed companies. To generate results relevant to the research problem, the model's accuracy rate, error rate, and Chi-square test were conducted.

Based on the results obtained by data analysis for one and two years, the revised Altman's Z''-score model has a higher accuracy rate in predicting delisting companies than the Zmijewski X-score model in the Sri Lankan context. Zmijewski's X-score model tends to misclassify delisted firms as listed, resulting in a type 1 error rate of 25%. Therefore, compared to the accuracy level of Altman's Z''-score model, the Zmijewski X-model is not suitable for predicting the delisting of companies. According to the overall results obtained from the analysis, it can be concluded that the revised Altman's Z''-score model can be used as a predictor of delisting companies and has a higher predictive ability than the Zmijewski X-score model, especially when assessing the delisting possibility during a period of national economic crisis.

This study offers several implications for various stakeholders, including investors and corporate decision-makers. Stakeholders can enhance their decision-making by analysing the

company's financial status using Altman's Z-score model. Companies can utilise Altman's Z-score model as a predictive measure in anticipation of delisting, as it provides early warning signals about potential future financial distress and delisting, particularly during uncertain environmental conditions resulting from economic crises. Investors and creditors can perform predictive analysis on companies using Altman's Z-score model, and therefore, they can make informed decisions that will help them minimise credit losses. For corporate decision-makers, identifying companies at risk of delisting well in advance is essential to take preventive measures and mitigate potential financial losses. Therefore, they can use Altman's Z-score model as a predictor of delisting.

Although the study makes significant contributions, a few limitations should be noted, which pave the way for future studies. The study is limited by restricted access to previous years' financial data of delisted companies, as their annual reports were removed from the Colombo Stock Exchange library after delisting. This poses a challenge in collecting a substantial sample, which may affect the generalizability and statistical power of the findings. Another limitation is that this study only examined the validity of Altman's Z''-score model and Zmijewski's X-score model. Future studies can test the validity of other bankruptcy prediction models, such as the Springate model, the Ohlson model, the Groever Model, and the CA-Score model, in special environmental conditions similar to those of this study. The results can be extended to similar countries in the South Asian region, but may not be generalizable to developed countries or nations with larger stock markets. Therefore, future follow-up studies comparing Altman's Z-score model with the Zmijewski X-model, using data from countries other than Sri Lanka, especially developed and larger countries, will provide further insights.

## Reference

- Altman, E. I. (1968). Financial Ratios, Discriminant Analysis, and the Prediction of Corporate Bankruptcy. *The Journal of Finance*, 23(4), 589–609.
- Altman, E. I. (2006). Default recovery rates and LGD in credit risk modelling and practice: an updated review of the literature and empirical evidence. *Journal of Risk Management in Financial Institutions*, 1(1), 1–17.
- Anugrah, M. D. (2019). Analysis of the Altman, Taffler, and Zmijewski Models in Predicting Companies Forced to Delist Due to Financial Failure from the Indonesian Stock Exchange for the Period 2010-2014. *TECHNOBIZ: International Journal of Business*, 2(1), 38–45.

- Belyaeva, E. (2014). *On a new logistic regression model for bankruptcy prediction in the IT branch* (Master's thesis, Linnaeus University). Linnaeus University, Sweden.
- Benny, L., & Hutagaol, Y. (2013). Empirical Investigation of Determinant Factors of Company Delisting: Evidence from Indonesia. *Journal of Applied Finance and Accounting*, 6(1), 25–66.
- Berg, A., Borensztein, E., & Pattillo, C. (2005). Assessing early warning systems: how have they worked in practice? *IMF Staff Papers*, 52(3), 462–502.
- Bortolon, P. M., & Silva, A. da. (2015). Determining factors for delisting of companies listed on BM&FBOVESPA. *Revista Contabilidade & Finanças*, 26(68), 140–153.
- Celli, M. (2015). Can Z-score model predict listed companies' failures in Italy? An empirical test. *International Journal of Business and Management*, 10(3), 57.
- Chan, N. (2016). The Analysis of Delisting Decision of Garment Companies Observed from the Aspect of Bankruptcy Prediction, Compatibility with Income Statement and Auditor's Opinion. *International Journal of Organisational Innovation*, 9(2).
- Croci, E., & Giudice, A. Del. (2014). Delistings, controlling shareholders and firm performance in Europe. *European Financial Management*, 20(2), 374–405.
- Duwipa, F. (2013). Sistem Peringatan Dini (Early Warning System). *Lembaga Penelitian & Pengembangan Kesejahteraan Sosial LPPK*.
- Endri, E., Kasmir, K., & Syarif, A. (2020). Delisting sharia stock prediction model based on financial information: Support Vector Machine. *Decision Science Letters*, 9(2), 207–214.
- Fatmawati, M. (2012). The use of the Zmijewski Model, the Altman Model, and the Springate Model as predictors of delisting. *Jurnal Keuangan Dan Perbankan*, 16(1).
- Grice Jr, J. S., & Dugan, M. T. (2003). Re-estimations of the Zmijewski and Ohlson bankruptcy prediction models. *Advances in Accounting*, 20, 77–93.
- Gunathilaka, C. (2014). *Factors influencing stock selection decision: The case of retail investors in the Colombo Stock Exchange* [Master's thesis, University of Sri Jayewardenepura]. University of Sri Jayewardenepura Institutional Repository.
- Hadi, S., & Anggraeni, A. (2008). Selection of the best delisting predictor (comparison between the Zmijewski model, the Altman model, and the Springate model). *Jurnal Akuntansi Dan Auditing Indonesia*, 12(2).

- Hari, Z. T., Endri, E., & Anwar, S. (2019). Delisting prediction model in Sharia stock using logistic regression. *Jurnal Produktivitas: Jurnal Fakultas Ekonomi Universitas Muhammadiyah Pontianak*, 6(2), 175–185.
- Husein, M. F., & Pambekti, G. T. (2014). Precision of the models of Altman, Springate, Zmijewski, and Grover for predicting the financial distress. *Journal of Economics, Business, and Accountancy Ventura*, 17(3), 405–416.
- Hwang, I. T., Kang, S. M., & Jin, S. J. (2014). A delisting prediction model based on nonfinancial information. *Asia-Pacific Journal of Accounting & Economics*, 21(3), 328–347.
- Kaminsky, G. L., & Reinhart, C. M. (1999). The twin crises: the causes of banking and balance-of-payments problems. *American Economic Review*, 89(3), 473–500.
- Kpodoh, B. (2010). *Bankruptcy and financial distress prediction in the mobile telecom industry* [Master's thesis, Blekinge Institute of Technology]. Blekinge Institute of Technology Repository.
- Martinez, I., & Serve, S. (2017). Reasons for delisting and consequences: A literature review and research agenda. *Journal of Economic Surveys*, 31(3), 733–770.
- Najib, A. S., & Cahyaningdyah, D. (2020). Analysis of the bankruptcy of companies with Altman model and Ohlson model. *Management Analysis Journal*, 9(3), 243–251.
- Nanayakkara, K. G. M., & Azeez, A. A. (2015). Predicting corporate financial distress in Sri Lanka: an extension to the Z-score model. *International Journal of Business and Social Research*, 5(03), 41–56.
- Nenengsih, N. (2018). Selection of the Best Delisting Predictor Comparison of Modified Altman, Springate, Zmijewski, Ca-Score and Groever Models. *Journal Profiet*, 1(1), 67–86.
- Pavlović, V., Muminović, S., & Cvijanović, J. M. (2012). Adequacy of Applying the Zmijewski Model on Serbian Companies. *Industry/Industrija*, 40(4).
- Rachmania, F. B. (2016). *Analysis of the Best Delisting Predictors Between the Modified Altman Z-Score, Springate, and Zmijewski Models*. STIE Perbanas Surabaya.
- Radivojac, G., Krčmar, A., & Mekinjić, B. (2021). Comparison of Altman's Z-Score Model and Altman's Z"-Score Model on the Sample of Companies Whose Shares are Included in the Republic of Srpska Stock Exchange Index. *Proceedings of the Faculty of Economics in East Sarajevo*, 22, 11–20.



- Ross, S. A. (1977). The Determination of Financial Structure: The Incentive-Signalling Approach. *The Bell Journal of Economics*, 23–40.
- Siripokakit, W. (2005). *Prediction Model for Delistings: Evidence from the Stock Exchange of Thailand*. Alliant International University, San Diego.
- Supitriyani, S., Astuti, A., & Azwar, K. (2022). The implementation of Springate, Altman, Grover and Zmijewski Models in measuring financial distress. *International Journal of Trends in Accounting Research*, 3(1), 1–8.
- Wang, Y., & Campbell, M. (2010). Do Bankruptcy Models Really Have Predictive Ability? Evidence using China's Publicly Listed Companies. *International Management Review*, 6(2).
- Whitaker, R. B. (1999). The early stages of financial distress. *Journal of Economics and Finance*, 23(2), 123–132.
- Winaya, G. Y., RM, K. M., Budiasih, I., & Wiratmaja, I. D. N. (2020). Analysis of Altman Z-Score and Zmijewski Bankruptcy Prediction in Telecommunication Sub-Sectors Registered in the Indonesia Stock Exchange in 2016-2018. *American Journal of Humanities and Social Sciences Research*, 4(1), 313–322.
- Zmijewski, M. E. (1984). Methodological issues related to the estimation of financial distress prediction models. *Journal of Accounting Research*, 59–82.

## CHAPTER FIVE

### Impact of Board Gender Diversity on Sustainability Reporting Quality of Listed Commercial Banks in Sri Lanka

Perera J.A.A.D. & Fernando K.D.U.D.

Department of Accountancy and Finance, Faculty of Management Studies  
Sabaragamuwa University of Sri Lanka  
[ashendinujayaperera@gmail.com](mailto:ashendinujayaperera@gmail.com)

#### Abstract

*This study examines the intricate relationships between the quality of sustainability reporting, bank size, return on equity (ROE), and board gender diversity in Sri Lankan domestically listed commercial banks. This study examines the intricate relationships between these variables and their implications for corporate social responsibility and governance practices, with a specific focus on the country's banking industry. The study emphasises the critical role that diverse gender representation plays in decision-making processes by highlighting the favourable association between gender diversity on corporate boards and the calibre of sustainability reporting. Furthermore, the study reveals a favourable correlation between bank size and the quality of sustainability reporting, highlighting the role that organisational resources and competencies play in shaping comprehensive reporting processes. The study's development of the Sustainability Reporting Quality Score, a novel assessment instrument specifically designed for Sri Lanka's banking sector, is one of its unique contributions. The suggestions include promoting gender parity, allocating resources for capacity-building training, enhancing transparency, integrating sustainability concepts into decision-making processes, and establishing clear reporting standards. Through the adoption of these suggestions, the banking industry can move toward a future where corporate identity is grounded in sustainability, inclusion, and transparency, thereby promoting a more just and equitable global community.*

**Keywords:** Gender Diversity, Governance Practices, Sri Lankan Banking Sector, Sustainability Reporting Quality.

## 1. Introduction

Sustainability reporting is now crucial for corporate governance, offering insights into environmental, social, and economic performance (Gerwing et al., 2022). Recently, the global business environment has shifted toward sustainable practices (Ranald, 2002a), driven by societal expectations, regulations, and ethics. Sri Lanka, like other nations, faces the challenges and benefits of sustainability reporting.

For Sri Lankan enterprises, transparent reporting is key in a changing market with unique environmental and social issues (Dissanayake et al., 2019). The country's rich biodiversity and economic growth highlight the need for sustainable business practices. Companies, especially banks, must balance expansion with their environmental and social responsibilities, requiring a deep understanding of corporate behaviour, disclosure, and financial results (Sandali et al., 2020).

Globally, gender diversity on boards has been linked to improved financial performance, enhanced governance, and increased innovation (Singhania et al., 2023). The organisation's policies and practices, including its sustainability reporting, are heavily influenced by the board of directors, which serves as the primary decision-making body for the company. According to research, gender diversity on boards contributes to a range of viewpoints and ideas that foster creativity and informed decision-making (Adams & Ferreira, 2009). Examining the gender makeup of business boards becomes more important in the particular context of Sri Lanka, where gender biases are pervasive.

However, research on the impact of board gender diversity on the quality of sustainability reporting in Sri Lankan commercial banks remains unexplored (Bakar et al., 2019; Erin et al., 2022; Gerwing et al., 2022; Singhania et al., 2023). Sri Lanka's corporate world is characterised by a patriarchal culture, with men often holding leadership positions (Vithanage, 2015). The prevalence of gender disparities in corporate governance, including the underrepresentation of women on boards, may hinder the progress of sustainable practices in the banking sector. The influence of patriarchal norms and cultural biases on board appointments and decision-making processes cannot be overlooked when examining gender diversity in Sri Lankan commercial banks (Gerwing et al., 2022). Gender disparities could slow sustainable progress, and cultural biases influence board appointments (Gerwing et al., 2022).

This study examines the impact of board gender diversity on sustainability reporting, acknowledging the influence of patriarchal norms. By investigating the relationship between gender diversity on boards of directors and the quality of sustainability reporting, this

research acknowledges the potential impact of patriarchal norms on corporate governance practices in Sri Lanka. It aims to provide empirical evidence on the extent to which gender diversity within boards influences the quality of sustainability reporting in the specific context of locally listed commercial banks. The research aims to highlight the significance of gender diversity in promoting sustainability practices and fostering inclusive governance in patriarchal societies (Singhania et al., 2023). The findings would provide valuable insights into policymaking, corporate strategy formation, and investor decision-making, encouraging gender diversity and sustainable practices in the banking sector.

### **1.1. Objectives of the Study**

The main objectives of this research are as follows:

1. To investigate the relationship between gender diversity and sustainability reporting quality.
2. To examine time-specific impacts on sustainability reporting quality.

## **2. Literature Review**

### **2.1. Theoretical Review**

The agency theory provides a sound theoretical framework for this study, which examines how the gender diversity of the board of directors affects the quality of sustainability reporting in locally listed commercial banks in Sri Lanka (Panda & Leepsa, 2017). The agency theory posits that corporations are characterised by principal-agent relationships, where managers (agents) act on behalf of shareholders (principals), leading to potential conflicts of interest due to information asymmetry. Agency theory becomes particularly relevant in understanding corporate governance dynamics, as noted by de Klerk & de Villiers (2012). This research sheds light on the connection between gender-diverse boards and the calibre of sustainability reporting. The presence of diverse perspectives, experiences, and skills on corporate boards, specifically in terms of gender diversity, can influence the decision-making process and enhance the quality of sustainability reporting. According to research, boards with diverse membership are more likely to consider social and environmental issues, alongside other stakeholder interests (Adams & Ferreira, 2009). This study, which adopts the agency theory, explores the relationship between gender diversity on the board of directors and the quality of sustainability reporting, accountability, and transparency in Sri Lankan commercial banks.

Moreover, within the framework of this research on how the gender diversity of the board of directors affects the quality of sustainability reporting for locally listed commercial banks in

Sri Lanka, the legitimacy theory serves as a theoretical framework, providing insights into the connection between corporate governance and sustainability disclosure. Legitimacy theory, as articulated by Buhr (2002), asserts that organisations must conform to societal norms and expectations to ensure their continued existence. This idea aligns with the study in that the quality of commercial banks' SR is inextricably linked to their legitimacy within the specific socioeconomic and cultural context in which they operate.

## **2.2. Empirical Review**

Gender diversity in governance has become a significant topic in discussions about corporate performance and governance. Corporate governance is a concept with dimensions that involves intricate relationships between shareholders, management teams and other stakeholders (Ibrahim & Hanefah, 2016). Researchers have examined this topic from perspectives with an emphasis on the inclusion of women in boardrooms and top-level management roles (Francoeur et al., 2008). These relationships shape the organisation's purpose and the distribution of power (Freeman et al., 2004). Out of these dimensions, the representation of women on boards emerges as a crucial area of investigation. Historically, the separation of ownership and control in publicly held companies has led to conflicts of interest between principals (board of directors) and agents (managers), making governance mechanisms essential to mitigate agency costs (Fox & Hamilton, 1994). Studies suggest that diverse boards, including those with women, bring fresh perspectives, thereby enhancing decision-making (Carter et al., 2003; Wellalage & Locke, 2013). However, there is debate about its impact on firm performance, with some studies showing positive effects, while others report negative or inconclusive results (Dutta & Bose, 2007).

Sustainability reporting, as defined by the Global Reporting Initiative (2011) (Jain, 2017), is the process of evaluating, disclosing, and taking responsibility for a business's performance in achieving sustainable development. It has become a staple of global reporting. Sustainability reporting, sometimes referred to as Triple Bottom Line (TBL) reporting or Corporate Social Responsibility (CSR) reporting, is an evolving practice that represents an organisation's recognition of its effects on social structures, environmental systems, and stakeholder economic situations (Alhaddi, 2015; Halkos & Nomikos, 2021). Firms today are under increasing pressure to account not only for their financial standing but also for their Environmental, Social, and Governance (ESG) performance, in order to make more informed investment decisions and adopt sustainable practices. Stakeholders and investors want clear information on non-financial elements (Hubbard, 2009).

Several studies have examined the relationship between gender diversity on boards and the quality of sustainability reporting, highlighting positive correlations (Aggarwal & Singh,

2019; Pareek et al., 2023). Research in India, for instance, has examined how gender diversity on corporate boards improves sustainability reporting. A study of 432 BSE-listed companies over eight years found a strong positive correlation between the presence of female directors and improved sustainability reporting, highlighting the importance of increasing the representation of women in boardrooms (Pareek et al., 2023). However, the study's subjective content analysis and lack of differentiation in gender diversity degrees suggest areas for further research, particularly in developing economies.

In Nigeria, a study of 120 firms (2013-2018) revealed that smaller boards, more female directors, larger audit committees, and frequent meetings all improved the quality of sustainability reporting (SRQ). The research also highlighted the importance of external assurance and sustainability committees in enhancing the credibility of reporting (Erin et al., 2022). Despite the study's significant contributions, its limited sample size suggests the need for broader comparative research across nations.

Additionally, gender diversity has a positive influence on the adoption of sustainable reporting and external assurance. Companies with more women on boards were more likely to opt for independent assurance, corroborating existing literature (Al-Shaer & Zaman, 2016). The study also found that younger boards were more inclined to adopt these practices, reflecting a generational shift in values. Furthermore, organisations in environmentally sensitive industries showed higher adoption rates, emphasising the role of stakeholders in shaping corporate sustainability strategies (Mnif Sellami et al., 2019). This research underscores the significance of gender diversity in corporate leadership in fostering sustainability and ethical practices in both low- and middle-income countries (Correa-Garcia et al., 2020).

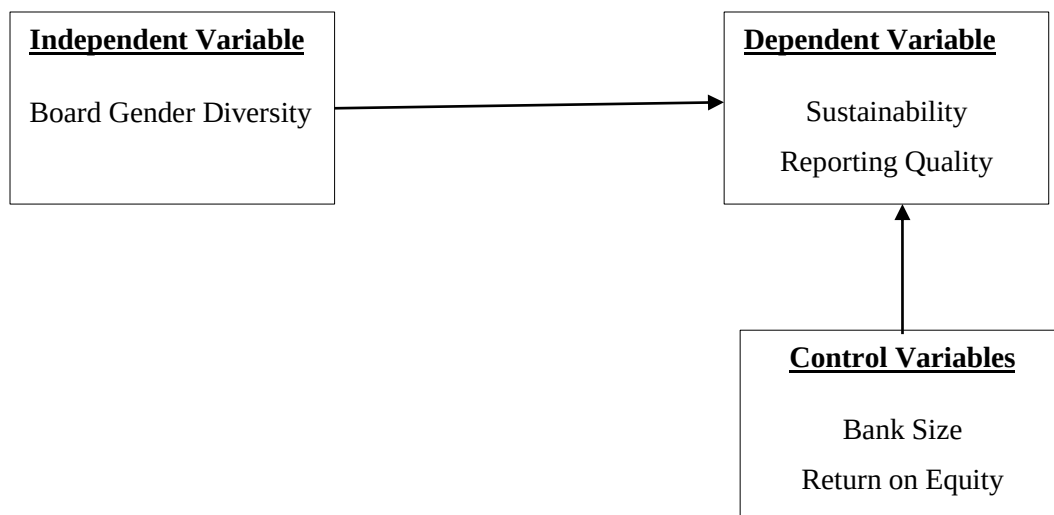
### **3. Methodology**

#### **3.1. Research Design**

This study employs a quantitative research design to investigate the relationship between board gender diversity and the quality of sustainability reporting in Sri Lankan commercial banks. The study is based on quantitative data from 11 banks over six years (2017-2022).

#### **3.2. Conceptual Framework**

The framework examines the relationship between board gender diversity and the quality of sustainability reporting, drawing on agency and legitimacy theories while accounting for the sociocultural influence of patriarchy.



**Figure 3.1:** Conceptual Framework

Source: Empirical Review

### 3.3. Sample and Data Collection

Eleven of Sri Lanka's twenty-four domestically listed commercial banks were selected. Specifically, these include the Bank of Ceylon, Commercial Bank, DFCC Bank, HNB, NDB, NTB, Pan Asia Bank, Peoples' Bank, Sampath Bank, Seylan Bank, and Union Bank. These banks were chosen as the research sample because they are easily accessible and provide a good representation of the banking industry in Sri Lanka. These banks provide consistency and comparability for research (Wellalage & Locke, 2013). Secondary data from 2017 to 2022 was gathered from financial databases, annual reports, and regulatory filings.

### 3.4. Model Specification

A panel regression model is employed to examine the effect of board gender diversity on the quality of sustainability reporting. The model controls for bank size and financial performance. The model is expressed as follows:

$$SRQS_{it} = \beta_0 + \beta_1 \times Gdratio_{it} + \beta_2 \times BankSize_{it} + \beta_3 \times ROE_{it} + \epsilon \quad (1)$$

Where:

$\beta_0$  = intercept

$\beta_1$  = impact of Board Gender Diversity Ratio on Sustainability Reporting Score

$\beta_2$  and  $\beta_3$  = coefficients for Bank Size and Bank Performance, respectively

$\epsilon$  = error term

### 3.5. Operationalisation

#### Gender Diversity Ratio

Computed as the number of female directors divided by the total number of directors. This ratio quantifies gender inclusivity on the boards. (Carter et al., 2003).

$$\text{Gender Diversity Ratio} = \frac{\text{Number of Female Directors}}{\text{Total Directors Count}}$$

#### Sustainability Reporting Quality Score

Based on six components: sustainability reporting availability (a), reporting committee availability (b), GRI standards adherence (c), materiality assessment availability (d), external assurance €, and Big five audit firm involvement (f). A higher score indicates better sustainability reporting practices. (1 or 0): Available (1) or Not Available (0)

**Table 3.1:** Sustainability Quality Score Calculation – Sum of 6 years

| Bank    | a | b | c | d | e | f | Total |
|---------|---|---|---|---|---|---|-------|
| BOC     | 6 | 6 | 6 | 6 | 6 | 4 | 34    |
| COMBANK | 6 | 1 | 6 | 6 | 6 | 6 | 31    |
| DFCC    | 6 | 0 | 6 | 6 | 6 | 6 | 30    |
| HNB     | 6 | 0 | 6 | 6 | 6 | 6 | 30    |
| NDB     | 6 | 1 | 6 | 6 | 6 | 6 | 31    |
| NTB     | 6 | 0 | 6 | 6 | 6 | 6 | 30    |
| PANASIA | 0 | 0 | 0 | 1 | 1 | 1 | 3     |
| PEOPLES | 6 | 1 | 6 | 6 | 6 | 6 | 31    |
| SAMPATH | 6 | 6 | 6 | 6 | 6 | 6 | 36    |
| SEYLAN  | 6 | 6 | 6 | 6 | 6 | 6 | 36    |
| UNION   | 6 | 0 | 6 | 6 | 6 | 6 | 30    |

**Source:** Author Calculation

The Sustainability Reporting Quality Score is calculated by summing the values of these components, resulting in a score ranging from 0 to 6. A higher score indicates a more comprehensive and robust sustainability reporting framework within the banks.

### 3.6. Data Analysis Techniques

Pooled OLS, Fixed Effects, and Random Effects regressions are employed to examine the relationship between board gender diversity and the quality of sustainability reporting. These models help control for unobserved heterogeneity and allow for nuanced insights (Al-shaer & Zaman, 2016).



The Hausman Test is employed to determine whether the fixed or random effects model is more appropriate. It compares the estimators from both models to choose the one that provides consistent results. (Singhania et al., 2023). The Hausman Test helps ensure that the chosen model is the most efficient and suitable for this study's context, thereby enhancing the accuracy and reliability of the regression analysis (Hahn et al., 2011).

## 4. Results and Discussion

### 4.1. Descriptive Statistics

Table 4.1 below summarises the descriptive statistics, providing insights into the central tendencies and distributions of the data.

**Table 4.1:** Descriptive Statistics

| Variable       | Mean  | Std. Dev | Min  | Max   |
|----------------|-------|----------|------|-------|
| srqualityscore | 4.88  | 1.50     | 0    | 6     |
| Gdratio        | 0.16  | 0.11     | 0    | 0.40  |
| Banksize       | 8.82  | 0.43     | 8.07 | 9.63  |
| Roe            | 12.19 | 5.10     | 1.71 | 26.60 |

**Source:** STATA Output

The Sustainability Reporting Quality score yields an average of 4.88, with a range of 0 to 6. This implies that the study's banks generally adhere to sustainability reporting standards to a moderate to high degree. With a standard deviation of 1.50, the degree of variability around the mean score is moderate. The gender diversity ratio indicates that, on average, 16.3% of the board members in the banks under study are female, with a mean of approximately 0.16. This implies that there is not much diversity in terms of gender on the boards. The gender diversity ratios across the banks exhibit modest heterogeneity, as indicated by the standard deviation of 0.11.

### 4.2. Data Analysis

This study examined the relationship between the quality of sustainability reporting and board gender diversity in Sri Lankan commercial banks, using a panel regression analysis. Three distinct regression techniques — namely, Pooled Ordinary Least Squares (OLS), Fixed Effects, and Random Effects — are utilised to analyse the data and capture nuanced insights (Al-Shaer & Zaman, 2016).

Pooled OLS regression is initially employed to provide an overall assessment of the relationship between board gender diversity ratios and Sustainability Reporting Quality Scores. To account for potential time-invariant unobserved heterogeneity across banks, fixed

effects regression is applied. The use of Fixed Effects modelling accounts for stable bank-specific features that may ultimately affect the quality of sustainability reporting, as well as board gender diversity. Random Effects regression is employed to address both time-invariant and time-variant unobserved heterogeneity. This technique assumes that some unobserved factors may be constant over time, while others may vary. The results are summarised in Table 4.2 below.

**Table 4.2:** Panel Regression Results

| <b>Pooled OLS Model</b>                          |                    |                 |                               |                 |
|--------------------------------------------------|--------------------|-----------------|-------------------------------|-----------------|
| <b>R-squared = 0.5539</b>                        |                    |                 | <b>Adj R-squared = 0.5323</b> |                 |
| <b>F (8, 57) = 25.66</b>                         |                    |                 | <b>Prob &gt; F = 0.000</b>    |                 |
| <b>Variable</b>                                  | <b>Coefficient</b> | <b>Std. Err</b> | <b>t</b>                      | <b>P&gt; t </b> |
| gdratio                                          | 6.087              | 1.215           | 5.01                          | 0.000           |
| banksize                                         | 2.362              | 0.317           | 7.43                          | 0.000           |
| roe                                              | -0.075             | 0.027           | -2.70                         | 0.009           |
| _cons                                            | -16.034            | 2.744           | -5.84                         | 0.000           |
| <b>Random Effect Model</b>                       |                    |                 |                               |                 |
| <b>Wald chi-square F (3,52) = 29.22</b>          |                    |                 |                               |                 |
| <b>Prob &gt; F = 0.0000</b>                      |                    |                 |                               |                 |
| <b>Variable</b>                                  | <b>Coefficient</b> | <b>Std. Err</b> | <b>z</b>                      | <b>P&gt; t </b> |
| gdratio                                          | 2.502              | 0.826           | 3.03                          | 0.002           |
| banksize                                         | 1.481              | 0.504           | 2.94                          | 0.003           |
| roe                                              | -0.021             | 0.015           | -1.35                         | 0.176           |
| _cons                                            | -8.335             | 4.516           | -1.85                         | 0.065           |
| <b>Fixed Effect Model</b>                        |                    |                 |                               |                 |
| <b>F (3,52) = 7.2</b>                            |                    |                 |                               |                 |
| <b>Prob &gt; F = 0.0004</b>                      |                    |                 |                               |                 |
| <b>F test that all u_i=0: F (10, 52) = 37.40</b> |                    |                 | <b>Prob &gt; F = 0.0000</b>   |                 |
| <b>Variable</b>                                  | <b>Coefficient</b> | <b>Std. Err</b> | <b>z</b>                      | <b>P&gt; t </b> |
| gdratio                                          | 2.292              | 0.827           | 2.63                          | 0.011           |
| banksize                                         | 1.187              | 0.746           | 1.59                          | 0.118           |
| roe                                              | -0.022             | 0.018           | -1.25                         | 0.218           |
| _cons                                            | -5.689             | 6.672           | -0.85                         | 0.398           |

**Source:** STATA Output

The probability of the F-test (0.0000) in the FE Model is observed to be below the conventional significance level of 0.05, suggesting that there exists a strong relationship between quality and at least one of the independent variables. Therefore, it is recommended to opt for the FE regression model.

The Breusch and Pagan Lagrangian multiplier (LM) test is employed to evaluate the existence of random effects within the model, and the p-value (0.0000) obtained is statistically significant at a level lower than the standard significance level (0.05). This finding provides compelling evidence that the effects particular to each individual ( $\mu_i$ ) are statistically significant and make a substantial contribution to the variability observed in the quality of social relationships. Considering the statistically significant p-value ( $p = 0.0000$ ), it is recommended to opt for the random-effects (RE) model.

The Hausman test is used to assess the correlation between individual-specific effects and independent variables by comparing the coefficients derived from the fixed-effects (FE) model and the random-effects (RE) model. The p-value corresponding to the Hausman test is 0.1329, which is greater than the traditional threshold of significance set at 0.05. This finding suggests that there is insufficient evidence to reject the null hypothesis, which states that there is no compelling evidence to indicate that the coefficients derived from the fixed effects (FE) and random effects (RE) models exhibit substantial differences. Based on the findings of the Hausman test, it is recommended to select the random-effects (RE) model.

Accordingly, the gender diversity ratio was found to have a significant impact on the quality of sustainability reporting, with a coefficient of 2.502. It suggests that the Sustainability Reporting Quality Score and gender diversity on the board of directors have a positive association. The Sustainability Reporting Quality Score typically rises by 2.505 points for every unit increase in the gender diversity ratio. This finding is consistent with earlier research that highlights the beneficial influence of gender diversity on the quality of sustainability reporting (Erin et al., 2022; Pareek et al., 2023). Moreover, the research findings align with the broader theoretical frameworks utilised. Stakeholder theory, agency theory, and legitimacy theory have all played important roles in explaining the relationship between gender diversity and the quality of sustainability reporting. According to de Klerk and de Villiers (2012), the agency theory approach emphasises the role of diverse boards in mitigating information asymmetry and enhancing decision-making processes, resulting in improved sustainability reporting (de Klerk & de Villiers, 2012).

The findings further reveal that the bank's size and the Sustainability Reporting Quality Score are positively correlated. It suggests that larger banks may be able to invest more heavily in thorough and superior sustainability reporting practices due to their greater operations and resource capacities (Erin et al., 2022). However, the ROE has a coefficient of -0.021, which is statistically insignificant. This surprising discovery casts doubt on the widely held notion that improved sustainability reporting is a direct result of increased profitability. Further research may be needed to fully understand the nuances of this relationship.

## 5. Conclusion

This paper examined the correlation between gender diversity, bank size, return on equity (ROE), and sustainability reporting quality (SRQ) in Sri Lankan commercial banks. The study found a positive link between gender diversity in corporate boards and better SRQ. Banks must take proactive measures to cultivate inclusive and diverse corporate cultures. Promoting gender diversity in the workplace, particularly in boardrooms, is not only morally right but also has a good effect on sustainability reporting. Banks can create awareness campaigns, training sessions, and mentorship programs to encourage diversity and inclusivity of women in decision-making.

Furthermore, it revealed that larger banks tend to have more effective sustainability reporting practices. This could be due to the availability of greater resources and expertise. Smaller banks can adopt best practices from larger banks to improve their reporting. Contrary to expectations, a negative correlation was found between ROE and SRQ, suggesting that higher profitability does not necessarily lead to better sustainability reporting. Further research is needed to explore this relationship.

This study introduces a novel Sustainability Reporting Quality Score, tailored to Sri Lanka's banking sector. This score integrates industry-specific criteria and international standards, such as GRI, offering a comprehensive tool for assessing sustainability reporting. Banks should promote gender diversity, invest in capacity building, enhance transparency in reporting, and integrate sustainability into their strategies. Policymakers should enforce gender diversity policies, encourage knowledge sharing, and offer incentives for eco-friendly projects, fostering an environment where sustainability is a core business practice.

Although the quality of sustainability reporting is positively correlated with gender diversity on boards, more research can examine the underlying causative processes of this association. Using techniques like focus groups and in-depth interviews, qualitative research methods can effectively capture the viewpoints of CEOs and board members.

## Reference

- Adams, R. B., & Ferreira, D. (2009). Women in the boardroom and their impact on governance and performance. *Journal of Financial Economics*, 94(2), 291–309. <https://doi.org/10.1016/J.JFINECO.2008.10.007>
- Aggarwal, P., & Singh, A. K. (2019). CSR and sustainability reporting practices in India: an in-depth content analysis of top-listed companies. *Social Responsibility Journal*, 15(8), 1033–1053. <https://doi.org/10.1108/SRJ-03-2018-0078>

- Alhaddi, H. (2015). Triple bottom line and sustainability: A literature review. *Business and Management Studies*, 1(2), 6–10.
- Al-Shaer, H., & Zaman, M. (2016). Board gender diversity and sustainability reporting quality. *Journal of Contemporary Accounting & Economics*, 12(3), 210–222. <https://doi.org/10.1016/J.JCAE.2016.09.001>
- Bakar, A. B. S. A., Ghazali, N. A. B. Mohd., & Ahmad, M. B. (2019). Sustainability Reporting and Board Diversity in Malaysia. *International Journal of Academic Research in Business and Social Sciences*, 9(2). <https://doi.org/10.6007/ijarbss/v9-i2/5663>
- Buhr, N. (2002). A structuration view on the initiation of environmental reports. *Critical Perspectives on Accounting*, 13, 17–38. <https://doi.org/10.1006/cpac.2000.0441>
- Carter, D. A., Simkins, B. J., & Simpson, W. G. (2003). Corporate Governance, Board Diversity, and Firm Value. *Financial Review*, 38(1), 33–53. <https://doi.org/https://doi.org/10.1111/1540-6288.00034>
- Correa-Garcia, J. A., Garcia-Benau, M. A., & Garcia-Meca, E. (2020). Corporate Governance and Its Implications for the Quality of Sustainability Reporting in Latin American Business Groups. *Journal of Cleaner Production*, 260, 121142. <https://doi.org/10.1016/J.JCLEPRO.2020.121142>
- De Klerk, M., & de Villiers, C. (2012). The value relevance of corporate responsibility reporting: South African evidence. *Meditari Accountancy Research*, 20(1), 21–38. <https://doi.org/10.1108/10222521211234200>
- Dissanayake, D., Tilt, C., & Qian, W. (2019). Factors influencing sustainability reporting by Sri Lankan companies. *Pacific Accounting Review*, 31(1), 84–109. <https://doi.org/10.1108/PAR-10-2017-0085>
- Dutta, P., & Bose, S. (2007). *Gender Diversity in the Boardroom and Financial Performance of Commercial Banks: Evidence from Bangladesh*.
- Erin, O., Adegboye, A., & Bamigboye, O. A. (2022). Corporate governance and sustainability reporting quality: evidence from Nigeria. *Sustainability Accounting, Management and Policy Journal*, 13(3). <https://doi.org/10.1108/SAMPJ-06-2020-0185>
- Francoeur, C., Labelle, R., & Sinclair-Desgagné, B. (2008). Gender Diversity in Corporate Governance and Top Management. *Journal of Business Ethics*, 81(1), 83–95. <https://doi.org/10.1007/s10551-007-9482-5>
- Freeman, R. E., Wicks, A. C., & Parmar, B. (2004). Stakeholder theory and 'The corporate objective revisited'. In *Organisation Science* (Vol. 15, Issue 3). <https://doi.org/10.1287/orsc.1040.0066>

- Gerwing, T., Kajüter, P., & Wirth, M. (2022). The role of sustainable corporate governance in mandatory sustainability reporting quality. *Journal of Business Economics*, 92(3). <https://doi.org/10.1007/s11573-022-01092-x>
- Halkos, G., & Nomikos, S. (2021). Corporate social responsibility: Trends in global reporting initiative standards. *Economic Analysis and Policy*, 69, 106–117. <https://doi.org/10.1016/J.EAP.2020.11.008>
- Hubbard, G. (2009). Unsustainable reporting. *CR Debates, The Royal Institution of Great Britain, London*. URL: [Www. Corporateregister. Com/Crra/2008-Ceremony/Research. Html](http://www.Corporateregister.Com/Crra/2008-Ceremony/Research.Html).
- Ibrahim, A. H., & Hanefah, M. M. (2016). Board diversity and corporate social responsibility in Jordan. *Journal of Financial Reporting and Accounting*, 14(2). <https://doi.org/10.1108/jfra-06-2015-0065>
- Jain, S. (2017). *Global Reporting Initiative: A Study on Global Reporting Initiative Standards as an Important Tool of Corporate Social Responsibility and an Improvement over Sustainability Reporting Standards*. 6. [https://rntujournals.aisect.org/assets/upload\\_files/articles/03575b1dda3cae029bb47ad76fe0c9ad.pdf](https://rntujournals.aisect.org/assets/upload_files/articles/03575b1dda3cae029bb47ad76fe0c9ad.pdf)
- Mnif Sellami, Y., Dammak Ben Hlima, N., & Jarboui, A. (2019). An Empirical Investigation of the Determinants of Sustainability Report Assurance in France. *Journal of Financial Reporting and Accounting*, 17(2), 320–342. <https://doi.org/10.1108/JFRA-02-2018-0019>
- Panda, B., & Leepsa, N. M. (2017). Agency theory: Review of theory and evidence on problems and perspectives. *Indian Journal of Corporate Governance*, 10(1). <https://doi.org/10.1177/0974686217701467>
- Pareek, R., Sahu, T. N., & Gupta, A. (2023). Gender diversity and corporate sustainability performance: empirical evidence from India. *Vilakshan - XIMB Journal of Management*, 20(1), 140–153. <https://doi.org/10.1108/XJM-10-2020-0183>
- Ranald. (2002a). The Business Case for Sustainable Development: Making a Difference towards the Earth Summit 2002 and Beyond. *Corporate Environmental Strategy*, 9(3), 226–235. [https://doi.org/10.1016/S1066-7938\(02\)00071-4](https://doi.org/10.1016/S1066-7938(02)00071-4)
- Sandali, W., Gunathilake, W., Deshapriya, M., Nirman, M. A. C., Lokeshwara, A. A., & Weeraratna, R. S. (2020). Challenges Faced in the Implementation of Sustainability Reporting: Empirical Evidence from Listed Companies in Sri Lanka. *Proceedings of International Conference on Business Management*, 17.
- Singhanian, S., Singh, J., Aggrawal, D., & Rana, S. (2023). Board gender diversity and sustainability reporting quality: a generalised ordered logit approach. *Kybernetes, ahead-of-print*(ahead-of-print). <https://doi.org/10.1108/K-07-2022-0963>

- Vithanage, D. S. (2015). Understanding the Nature and Scope of Patriarchy in Sri Lanka: How Does it Operate in the Institution of Marriage? *Culminating Projects in Social Responsibility*.
- Wellalage, N. H., & Locke, S. (2013). Corporate governance, board diversity and firm financial performance: new evidence from Sri Lanka. *International Journal of Business Governance and Ethics*, 8(2), 116–136. <https://doi.org/10.1504/IJBGE.2013.054416>

***Published by***

Department of Accountancy and Finance

Faculty of Management Studies

Sabaragamuwa University of Sri Lanka

PO. Box 02

Belihuloya, 70140

Sri Lanka.



9 772827 734000

**ISSN: 2827-7341 (Online)**