An Assessment of the Application of Various Models in Share Selection, Portfolio Construction and Analysis among East African Stock Exchanges

By

Shamis Said Moh'd

Thesis Submitted in Fulfillment of the Requirements for the Degree of Doctor of Philosophy

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AN ASSESSMENT OF THE APPLICATION OF VARIOUS MODELS IN SHARE SELECTION, PORTFOLIO CONSTRUCTION AND ANALYSIS AMONG EAST AFRICAN STOCK EXCHANGES

By

SHAMIS SAID MOH'D

ABSTRACT

The purpose of this study is to examine the applicability of equity portfolios in various East African stock exchanges using Markowitz portfolio model and Capital Asset Pricing model (CAPM), that can be used by institutional investors and young people within the region in making investment decisions, broaden their knowledge of quantitative techniques of portfolio construction and narrow the heuristic common-sense approach. The value investing theory, modern portfolio theory, capital market theory and Tobin separation theory are the underpinned theories used in this study. The related models of these theories such Mean Variance Covariance Model (MVCM) and Capital Assets Pricing Model (CAPM) were separately merged with Data Envelopment Analysis (DEA) and the resulted hybrid models which are DEA-MVCM and DEA-CAPM was used in this study. The efficient assessment of the questions in this study can be attained using a quantitative research design and more specifically descriptive design. The data related to country economy, economic sectors, capital markets, companies' fundamentals, closing share prices, markets indices and exchange rates from 2015 to 2018 were collected in respective database available online. A judgemental sampling technique was adapted while collecting data, whereby, out of 115 listed companies only 52 are found to have all data required in specified time frame. The MATLAB program was used to analyse the data. Furthermore, the independent sample t test and ANOVA were used to measure the statistical significance of the hypothesis. In relation to share selection, the findings revealed that all listed companies from USE, RSE, and all companies from the service and manufacturing sectors in all capital markets were not attained the minimum performance stated, therefore were excluded for further analysis. Only some companies that fall under the industry sector in Kenya and Tanzania were shortlisted as their combined performance is equal or above the benchmark. Out of 52 companies, only 11 companies were qualified for further analysis. Among them, 6 companies are from Kenya which is equivalent to 16 percent of the total companies, and 5 from Tanzania which is equivalent to 56 percent of the total companies evaluated from Kenya and Tanzania, respectively. Impliedly, combining the performance of country economy, economic sectors and company's fundamentals has a major impact on screening the stocks to be used for portfolio construction. The results further revealed that portfolio construction, performance and optimization varied with portfolio size and model used. Moreover, different states of economy generated different portfolio risk and returns. Therefore, it is recommended to the management of capital markets, regulatory bodies and listed companies to ensure managerial and operational performance of the institutions. Since this study was limited to short time frame due to data availability future studies can incorporate more data range. Likewise, this study employs a bottom-up approach to combine various components such as country economy, stock markets development, economic sectors, and company fundamentals instead of using both bottom-up and top-down approaches. Although the methodology is still new in the field of stock selection, also limited literature demonstrated quantitatively performance evaluation of each component yet is recommended by the scholars when the combined components involve more than one country.

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DEDICATION

This dissertation is dedicated to my father Almarhum Sheikh Said Moh'd Sleyyum Al-Kharousy who passed away when I was in the fifth semester of my undergraduate degree. He spent all his time teaching people both religious and secular education in a different part of Pemba Island, Zanzibar-Tanzania. I hope this piece of work will remind his love and passion for education to many people in his cycle.

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LIST OF ABBREVIATIONS

MPT	Modern Portfolio Theory
MVCM	Mean-Variance Covariance Model
CAPM	Capital Asset Pricing Model
ICAPM	Intertemporal Capital Asset Pricing Model
APT	Arbitrage Pricing Theory
MFM	Multifactor model
CCAPM	Consumption Capital Assets Pricing Model
FF3F	Farma and French three-factor model
FF5F	Farma and French Five-factor model
DEA	Data Envelopment Analysis
DMU	Decision-Making Units
EMH	Efficient Market Hypothesis
NSE	Nairobi Securities Exchanges
DSE	Dar es salaam Stock Exchanges
USE	Uganda Securities Exchanges
RSE	Rwanda Stock Exchanges
EACMs	East African Capital Markets
IOSCO	International Organization of Securities Commissions
EASRA	East African Securities Regulatory Authorities
EASEA	East African Stock Exchanges Association
CMIPC	Markets Insurance and Pensions Committee
EABP	East African British Protectorate
EAC	East African Community
CSDs	Central Securities Depositories
VIT	Value Investing Theory
TST	Tobin Separation Theory
CMT	Capital Market Theory
CML	Capital Market Line

CRS	Constant Return to Scale
VRS	Variable Return to Scale
OTE	Overall Technical Efficiency
PTE	Pure Technical Efficiency
SE	Scale Efficiency
IO	Input Oriented
OO	Output Oriented
CCR	Charnes, Cooper, and Rhodes
BCC	Banker, Charnes, and Cooper
PCA	Principal Component Analysis
GDP	Gross Domestic Product
OECD	Organization for Economic Co-operation and Development
FSDI	Financial Sector Development Indicators
EI	Expert Information
MAR	Minimum Accepted Returns
VaR	Value at Risk
CVaR	Conditional Value at Risk
MOO	Multi-Objective Optimization
SOO	Single Objective Optimization
SD	Stochastic dominance
AA	Ambiguity Aversion
RO	Robust Optimization
SRIs	Socially Responsible Investments
SEE	Social, Environmental, or Ethical
MAD	Mean Absolute Deviation
LP	Linear Programming
MILP	Mixed-integer Linear Programming
BL	Black-Litterman
CCMV	Cardinality Constrained Mean-Variance
CCMSV	Cardinality Constrained Mean-Semi Variance

FA	Firefly Algorithm
ICA	Imperialist-Competitive Algorithm
CWs	Company’s Websites
MATLAB	Matrix Laboratory
ANOVA	Analysis of Variance

CHAPTER 1

INTRODUCTION

1.1 Introduction

Starting from the pioneering work of Markowitz (1952) that lead to the birth of Modern Portfolio Theory (MPT), a quantitative technique of measuring risks and returns was introduced, and the investors were confident to trade equity in stock markets. They start buying, selling, or holding shares with the respect to mean returns and risk. They were able to allocate more funds to those shares which have higher returns at a certain level of risk or to those shares which have low risk in a certain level of returns.

The MPT theory bridges the gap of absence of investment theory that explains the relationship between risk and returns, correlation, efficient shares, and the effect of diversification which results in the development of the Mean-Variance Covariance Model (MVCM) of portfolio construction. Further improvement of MPT suggested by Tobin (1958) segregated the investments in stock markets into two main parts which are risky and riskless. The equity investment gets more weight and allocated as a risky investment which is associated with higher returns, the investors can allocate more funds on equity than bonds or other fixed returns investments because they are riskless, and their returns are small.

The parting of risk into two, suggested by Tobin lead to the development of Tobin Separation Theorem which was further reviewed by Treynor (1962), Sharpe (1964), Litner (1965), and Mossin (1966) and introduced the Capital Asset Pricing Model

(CAPM). The inception of CAPM has opened the debate about the relationship between the share returns and market index measured returns. While the CAPM hypothesis claimed a direct positive linear relationship between returns of shares and market returns, studies testing the hypothesis in various stock markets show different results.

The complex behavior of CAPM is associated with its unrealistic assumptions such as borrowing an unlimited amount of risk-free assets, no tax, no transaction cost, the existence of a market portfolio, only market risk affects the expected returns, etc. Thereafter, various versions of CAPM were developed to overcome the addressed pitfall such as Black, Jensen, and Scholes (1972) introduced the zero-beta model which removed the assumption of borrowing an unlimited amount of risk-free assets and proposed the use of unrestricted short sale of risk assets. Merton (1973) introduced the Intertemporal Capital Asset Pricing Model (ICAPM) which refereed as the CAPM based on investment opportunity over time which results in multiple risk factors associated with economic events.

Ross (1976) shift completely to CAPM and come-up with Arbitrage Pricing Theory (APT). He criticized that market risk cannot explain the expected returns, instead, multiple risk factors can strongly affect the expected returns of shares which result from the Multifactor model (MFM). Lucas (1978) and Breeden (1979) developed the Consumption Capital Assets Pricing Model (CCAPM) whereby market beta is replaced by consumption beta which is measured by risk premium against consumption growth of investors. Some studies have been conducted from the early 80s to 90s to explore various factors that influence the expected returns of shares and portfolios. The common factors which have been addressed including size which is measured by market capitalization and value measured by book to market value of the firm (Banz, 1981; Rosenberg, Reid, and Lanstein, 1985; Chan, Yasushi, and Josef, 1991).

Although the question of value has been inspired by Graham and Dodd (1934) when they laid down the framework of investment strategy that involves share selection based on intrinsic value while maintaining a margin of safety. That hot discussion leads to Farma and French (1993) to develop a combined model which include market factor suggested by CAPM, size, and growth of the firm to form the Farma and French three-factor model (FF3F).

Likewise, the study of DeBondt & Thaler's (1985, 1987) on irrationality in stock returns lead to Cahart (1997) introduced momentum factor which referred to as the tendency of rising and falling of share price which becomes the fourth factor. Thereafter, more factors have been addressed such as trading activity as a proxy of share liquidity (Chordia, Subrahmanyam, and Anshuman, 2001). Investment is measured by the capital expenditure of a given year to the average capital expenditure of the three preceding years (Titman, Wei & Xie, 2004). Profitability on expected returns measured by current earnings on a per-share basis (Farma and French, 2006). Although some critics have been raised by Novy-Marx (2013) on the methodology of measuring profitability. Furthermore, Farma and French (2015) introduced a new model that combines the FF3F model with Investment and profitability factors based on Novy-Marx methodology and refereed as Farma and French Five-factor model (FF5F).

Generally, the series of scholars' works explained above were focused on identifying factors which are broadly fall on economic and company fundamentals. Although the discussion is still going on until today, some recent studies become more specific on identifying factors that are more closely to the real environment such as analyst's expectation (Guerard, Markowitz and Xu, 2015), expert information (Shen and Tzeng, 2015), expectation management (Kim and So, 2017), market timing (Rashid and Sadak, 2017; Zouaou, 2019) financial news (Chen, Chen and Lu, 2017), Economic and financial conditions of the companies (Tarczynski and Tarczynska-Luniewska, 2018), the efficiency of company's fundamental (Siew, Fai, and Hoe, 2017) as well as the economic policy uncertainty (Chiang, 2019).

Overall, the contributions of the scholars are rewarded, though some of the added factors have been discussed a long time ago by great scholars, for example, the study of Grant (1978) explained market timing and portfolio management, Jensen (1968) discussed management ability which is a reference of expectation management, expert information and analyst's expectation, Charnes, Cooper, and Rhodes (1978) introduced Data Envelopment Analysis (DEA) to measure the efficiency of Decision-Making Units (DMUs), Scholes & Williams (1977) and Dimson (1979) explained that the trading frequency greatly influences abnormal behaviour of sensitivity of returns. From the above kinds of literature, this thesis raises the following concerns.

While the current scholars are fighting on searching new factors that can add weight to estimating the future returns of shares and portfolios, this study is interested in evaluating managerial and operational efficiency, effectiveness, and performance of the DMUs holding those factors.

The recent literature is skewed on extracting factors from published company information like audited financial statements, financial news, etc. This study shed light on the other three components such as determinants of economic sectors growth, stock market development indicators, and country economic variables.

The current debate overlooked to address how investors can adjust the fund's allocation when there is a change in states of economy, this study can extend the portfolio models by including stress test to face any financial or economic crisis happening in the future both rare and extreme events.

1.2 Background of the study

The importance of managerial and operational efficiency and effectiveness of a company's fundamentals and its contribution to the expected returns of shares and portfolios has been witnessed by various scholars (Cheng, Mashayekhi and Omrani, 2016 and Siew, Fai and Hoe, 2017). It is quite possible is among the most critical factors that influence the investment decision for both individual and institutional investors. However, the studies which merging both efficiency and effectiveness and observe the combined effect are still limited especially to those related to investment in capital markets. According to Bartuseviciene and Sakalyte (2013) addressed that both efficiency and effectiveness are needed when evaluating the performance of the company or an institution.

It is remarkable to note that, the managerial and operational efficiency and effectiveness of a company's fundamentals alone are not enough to spread the risk and get maximum reward. Limited empirical studies come-up with a comprehensive model that measures the explanatory power of other components such as economic sectors, stock market development, and country economy on portfolio management. Although the study Ferreira (2016) reported that economic variables have significant contributions to the performance of an institution. To keep it vital and relevant, both individual and institutional investors need a broad understanding of the remaining components like the stock market, economic sector, and country economy to enhance the ability to predict the future movement of share prices and construct various portfolios.

From the background of Efficient Market Hypothesis (EMH) introduced by Farma and MacBeth (1973), various scholars developed several approaches to work out on issues raised on capital markets including the development of various methodology of share selection. Broadly, the methodologies were classified into parametric Stochastic Frontier Analysis (SFA) and non-parametric Data Envelopment Analysis (DEA) (Ferreira, 2016). It was stressed that SFA is still new in the capital market researches compare to DEA because DEA can evaluate technical performance by utilizing price-free input/output data. According to Maria and Sanchez (2007), parametric approaches require the imposition of a specific function form relating to dependent and independent variables as well as the assumption of the distribution of error terms. For these reasons, DEA methodology becomes the most used approach when analyzing the efficiency of various Decision-Making Units (DMUs) using multiple inputs and outputs.

However, for infant stock markets these techniques attract limited attention of researchers and practitioners. To fulfil the objective of this study DEA methodology was implemented for preliminary analysis of identifying active shares among those listed on various infant markets. The selected infant markets are East African stock exchanges which comprise Nairobi Securities Exchanges (NSE), Dar es salaam Stock Exchanges (DSE), Uganda Securities Exchanges (USE), and Rwanda Stock Exchanges (RSE). These four stock exchanges are all come under one umbrella of East African Capital Markets (EACMs). They have similar laws and regulations with few divergences at the level of market development.

Moreover, NSE, DSE, and USE have already become a member of the International Organization of Securities Commissions (IOSCO). Also, RSE has already applied to become a member although currently has developed laws that comply with IOSCO. Interestingly, there is subcommittee such as East African Securities Regulatory Authorities (EASRA) for securities regulators and East African Stock Exchanges Association (EASEA) for market participants which both fall under Capital Markets Insurance and Pensions Committee (CMIPC).

The EACMs date back to the 1950s with the establishment of NSE in 1954 in the East African British Protectorate (EABP). The NSE was the stock exchange for the entire EABP with listed companies from present-day Uganda, Kenya, and Tanzania. With the collapse of the East African Community (EAC) in 1977, the NSE remained a Kenyan outfit with all the non-Kenyan companies delisted and nationalized in their respective countries of Uganda and Tanzania. It was not until the 1990s that Uganda and Tanzania established their national stock exchange which is USE and DSE respectively. Rwanda the other partner of EAC was later established RSE in 2011.

According to EAC (2018), the performance of EACMs is illustrated in Figure 1.

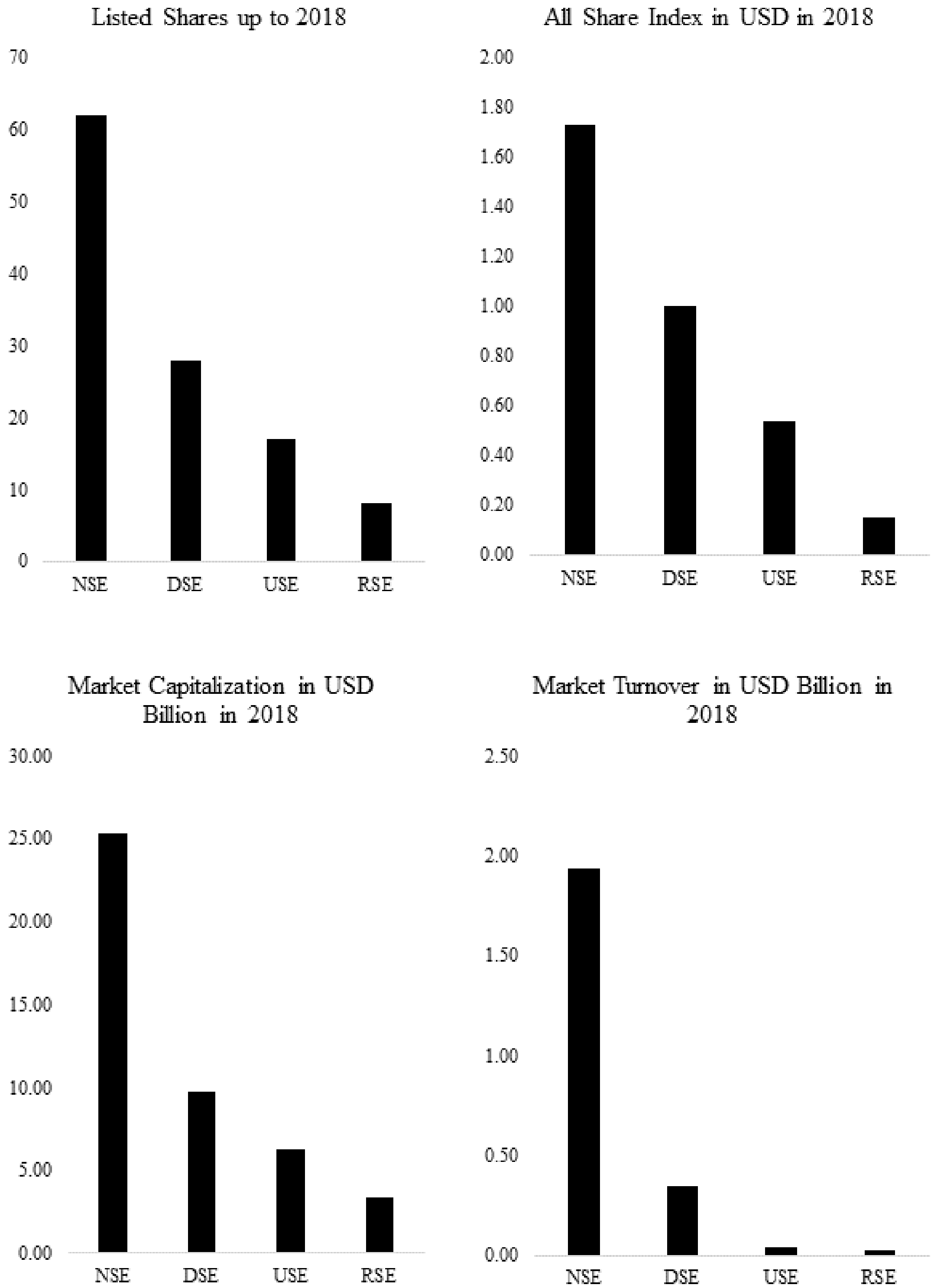


Figure 1.1 The Snapshot of EACMs for the year 2018

A total of 115 companies are listed on the four exchanges whereas 62 on the NSE, 8 on the RSE, 28 on the DSE, and 17 on the USE. Also, the total market capitalization for NSE is equivalent to US dollars 25 billion, DSE is US dollar 10billion, USE is US dollar 6 billion and RSE is US dollar 3 billion. Likewise, market turnover for NSE is equivalent to US dollar 2 billion, DSE is US dollar 0.4 billion, USE is US dollar 40 million and RSE is US dollar 30 million. Similarly, all share index for is equivalent to US dollar 1.7, DSE is US dollar 1, USE is US dollar 0.5 and RSE is US dollar 0.2. Regarding market infrastructure, both NSE and DSE use an automatic trading platform while USE and RSE are still manual using the open -outcry trading system. For clearance and settlement of securities, all four capital markets have Central Securities Depositories (CSDs). Only NSE and USE have two CSDs one for equity and another for bonds while DSE and RSE have only one for both. Contrary to the trading and settlement cycle, only RSE has a T+2 settlement cycles the rest of the market have T+3.

1.3 Motivation of the study

It can be observed in above mentioned recent works of literature that the added factors on top of fundamental factors like analyst expectation, expert information, market timing, financial news, economic and industrial indicators have been tested to have explanatory power of expected returns of shares and portfolios. Also, the studies are concentrated in advanced markets and few of them are from emerging markets, whereas infant markets like East African stock exchanges received limited attention. The researcher is worried about the development of these infant markets which are lagging and its gap with emerging markets become wider. The markets are rather young, and the trading platforms and infrastructures are not so well-established.

The insufficient knowledge of the share market among the East African investors and the public is also a point of concern. Taking the example of Tanzania which is the first growing country in the region (African Development Bank, 2019), only 2 percent of adults have engaged in the capital market while the target was 5 percent (National Financial Inclusion Council, 2018). Failure of an adult to participate in engaging in the capital market may have an adverse effect on the companies listed, those few investors who participate, the stock market, and the country economy at large. The listed companies are few and may rarely trade then the expected share returns will be affected.

From the theoretical background and various recent developed models that were highlighted previously, they have unnoticed that the managerial and operational efficiency, effectiveness, and performance of various identified components could be a comprehensive factor that can influence the estimation of expected returns of shares and portfolios. Therefore, the need for a hybrid model which will capture their influence of the country economy, stock market development, economic sectors, and company fundamental on portfolio management is foreseen.

1.4 Problem Statement

Equity is the best stock to trade in East Africa Stock Markets, it offers the higher returns than bonds, money market and real estates since 2007 (Kimani, P.M, Aduda, J. and Mwangi, M, 2017), yet young people and institutional investors across the region give less priority than other investments traded for decade. Since national stock markets are still in infant stage, most of shares do not follow random walk and the brokers are not competitive, local investors within the national stock markets are less confident on trading equity stock rather they invest on government bonds (Lukanima, 2014). It was advised by Yabara (2012) that diversifying on East Africa Stock markets will overcome some constraints that the local investors are facing due to varying degree of economy, number of listed companies, market capitalization, cross listed companies as well as Market harmonization. Still, the questions of constructing an efficient equity portfolio diversified on different stock markets still need attention of experts, the failure will lead to biases on asset selection and biases on choosing methodology. Studies conducted within the region are confined on specific country and employed only standard MVCM and CAPM to construct various portfolio (Okumu and Onyuma, 2015; Muiruri, 2014; Kaboneka, at. el.,2014; Mayanja, at. el., 2013). The insufficient knowledge of the share market among the East African investors and the public is also a point of concern. Taking the example of Tanzania which is the first growing country in the region (African Development Bank, 2019), only 2 percent of adults have engaged in the capital market while the target was 5 percent (National Financial Inclusion Council, 2018). Failure of an adult to participate in engaging in the capital market may have an adverse effect on the companies listed, those few investors who participate, the stock market, and the country economy at large. The listed companies are few and may rarely trade then the expected share returns will be affected.

It is the conventional practice of the researchers to regress several factors and estimate the expected returns of shares which are further used to design various portfolios. To mention a few the study Banz, et.al (1981) regress two factors which are size and value, Farma and French (1993) regress three factors which are market premium, size and value, Cahart (1997) regress four factors which includes three factors of Farma and French, and forth one was momentum, Chordial, et. al (2001) introduced another factor which was trading activity, Titman, et. al (2004) introduced Investment as another factor, Novy-max (2013) introduced profitability as another factor, Farma and French (2015) regress five factors, Guerard, Markowitz, and Xu (2015) considered 10 factors. Technically, the scholars look at the decomposition of systematic risk into several components depending on factors included in the model and conclude which factor has a higher influence on expected returns. Recently, scholars have shifted the paradigm of share selection and portfolio construction, they are more focused on examining managerial and operational efficiency and effectiveness of a company's fundamentals measured by Data Envelopment Analysis (DEA) and observe its contribution on expected returns of shares and portfolios (Cheng, Mashayekhi and Omrani, 2016; Jothiami, Shankar and Yadav, 2017; and Siew, Fai and Hoe, 2017). They are all witnessed that the DEA has significant capacity on estimating the level of efficiency of various shares to be used on portfolio constructed on whether MVCM or CAPM and determining possible sources of inefficiency through multiple inputs and outputs constraints which are considered. However, the previous scholars are mostly indulged on company's fundamentals which are not enough to spread the risk and get maximum reward. Other fundamental components such as economic sectors, stock market development, and country economy need to be considered (Tarczynski and Tarczynska-Luniewska, 2018).

Despite to the improvements which have been made in various models of share selection and portfolio construction are for the purpose of protecting investors' funds, the subject of the portfolio stress test received limited attentions. Few studies conducted including Best and Grauer (1991), Wong, et.al. (2003), Al Janabi (2009), Xiaohu (2013) as well as Franco, et.al (2018) are insisted that developing stress test framework by considering both rare and extreme events from the range of stock markets to macroeconomy is vital for portfolio management. Overall, this research has identified various issues that need immediate attention to improve the accuracy of estimating future returns of shares and portfolio specifically in EACMs. It includes considering the application of DEA on evaluating various components. Merging DEA with risk returns framework which is MVCM and CAPM while constructing various portfolios. Conduct various portfolio analyses including portfolio performance evaluation using Sharpe ratio and Treynor ratio, portfolio optimization, and portfolio stress test. It is believed that this research will have a great contribution to the body of knowledge of share selection and portfolio construction particularly in the East Africa region.

1.5 Research Objectives

The broad objective of the study is to examine the applicability of equity portfolios in various EACMs and compare them to assist institutional investors and young people within the region in making investment decision, broaden the knowledge of quantitative techniques and narrow the heuristic common-sense approach. Specifically, research objectives are set and outlines as follow.

i. To select the stocks listed on EACMs by evaluating the managerial and operational performance of company fundamentals, economic sector growth, development of the market listed, and economy of the country registered using DEA models.
ii. To compare the expected returns and risks of various portfolios constructed on selected stocks listed in EACMs using both MVCM– DEA and CAPM-DEA model.

iii. To evaluate the performances of the various portfolios constructed on selected stocks listed in EACMs using both Sharpe ratio and Treynor ratio.

iv. To examine the preferences among various portfolio constructed by the selected stocks listed in EACMs by applying multi-objective optimization approach.

v. To conduct stress test of the various portfolios constructed from different economies in term of return and risk to face financial crisis happening in future both rare and extreme events.

1.6 Research Questions

i. Which stocks can be selected among those listed on EACMs after evaluating the managerial and operational performance of company fundamentals, economic sector growth, development of the market listed, and economy of the country registered using DEA models?

ii. Are there any variability of expected returns and risks of various portfolios constructed on selected stocks listed in EACMs using both MVCM– DEA and CAPM-DEA model?

iii. What is the performance of the various portfolios constructed based on the selected stocks listed in EACMs evaluated using both Sharpe ratio and Treynor ratio?

iv. Which are the preferred portfolios among the portfolio constructed by the selected stocks listed in EACMs when multi-objective optimization approach was used?

v. What are the patterns, behaviours and directions of the various portfolios constructed will have during good times and extreme conditions?

1.7 Significance of the Study

Managerial and operational efficiency and effectiveness are among the parameters that received the attention of the academician and practitioners of the finance field in recent decades. They are aware that are among the factors that contribute to the investment decision. Among the things which have been overlooked is the scope of managerial and operational efficiency and effectiveness. Existing literature put more emphasis on the company's fundamental. Other components like the economic sector, stock markets, and country economy were unnoticed. Therefore, this research has identified some significance to investors, academician, government, and other stakeholders as shown below;

i. It is important to individual and institutional investors with EACMs to be able to gain a better understanding of measuring and combining the managerial and operational efficiency, effectiveness, and performance of various components such as listed companies, economic sectors, stock markets, and countries before making any investment decision.
ii. Findings of this study gave confidence to investors to understand which share they can trade among various shares listed in EACMs to gain extraordinary returns with a competitive advantage from management effectiveness of listed companies, sector, stock market, and country.
iii. This study is highly needed because of the growing interest of the governments of East African Community on establishing stock markets, harmonization of infrastructures of those markets supported by World Bank (Biau, 2018) that was expected to be started by 2018.

iv. Central to this study, aimed to spread financial knowledge particularly portfolio construction and portfolio management among young people, investors, and students in Tanzania and other neighbouring countries to promote the growth of the regional economy. It is well known that the growth of the country's economy is proportional to long term investment yet, financing the investment could be an obstacle. Stock exchange markets are the major source of finance (capital) that companies and government can access through the trading of shares or bonds (Akileng, Ogwang, and Ssendyona (2018).

1.8 Scope of the Study

This study scope is within East African Region especially Kenya, Tanzania, Uganda, and Rwanda. It covered the fundamental components such as the company's fundamentals, economic sectors, stock market development and country economy of the selected countries. All four components are evaluated based on managerial and operational efficiency, effectiveness, and performance using DEA models. The evaluation results were used as a base for share selection among those listed in each stock exchange such NSE, DSE, USE and RSE which are further used for portfolio construction and analysis.

All data extracted from trusted database after intensive data evaluation process as suggested by previous scholars. The data used have been insured that they meet the purpose of the study, the data sources are accepted and trusted, and the data are accurate and reliable (Muhen, 2010; Cheng and Philips, 2014; Johnston, 2014). All data used in this study were fall under the same time frame which is from 2015 to 2018. The scope was confined on selected database including world bank, capital market authorities, listed companies, and investing.com. The data related to country economy, economic sector and foreign exchange rate were extracted from world bank database. The data related to stock market development and company fundamentals were extracted from capital market authority and company database. Also, the data related share prices and market indices both were extracted from investing.com database.

Apparently, the study focused on fundamental components because of it offer great value to individual and institutional investors. Moreover, the framework that captures all these components at a time within the environment of infant stock exchanges like EACMs received limited attention. Although the region has been reported to record the highest economic growth rate compared to other region in the continent (African Development Bank, 2019). Regarding timeframe, this study was concerned with aging of data and therefore emphasized on more recent years. Also, there are limited availability of data for the previous years in some countries. For instance, NSE which was established in 1954, the DSE and USE were established in late 1996 and 1997 respectively while RSE was established in 2011. For, consistence purpose, the years in which all four countries and capital markets have all required data were considered.

1.9 Operational Definitions

Is an organized market where stocks, bonds, and other securities are traded. It maintains the infrastructure that allows companies to raise capital for expansion purposes through the trading of securities (James, Adegboye, Osayi, Okorie, and Ernest. 2015). It was stressed that it contributes to the growth of emerging economies on one side and also is a variable used to explain the growth of the developed economies on another side. Also, the capital market is a market for an intermediate and long term of corporate debt and equity securities. While the short term is up to one year, the intermediate-term is between one to five year and the long term is more than five year.

Share: According to Ching, Haniff, Sinnasamy, Ameer, and Hamid (2009) defined share as a basic unit of ownership interest in an incorporated company. It is issued in the form of a certificate to its owners in exchange for their investments in the business. A share of stock is the smallest unit of ownership in a company. If you own a share of a company's capital, you are a part of the owner of the company. the main classes of shares are ordinary and preference shares. Initially, the company's shares are held by a group of individuals but when the company is going through significant growth and it needs substantial capital, it can offer to the general public and that is said "going public".

Portfolio: It is the mixing up of different assets that are acquired at time zero and sold at the same or future time, the mixing up process can at least follow two approaches which are either 'data-based' that follow Markowitz approach or 'model-based' which rely on asset pricing model intending to find the optimal allocation of fund among different assets (Pastor, 2000). When constructing a portfolio an investor must take into account the flow of income, financial goal, time horizon, or holding period of assets and the level of risk tolerance. According to Chen (2020), portfolio investment can be either strategic which involve buying assets and holding them for long term growth potential, or it can be a tactic that involves active buying and selling to get a short term gain.

Institutional Investors: Are the business entity like banks, insurance companies, public pension funds, mutual funds, foundation, Sovereign Wealth Funds (SWF), hedge funds, or Real Estate Investment Trusts (REITs) which raise funds from individuals or other entities and invest in different assets like equity, bonds, real estates (Harasheh and Nijim, 2010; Boubakri Coset and Some, 2011). Broadly, there are traditional institutional investors which included pension funds, investment funds, and insurance funds, also there are alternative institutional investors which comprise all new institutional investors like hedge funds, private equity funds, SWF and exchange traded funds, lastly asset managers who are also considered as intuitional investors although they invest directly on the name of the client which is quite opposite to another type in institutional investors (Celik and Isaksson, 2014).

Efficiency: A simple definition of efficiency is a measure of operational quality or productivity. Generally, efficiency is more on minimizing cost and improve operational margins (Bartuseviciene and Sakalyte, 2013; Novickyte and Drozdz, 2018). It was stressed that that efficiency doesn't mean that the organization is achieving excellent performance in the market, although it reveals its operational excellence in the source of a utilization process. A company or an institution is referred to efficient when the efficiency score is 100 percent off when expressed in ratio must be 1 otherwise is referred to as inefficient.

Effectiveness: The general meaning of effectiveness describes the capability of an individual, a group, or a system to achieve the assigned goals with disposable resources. A business perspective is regarded as the measure of the degree to which a business goal is achieved (Yannick, Hongzhong, and Thierry, 2016). Effectiveness oriented companies are concerned with output. A company or an institution is referred to effective when the score is 100 percent off when expressed in ratio must be 1 otherwise is referred to as ineffective.

Performance: Quantitatively, performance can be defined as the product of efficiency and effectiveness (Bartuseviciene and Sakalyte, 2013). Therefore, to measure the performance it is required to quantify the efficiency and effectiveness. It was intensified that the efficiency and effectiveness both must be high for the company or an institution to succeed at minimum cost. Otherwise, it will succeed at maximum cost when it is effective but not efficient, start to fail slowly when it is efficient but not effect and fail very fast when it is ineffective and inefficient.

1.10 Assumptions of the Study

Due to the nature of this study, there are some of assumptions are identified in order to meet the intended objectives. Such assumptions are as follow;

i. The shares must be listed from January 2015 or before and must be active for the period of four years consecutively up to 31 December 2018.
ii. All shares which does not show any price change for the whole year will be excluded for analysis.
iii. Only domestic shares of each stock exchange will be taken for analysis. The cross listed shares will considered as the share of the stock market which is initial listed.
iv. There are no stock split or stock divide for any listed share. Any company which undergo stock split exercise will be excluded for analysis.
v. There are no merging among the listed shares Any company which undergo any type of merger will be excluded for analysis.

vi. All the stock exchanges follow the common rules and regulations including number of trading days, start time and closing time of trade.

vii. The value which is in local currency will be converted to US dollars using closing exchange rate of the corresponding date.

viii. The investors from any of country forming EACMs are free to trade in any of the stock exchange.

1.11 Organisation of the thesis

This thesis is primarily structured into five chapters which are organized as follows:

Chapter 1 introduced the topic. It covers a brief introduction about the development of the portfolio theories and various emerging models. Also, it discloses the background information about the problem and the variables used in this study which further leads to address the statement of the problem, the objective of the study, research questions, its significance, scope, operational definitions, underlined assumptions, and lastly, thesis framework.

Chapter 2 explained the theoretical framework, various models that are going to be used, related literature, and conceptual framework which further lead to hypothesis development. The theoretical framework covers the Value Investing Theory (VIT), Modern Portfolio Theory (MPT), Tobin Separation Theory (TST), and Capital Market Theory (CMT) and corresponding models which MVCM and CAPM. Also, the DEA that was incorporated together risk-returns framework. While literature review will cover the recent studies related to the applicability of DEA in evaluating a country economy, stock market, economic sector and listed company, portfolio construction, portfolio analysis including portfolio performance, optimization, and tress testing.

Chapter 3 outlined the methodology that will be used during the research process among another thing will detail the study design, population and sampling, justification of study area, data collection methods, data collection process, data transformation, evaluation of managerial and operational efficiency, effectiveness and performance, portfolio construction and portfolio analysis.

Chapter 4 presents the results of the various analyses conducted in the form of tables and graphs. It includes managerial and operational efficiency, effectiveness, and performance of various components such as listed companies, economic sector, stock market, and country economy. Results related to various portfolio constructed, portfolio performances, optimization, and stress tests. Also, results related to hypothesis testing conducted.

Chapter 5 contains a summary of the findings and recommendations for individual and institutional investors, management of the stock markets, government officials, and academicians. Furthermore, addresses the limitations of the study and area for further studies. The summary of the thesis framework is illustrated in Figure 1.2.

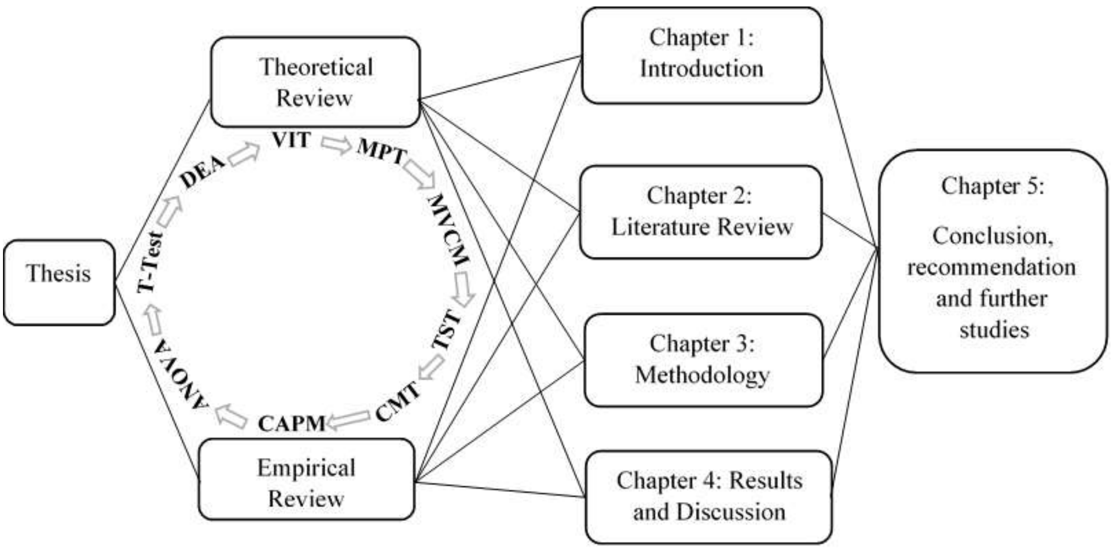


Figure1.2: Thesis organisation

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter mainly explains the underpinning theories and related models, review of related literature, conceptual framework, and hypothesis development. The theories used are Value Investing Theory (VIT), modern portfolio theory (MPT), Tobin separation Theory (TST), and Capital Market Theory (CMT), while the models used are MVCM, CAPM, and DEA. The review of literature related to this study based on the following themes: Applicability of DEA in measuring efficiency, effectiveness, and performance of country's economy, stock market, economic sector, company's fundamentals, and their relationships with expected returns of shares and portfolios. Portfolio construction, Portfolio performance measures such as Sharpe ratio and Treynor, portfolio optimization, and portfolio stress testing.

2.2 Value Investing Theory (VIT)

According to Otuteye and Siddiquee (2015) value investing theory is the fundamental based theory that pioneered by Graham and Dodd (1934). It was explained that selection of share is based on in-depth analysis of share, assurance of safety of invested funds and satisfactory expected returns. The cornerstone of the theory is the measurement of margin of safety where value investors fighting to maximize. The theory used future earnings to estimate the intrinsic value of shares and compute margin of safety using intrinsic value and market price of shares (Kok, Ribando and Sloan, 2017; Kabrt, 2015). While, analysis of shares follows screening criteria which are classified into measure of cheapness and measure of quality of shares that are all extracted from audited financial statements of the listed companies (Lee, 2014). Recent study of Tarczynski and Tarczynska-Luniewska (2018) reconsidered the framework by including other components like macroeconomic and sectoral analysis to account companies' fundamental strength that can lead to long term sustainability. In fact, Graham and Dodd approach was not restricted on defined share screening criteria, instead it recommended to look more further and capture any useful information that can increase the accuracy of estimating intrinsic value (Kahn, 2018). Figure 2.1 illustrate main components of fundamental analysis which are currently used to evaluate stocks.

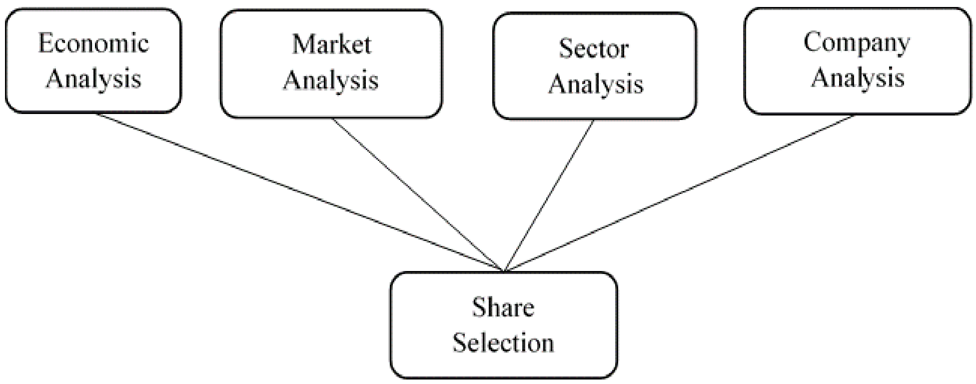


Figure 2.1: Fundamental Analysis of Stock Selection

2.3 Modern Portfolio Theory (MPT)

The MPT was first introduced by Markowitz (1952) to bridge the gap of absence of value investment theory that explained the effect of diversification, the correlation among assets risks, the difference between efficient and inefficient portfolios as well as the determination of risk-return trade-off. The theory explained that the investor will invest in assets that have higher mean returns in a certain level of risk or will invest in assets with minimum risk at a certain level of mean returns (Esfahani, Sobhiyah and Yousefi, 2016; Akansu, Kulkarni and Malioutov, 2016).

It was stressed that the mean returns of the portfolio are equal to a weighted average of the mean return of individual assets and the risk of the mean returns is the function of the standard deviation of individual assets, corresponding weights, and their correlations. Generally, the mean returns and variance of the mean returns of the portfolio are the basic criteria of portfolio selection. For the best combination of assets, the investor has the choice to minimize portfolio variance to meet the required level of returns or maximizing returns for the required level of variance (Aukea, Diagne, Nguyeni, and Stalin, 2017). Figure 2.1 illustrate the basic criterion that Markowitz used in assets selection.

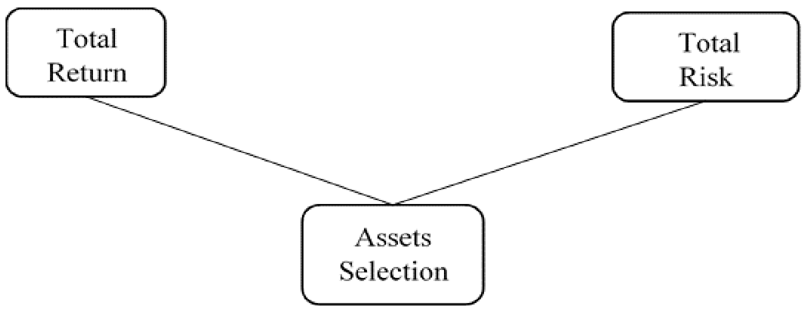


Figure 2.2: Markowitz Framework of Assets Selection

2.3.1 Markowitz Model

In Markowitz model or mean-variance-covariance model (MVCM), the rate of returns of a stock is considered as random variables. When the required portfolio comprises n assets $A_i(r_i, \sigma_i^2)$, where $i = 1,2, \dots n$, $\overline{r_i}$ is the expected returns and σ_i^2 is the variance of the returns which is the measure of risk or volatility of the assets. On each asset A_i, the proportion of funds invested represented by vector $w = (w_1, w_2, \dots w_n)$ such that $\sum_{i=1}^{n} w_i = 1$ and the covariance matrix between assets C . Therefore, the expected returns of the portfolio $\bar{r}_p$ using equation 2.1

$$\bar{r}_p \quad = \quad \sum_{i=1}^{n} w_i \bar{r}_i \tag{2.1}$$

And volatility of the portfolio can be computed using equation 2.2

$$\sigma_p^2 \quad = \quad w^T C w \tag{2.2}$$

The most challenging task in Markowitz model is efficient allocation of funds in a portfolio in order to achieve an acceptable baseline return, r_b or investors' required rate of returns under minimum volatility. According to MPT, the investor will opt to invest in risky assets only when the expected returns is sufficient to compensate the expected risks. Therefore, efficient allocation of funds can be attained through solving an optimization problem shown in equation 2.3.

Minimise

$\frac{1}{2} w^T C w$

Subject to:

$\bar{r}_p \geq r_b$

$\sum_{i=1}^{n} w_i = 1$

(2.3)

The main concern on Markowitz framework was on definition of risk, the framework considered a total risk as shown in the Figure 2.2.

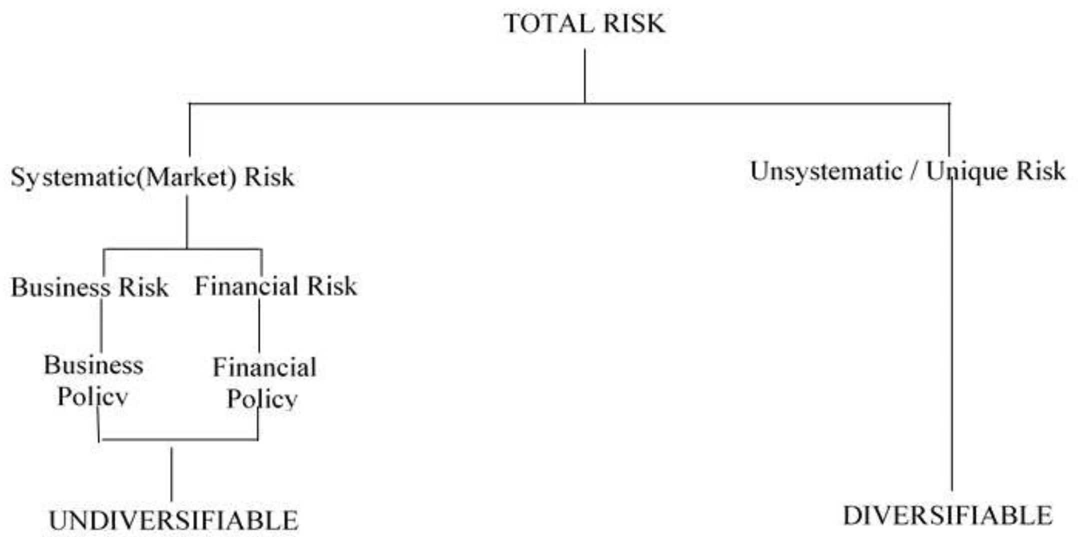


Figure 2.3: The Inter-relationship of risk Concept
Source: Portfolio Theory and Financial Analysis (Hill, 2010)

Total risk comprises the risk associated with market or business which is commonly known systematic risk and the risk which is beyond to human control like strike, outcome of unfavourable litigation or natural catastrophe which is called unsystematic risk as shown in Figure 2.3 (Hill, 2010). It was claimed that unsystematic risk can be overcome when the investors allocate funds in different securities. Generally, the Markowitz model is governed by list of assumptions some of them are stated as follow.

i. The market where the stocks are traded are assumed to be efficiency and therefore the past information can be used to estimate the stock returns.
ii. Investors in the stock market have common goal in making investment decision which is minimizing of risk and maximizing stock returns.
iii. The assets returns are normally distributed random variables and are correlated to each other.
iv. The risk can be minimized when the assets are combined to form portfolio and become more less when the number of assets is added in the portfolio.
v. The maximum investment returns can be realized by determining the efficient set of security which are those assets lied on efficient frontier.
vi. Taxes and other transaction cost are not considering when constructing asset portfolio.

2.4 Tobin Separation Theorem (TST)

Tobin (1958) doubted that not all traded assets are exposed to market risk, some of them only influenced by unique risk like government bonds which referred as risk-free assets. Therefore, he revisited Markowitz framework of securities selection and classified the traded securities into risky and riskless. The TST come-up with three options of asset selection and portfolio construction.

- Portfolio formed wholly by risky assets its selection criterion will be market returns, market risk and unique risk.
- Portfolio formed by risky assets and risk-free assets will be influenced by market return, risk free return, market risk and unique risk.
- Portfolio formed wholly by risk free assets will be influenced by risk free returns and unique risk.

Figure 2.4 illustrate the Tobin framework of asset selection and portfolio construction (Noor, 2019; Kuffour and Adu, 2019; Verlaine, 2019; Ruhani, Islam and Ahmad, 2018; Dybvig and Liu, 2016).

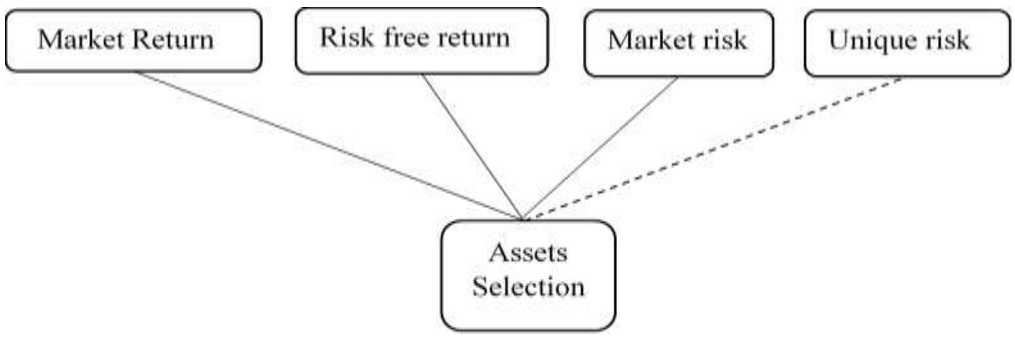


Figure 2.4: Tobin Framework of Asset Selection

Verlaine (2019) stressed that the rational investors with similar information sets should invest in a risky portfolio and mixes them with risk-free assets. The investors must balance between risky and non-risky investments, although small investors mostly hold non-diversified portfolios. Likewise, Ruhani, et. al. (2018) insisted that two investment decisions made by investors are independent and separate. The first thing is to determine the most efficient risky asset portfolio. The second is to define the proportion of funds to be allocated to risky assets and risk-free assets. The Tobin approach considers the efficient portfolio will be allocated to Capital Market Line (CML) and portfolio mean return calculated using equation 2.4.

$$\bar{r}_p \quad = \; r_f + \left[\left(\bar{r}_m - r_f\right)/\sigma_m\right]\sigma_p \tag{2.4}$$

Where $\bar{r}_p$ is the portfolio returns, r_f is the risk-free return, $\bar{r}_m$ is the market mean return, σ_m is the standard deviation of the market mean returns and σ_p is the standard deviation of portfolio mean returns. The CML is a simple regression line with positive intercept at vertical line (portfolio mean returns) which is equal to risk free returns and constant slope which is called market price of risk as shown in equation 2.5.

$$Slope_{CML} \quad = \quad \left(\bar{r}_m - r_f\right)/\sigma_m \tag{2.5}$$

The optimal portfolio corresponds to the portfolio with highest Sharpe ratio which is located at the point of tangency between CML and efficient frontier curve as shown in the Figure 2.5

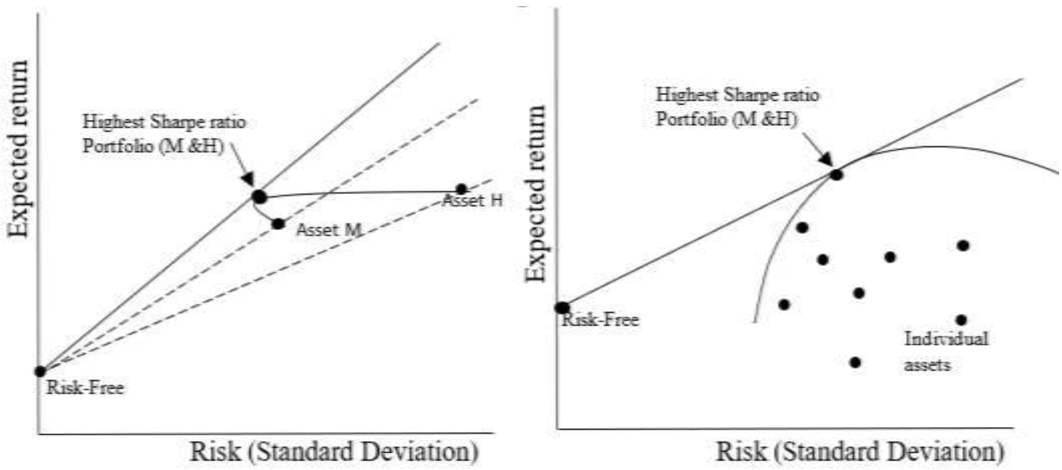


Figure 2.5: Capital Market Line of Two Risky Asset (Left) and Many Risk Assets (Left).

2.5 Capital Market Theory

Capital Market Theory (CMT) explained the method of identifying and measuring the share returns and risk, contrary to MPT that explains the portfolio returns and risk. Both MPT and TST provides the base of development of CMT. It was developed jointly by Treynor,1962; Sharpe,1964; Lintner,1965 and Mossen,1966 (Urooj, 2017; Ruhani, et.al, 2018; Elshqrat, 2018; Kristoufek and Ferreira, 2018). While Treynor insisted on the concept of dominance which was explained by Tobin, Sharpe and Lintner stressed the unique risk of share and market risk and use the beta coefficient to measure the size of the market risk of the asset relative to market portfolio (Hill, 2010). Contrary to Mossin, who was more worried about identifying an equilibrium point where the investor can decide to exchange the shares either buy or sell, which Sharpe was left indefinite to be decided through investor preferences. This theory results in the Capital Asset Pricing Model - CAPM (Fabozzi & Grant, 2001).

2.5.1 Capital Asset Pricing Model (CAPM)

The CAPM express the relationship between the mean returns of individual shares and the market risk measured by beta as shown in the equation 2.6.

$$\bar{r}_i = r_f + \beta_i(\bar{r}_m - r_f) \tag{2.6}$$

Where the $\bar{r}_i$ expected returns of share, r_f is the risk-free returns, $\bar{r}_m$ is the expected market returns. The asset beta β_i is the ratio of covariance of asset i and market portfolio m with the variance of mean returns of portfolio m. The expression of beta calculation will be in the form of equation 2.7.

$$\beta_i = \frac{Cov(i,m)}{Var(m)} \tag{2.7}$$

Kristoufek and Ferreira (2018) stressed that CAPM equation correspond to Ordinary Least Square (OLS) estimator of a simple linear regression. The relationship can be presented in standard regression model as shown in equation 2.8.

$$\bar{r}_i - r_f = \alpha_i + \beta_i(\bar{r}_m - r_f) + \varepsilon_i \tag{2.8}$$

Where, ε_i is the error term and α_i is the deviation from equilibrium returns such that when $\alpha_i = 0$ represent the equilibrium situation, when $\alpha_i > 0$ suggests overpricing and when $\alpha_i < 0$ suggests underpricing. Likewise the β_i coefficient has significant contribution in the model, when β_i is negative signify that assets move against market, when $0 < \beta_i < 1$ shows that assets move with the market but with low volatility, when $\beta_i = 1$ meaning that the assets copied the market and $\beta_i > 1$ represents that assets move in the same direction with the market with higher volatility. Basically, the proposed model based on the following assumptions.

i. **Rational Investor:** Investors are always risk averse and also aims to maximize utility of their investments.

ii. **Marketa are Ideal**: There is no transaction fees and no taxes charged for an investment traded in the market. Also, there is no restriction on short-selling or inflation.

iii. **Homogeneity of investor's expectations**: It is assumed that every investor in the market have similar expectation about returns and risk of assets.

iv. **Equal Access of Information**: The base of this assumption is on equal accessibility of information about any asset traded in the market.

v. **Assets returns follows normal distribution Function**: The returns of an assets in which the investor can choose to construct various portfolios are normally distribute.

vi. **Risk-free Lending and Borrowing**: This assumption allowed the investor to allocate funds to risk-free assets and expect predetermined returns which is an interest rate. Moreover, the investor allowed to borrow the funds with fixed rate and invest in risky investment.

vii. **Beta is the only Measure of Risk**: The CAPM assume that only the coefficient of beta can explain the level of risk in the market.

viii. **Assets are Divisible**: All investments can be easily traded in the open market also can divided into small units.

ix. **Fixed Amount of Assets:** It is assumed that the quantity of assets available in market are the same in each period.

x. **Market Equilibrium**: Investor never influence the price in the market instead they trade based on the asset price available in the market.

Since the CAPM was enacted, it undergoes various transformations. Some scholars disclose number of anomalies (Basu, 1983; Banz, 1981; Statman, 1980; Bahndari, 1988; Reid and Lanstein, 1985). Others proposed alternative models of asset pricing (Mayer, 1972; Merton, 1973; Breeden, 1979). Some of them focused on theoretical argument (Rose, 1976; Chen, Roll and Ross, 1986) and other recommended various theoretical models (Farma and French, 1993, 2015; Cahart, 1995). These empirical contradictions of CAPM parenthetically brought two major conclusions which are variation of expected returns and failure of market beta to explain the risk of shares (Herbet, Nwude and Onyilo, 20117).

2.6 Data Envelopment Analysis (DEA)

The DEA model is a linear programming model used to evaluate the efficiency of multiple Decision-Making Units (DMUs). It was developed by Charnes, Cooper, and Rhodes (1978) from the idea introduced by Farrell (1957) while measuring productivity efficiency. It is simple defined that the efficiency of multiple DMUs that have multiple inputs and multiple outputs, it is the ratio sum weighted of virtual output to the sum weighted virtual inputs.

There are two standard DEA models that are commonly used. The first model is Charnes, Cooper, and Rhodes (CCR) model introduced in 1978. This model is supported by four postulates which are strong free disposability of outputs and inputs, no output to be produced without inputs, Constant Return to Scale (CRS), and minimum extrapolation. The second model is the Banker, Charnes, and Cooper (BCC) model introduced in 1984. They only replaced the CRS postulate by Variable return to scale (VRS) and maintained other postulates of CCR. For understanding such assumptions are explained below.

i. **Strong free disposability of outputs and inputs**: Since the disposing of undesirable outputs or inputs normally require additional costs, this assumption held means there must be free of cost on disposing any unwanted inputs or outputs.

ii. **No output to be produced without inputs:** For any output to be produced must be an input used. When k-times of original inputs were used, the k-times of original outputs are produced.

iii. **Constant Return to Scale (CRS):** Any change of inputs used should produce proportional change of output. Basically, there are constant inputs and outputs variables used.

iv. **Variable return to scale (VRS):** Any change of inputs or outputs does not produce proportional change of inputs or outputs. When the increase in inputs lead to the increase of outputs, the returns to scale referred as Increase Returns to Scale (IRS). When the increase of increase of inputs leads to the decrease of outs, the returns to scale referred as Decrease Returns to Scale (DRS).

v. **Minimum extrapolation**: Production possible set which were used to produce production frontier that judge the validity of DMUs, is the intersection of all requirements of above assumptions.

Both CCR and BCC can be presented in either Input Orientation (IO) or Output Orientation (OO). The IO approach focuses on minimizing input to produce the required level of output. More specifically, it evaluates the efficient use of resources. Contrary to the OO approach which aims to maximize the level output in each level of inputs. It simply measures the effective utilization of resources. It can be understood that when the input/output variables are increased the DMU's efficiency also increase. The larger the size of input/output increase the dimension of the data set and results in a complication on solving an optimization problem. Too few DMUs and too many variables result in the curse of dimensionality (Cooper, Lawrence, and Zhu, 2011).

Generally, the efficiency frontier of the CCR model is a straight line from the origin, when the number of input/outputs increases the DMUs become more efficient. Basically, CCR follows a prior assumption of constant proportional change of sum weighted virtual outputs to sum weighted virtual inputs. The efficient DMUs will lie on that straight line otherwise, the DMU will be considered inefficient which was a very general conclusion. While in BCC there is a flexibility of proportional change of sum weighted outputs to sum weighted inputs (return to scales) increasing, decreasing, or constant. This leads the linear relationship between outputs and input variables to change to a convex curve.

It was stressed that the rule of thumb state that the minimum number of DMUs is three times the sum of inputs and outputs variables or a product of the number of inputs and number of outputs. If n is the number of DMUs, m is the number of inputs and s is the number of outputs, therefore $n \geq 3 \times (m + s)$ or $n \geq (m \times s)$. The scholars incorporated dimension reduction techniques like Principal Component Analysis (PCA) in DEA model to overcome the expected problem (Jothiami, Shankar and Yadav, 2017). It was claimed that the PCA help to reduce the dimensionality problem and increase the DEA discrimination power. However, significance test needs to be conducted to compare the difference between DEA and PCA-DEA models. In the study of Wong and Deng (2017) restricted on minimum requirement of number of DMUs equal to at least two times the sum of inputs and outputs variables ($2 \times (m + s)$).

2.6.1 DEA Models

Assume multiple DMU represented by DMU_j where $j = 1,2, \dots n$, multiple inputs represented by x_{ij} where $i = 1,2, \dots . m$, multiple outputs represented by y_{rj} where $r = 1,2, \dots s$, the proportional weight of inputs variables represented by v_i and the proportional weight of output variables represented by u_r. The value of u_r and v_i are used to make decision on whether the DMU is efficient or not. They are generated through optimization process of DEA unlike other multicriteria decision methods whereby they assigned manually. Therefore, the efficiency of DMU_j (θ) can be computed using equation 2.9

$$\theta \ = \sum_{r=1}^{s} u_r y_{rj} \Bigg/ \sum_{i=1}^{m} v_i x_{ij} \tag{2.9}$$

For CCR, to maximize efficiency of DMU_o which have weighted outputs $u_r y_{ro}$ and weighted inputs $v_i x_{io}$ by minimizing the inputs usage, the objective function need to be constructed, following constraints were imposed and model was formulated as shown in the equation 2.10.

The inputs and output weights need to be combined and present by multiplier λ_j and always should be positive i.e $\lambda_j \ \geq 0$ for $j = 1,2, \dots n$. Proportional increase of outputs (S_r^+) and proportional decrease of input (S_i^-) also should be positive $S_i^- \geq 0$ for $i \ = 1,2, \dots m$ and $S_r^+ \ \geq 0$ for $r = 1,2, \dots s$

$$\min_{u,v} \theta - \ \varepsilon \left(\sum_{i=1}^{m} S_i^- + \sum_{r=1}^{s} S_r^+ \right)$$

Subject to;

$$\left.\begin{aligned}
&\sum_{j=1}^{n} x_{ij}\lambda_j + \ S_i^- \ = \theta x_{io} \quad or \ i \ = 1,2, \dots m \\
&\sum_{j=1}^{n} y_{rj}\lambda_j - \ S_i^- = y_{io} \quad for \, r = 1,2, \dots s \\
&\lambda_j \ \geq 0 \qquad\qquad for \, j = 1,2, \dots n \\
&S_i^- \geq 0 \ ; \quad S_r^+ \ \geq 0
\end{aligned}\right\} \tag{2.10}$$

When the objective is to maximize the out produced, similar constraints were imposed but the objective function has been changed, and the model was formulated as shown in the equation 2.11

$$\min_{u,v} \vartheta_j + \varepsilon\left(\sum_{i=1}^{m} S_i^- + \sum_{r=1}^{s} S_r^+\right)$$

Subject to;

$$\left.\begin{aligned}
&\sum_{j=1}^{n} x_{ij}\lambda_j + S_i^- = \theta x_{io} \quad or\ i = 1,2,\ldots m \\
&\sum_{j=1}^{n} y_{rj}\lambda_j - S_i^- = y_{io} \quad for\, r = 1,2,\ldots s \\
&\lambda_j \geq 0 \qquad for\, j = 1,2,\ldots n \\
&S_i^- \geq 0\ ; \qquad S_r^+ \geq 0
\end{aligned}\right\} \tag{2.11}$$

Both CCR model presented above in the equation 2.10 and 2.11 can be transformed to BCC model by introducing additional constraint which is nonlinear programming constraints which is $\sum_{j=1}^{n} \lambda_i = 1$. It was stressed by Banker, Charnes and Cooper (1984) that the ratio of CCR efficiency to BCC efficiency is referred as scale efficiency. Also, overall technical and scale efficiency is the product of technical efficiency and scale efficiency.

2.6.2 Managerial and Operational Performance

Understanding of managerial and operational performance starting from efficiency and effectiveness. Several kinds of literature have been associated managerial and operational efficiency and effectiveness with technical efficiency of DMUs measures by various DEA models which are Constant Return to Scale (CRS) and Variable Return to Scale (VRS) model (Maria and Sunchez, 2007; Kumar and Gulati, 2008;

Wong and Deng, 2016). The scholarly work of Banker, Charnes, and Cooper (1984) addressed that CRS model measure the Overall Technical Efficiency (OTE) and VRS model measure Pure Technical Efficiency (PTE) and the ratio of OTE and PTE measure the Scale Efficiency (SE).

The study of Kumar and Gulati (2008) interpreted the OTE helps to determine inefficiency due to the input/output configuration as well as the size of operations, PTE measures the management performance and SE measures the management ability to choose the optimum size of available resources. While Maria and Sanchez (2007) reported the PTE as a measure of management effectiveness. Contrary to the study of Wong and Deng (2016) who are not interpreted, instead, they mentioned as the measure of efficiency. Somewhere across the lines, Wong and Deng compared PTE with effectiveness.

The study of Yannick, Hongzhong, and Thierry (2016) clarified that OTE can be broken into two which are PTE and SE, while PTE measures management efficiency which means how well resources are managed and SE measures operational efficiency how well resources are utilized or consumed. It was stressed the effectiveness requires goal achievement and efficiency requires minimization of resources used. It was further explained by Bartuseviciene and Sakalyte (2013) that the product of efficiency and effectiveness results in performance. This indirectly can be understood that Input Oriented (IO) DEA is more on efficiency, Output Oriented (OO) is more on effectiveness and product of IO and OO is the performance as illustrated in Figure 2.6. Therefore, mathematically management effectiveness can be defined as PTE computed using OO, management efficiency can be referred to as PTE computed using IO, and management performance is the product of PTE-OO and PTE-IO. Likewise, operational effectiveness corresponds to SE computed using OO, operational efficiency is the SE computed using IO and operational performance is the product of SE-OO and SE-IO.

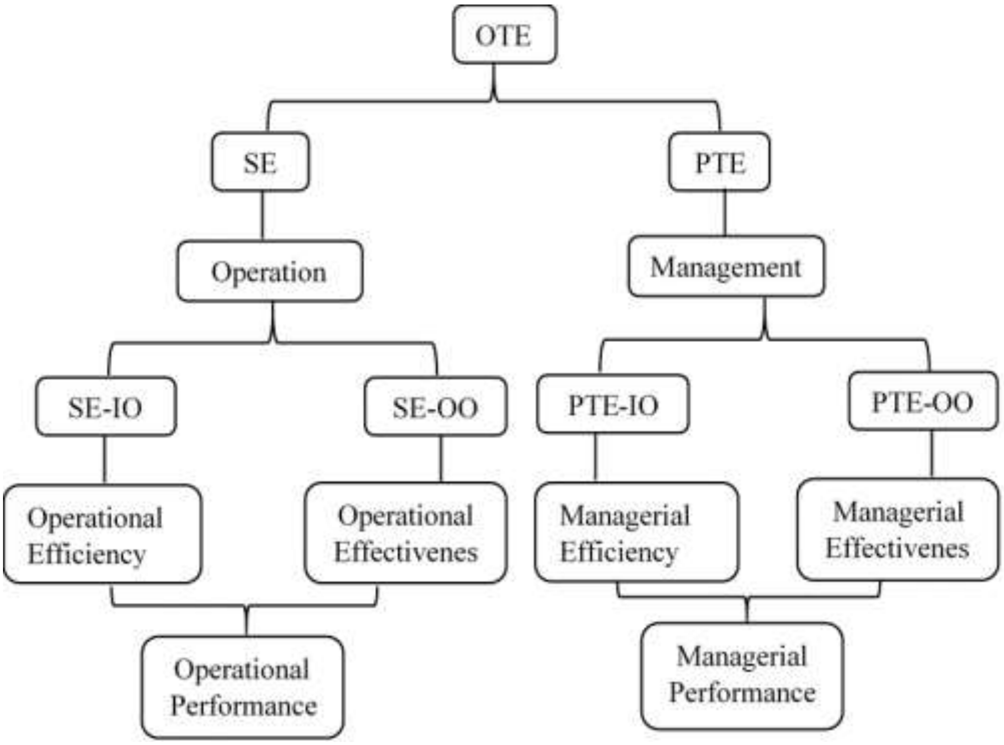


Figure 2.6 The Flow of Technical Efficiency

Giving the complexity of the phenomenon of managerial and operational performance, and the limited scope of the previous studies conducted, incorporating other components like stock market development, economic sector growth and country economy with MVCM and CAPM will add a piece of the puzzle in the body of knowledge portfolio management. Unfortunately, the influence of managerial and operational efficiency, effectiveness, and performance on portfolio management remains at the level of the theory and various models that have been used by various scholars. This thesis is plagued with conceptual and methodological issues that have precluded other researchers from concluding the influence of managerial and operational performance on expected returns of shares and portfolios.

2.7 Consolidated Theoretical Framework

Figure 2.7 illustrated the framework of the theories used in this study. It start with asset selection using VIT evaluated using DEA and portfolio constructed using MPT and CMT.

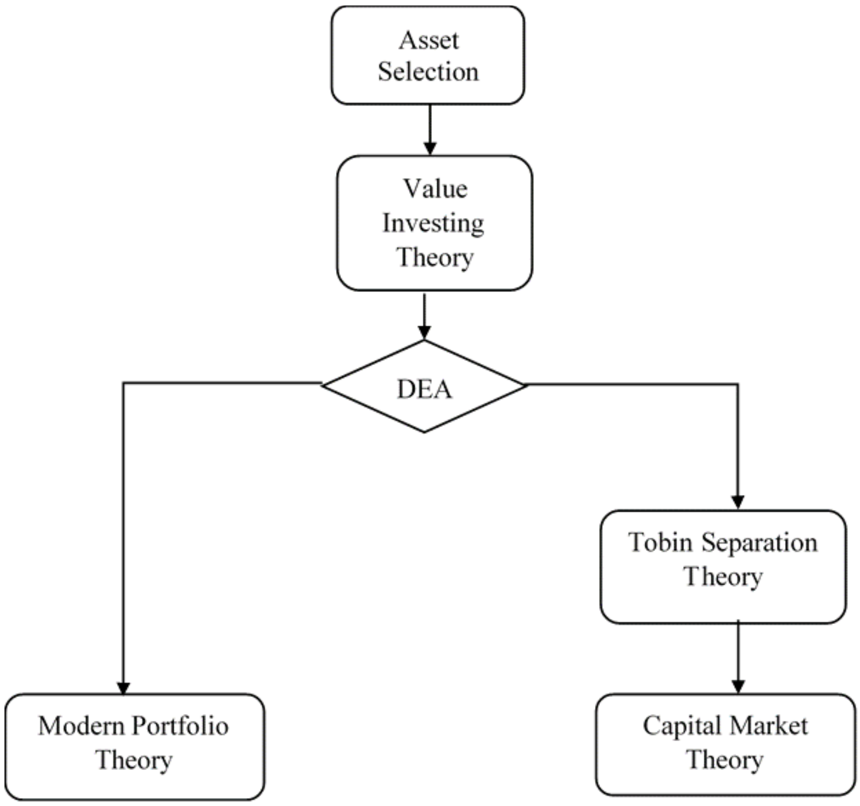


Figure 2.7 Asset Selection and Portfolio Construction

2.8 Stock Selection and DEA Evaluation

Investors or fund managers commonly use fundamental or technical analysis to select shares to be included in different portfolios. Though both analyses have common objectives of maximizing the accuracy of predicting the future price movement and profit of shares the approach is different. Fundamental analysis examines the proxies of the economy of the country, its stock market, industry, and company listed. While technical analysts are emphasizing on examining the behavior, trend, intensity, and quality of the past price of shares (Petrusheva and Jordanoski, 2016).

Studies conducted in different stock markets to compare fundamental and technical analysis found that fundamental outperform technical model (Jakpar, Tinggi and Tak, 2018; Beyaz, Tekiner, Zeng and Kean, 2018; Kulkarni and Kulkarni, 2013). Although various scholars suggested using a hybrid model that combines both fundamental and technical analysis for best results (Souza, Ramos, Pena, Sobreiro and Kimura, 2018; Bonga, 2015; Drakopoulou, 2015; Waworuntu and Suryanto, 2010; Swinkel and Dijk, 2008), few of them show the clear methodology of merging these two models.

Several studies confined on standard fundamental analysis framework by looking at screening criteria extracted from audited financial statements. Shen and Zheng (2015); Jothimani, Shankar, Yadav (2017) considered profitability, growth, liquidity, solvency, valuation, and operational efficiency ratios as screening criteria of fundamental analysis. Likewise, Wong and Deng (2016) used absolute value including assets, loans, deposits, investments, total cost, and interest on deposits.

A recent study of Tarczynski and Tarczynska-Luniewska (2018) reconsidered the Graham and Dodd framework by including other components like macroeconomic, sectoral analysis, and company financial conditions to account for companies' fundamental strength that can lead to long term sustainability. However, they overlooked the identification of the proxies used for economic, market, and sectoral analysis. Precisely, company liquidity, profitability, indebtedness, and management efficiency are the only criteria they used.

An empirical study by Baresa, Bogdan, and Ivanovic (2013) addressed the importance of incorporating macroeconomic and sectoral analysis during the share selection process. The GDP, unemployment rate, interest rate, budget deficit, and inflation key macroeconomic proxies that affect share returns. Similarly, different sectors within the market have a different level of risk, therefore diversification across different sectors will minimize risk and maximize the portfolio returns. Vagda and Kasela (2014) developed a trading strategy that captures economic determinants like consumer price index, producer price index, unemployment rate, retails sales, housing starts, building permits and found that they have an impact on the price of financial instruments. Sukcharoensin and Sukcharoensin (2013) analyzed stock market development in ASEAN-5 Equity Markets by looking into size, accessibility, efficiency, and stability of the stock market and able to classify the market development which is very useful information to investors who are interested to cross border share trading. Therefore, the broad scope of fundamental analysis includes an understanding of the country economic development, economic sectors, stock market, and listed company.

2.9 Country's Economy Evaluation

measure the sensitivity of macroeconomic variables on expected returns show contradicting results. Amtiran, Indiastuti, and Masyata (2017) confirmed that macroeconomic variables have a strong influence on stock returns. French (2017) reported that industrial production growth shows significant contribution and other variables are poorly explained the expected returns. Gabriel, Semion, and Akpoede (2016) and Elhusseiny, Michieka, and Bae (2019) both concluded that all macroeconomic variables have a very low contribution to stock returns. Recent scholars, therefore, opt to regress more variables such as a change in export, gross domestic product, unemployment rate, domestic credit, exchange rate and observe the effect on expected returns (Oyetayo and Adeyeye, 2017; Elshqirat, 2019). In fact, all those variables are commonly used to explain the country’s economic position.

Most of the cross-countries studies conducted were more interested in understanding collectively the efficiency of the country's economy. They classified macroeconomic variables into two main categories which are input factors and output factors and evaluated using the performance evaluation method commonly DEA.

Skare and Rabar (2016) emphasized that the DEA is the best measure of country economic efficiency, it provides valuable insights in cross-country comparisons and has been widely used in Organization for Economic Co-operation and Development (OECD) countries and somehow in developing and developed nations. It was stressed that different studies used different macroeconomic indicators to evaluate a country's economic efficiency ranging from the Gross Domestic Product (GDP), inflation, and unemployment, as the primary variables, to a series of less used variables such as consumer price index, access to credit, business cycles. Generally, the indicators range between 3 to 23 and different time periods range from 1 year to 50 years with a diversity of DEA approaches such as Malmquist productivity index, window analysis, Long-Memory DEA, undesirable DEA model, and benefit of the doubt.

Tasnim and Afzal (2018) argued the benefits of the global entrepreneurship system on the country’s economic efficiency over macroeconomic factors which are commonly used in other studies. Using data extracted from 59 countries and DEA, the results revealed the influence of the global entrepreneurship system as among the factors that can be used to evaluate the country's economic efficiency. It was insisted that the DEA was able to segregate the countries based on efficiency. Comparatively, the countries which are factor-driven are segregated as found inefficient compared to those which innovation-driven. The Tobit regression was conducted by taking efficiency scores as a function of all variables, the global entrepreneurship index was found to have a significant contribution in the model for efficient countries while labor force and gross capital formation were found to have more influence on inefficient countries. The study further recommended to policymakers shift the effort from physical capital and labor to the national entrepreneurship system.

Ozkan and Ayan (2017) used DEA to evaluate the efficiency of OECD countries on utilizing national income for social development. While national income was used as an input factor, Life expectancy at birth, infant survival rate, rate of college graduates, employment rate, internet use rate, female representation in politics, and per capita electricity consumption variables as out variables.

The finding disclosed that the high-income countries are not effective compared to others will low income on utilizing national income for social development. Due to the high level of income that the countries have, the social-economic development level is relatively low which impliedly the efficiency score become low. The authors recommended setting an unattainable target as the solution to measure their effectiveness although they associate the setting of the unrealizable target with an abundance of resources they have. Likewise, low-income countries are inefficient in providing social-economic development because of minimum financial resources.

Deliktas and Gulan (2016) conducted a comparative study between low-income, upper-middle and high-income countries on efficient use of labor, capital, and energy on economic growth using DEA. It was claimed that high-income countries are more efficient on input usage than low-income countries although they have a low growth rate. The higher efficiency score is associate with a high level of economic development. Also, the high growth rate of low-income countries is mainly because they still have room to grow than high-income countries which are almost saturated. Hence when the inputs increase to low-income countries even not efficiently utilized yet the growth rate will increase. It was generally concluded that input efficiency has less influence on the economic growth rate than input volume. this means that it is recommended to increase labor, capital, and energy in order to influence economic growth.

Overall, the studies witnessed the power of DEA on identifying the efficient country and they recommended using the technique to evaluate the individual or cross-country efficiency (Skare and Rabar, 2016). However, other scholars are more focused on comparing the countries with a wide gap of financial resources (Ozkan and Ayan, 2017; Deliktas and Gulan, 2016) which end-up to fail to draw a general conclusion. Still, there is a gap in a body of literature of cross-country efficiency comparison which has a comparable level of the economy. Although labour force and capital are observed to be common inputs used while GDP dominated as output factor. Some studies conducted include more inputs or outputs variables that fit with the study objective. Ozkan and Ayan (2017) included socio-economic development indicators as output variables since the study aims to determine the effectiveness of the countries on socio-economic development provision. Tasnim and Afzal (2018) involved the global entrepreneurship index as among inputs variable to observe its influence on the overall economy of the country however, the results were inconsistence compared to common input/output factors used.

2.10 Assessment of Stock Market Development

The analysis of stock market development was firstly understood by Calderon-Rossell in 1991 who come-up with a partial development model of stock market growth (Yartey, 2008 and El-Wassal, 2013). The model explained that stock market development is the function of stock market liquidity and country economic growth. In a broad perspective, the model captured market capitalization, number of listed companies, average share price as among the determinants of stock market liquidity on one side, also the proxies of the country's economic growth on another side. Most studies focused on evaluating the ability of the stock market on capital allocation, providing opportunities to investors to diversify the risk and to trade economically which are all classified as a proxy of market liquidity (Sukcharoensin and Sukcharoensin, 2013).

Further was elaborated that, until the World Bank introduced Financial Sector Development Indicators (FSDI) in 1996 which captures other dimensions of development such as access, stability, efficiency, and size. While stock market access can be assessed by looking number of listed companies and newly listed companies, market stability can be determined using market fundamental information extracted from its financial statements. Also, stock market efficiency can be measured by observing the proportion of listed companies with autocorrelations and zero returns, while the stock market size is which includes most of the elements of market liquidity suggested by Calderon-Rossell which are market capitalization, volume, and value of share traded. Studies conducted to observe the influence of stock market development indicators on stock returns reported mixed results.

Onoh, Ukeje, and Nkama (2017) investigated the effect of trade volume and market turnover on daily stock returns in Nigeria stock market and found that trade volume has a negative significant contribution while market turnover has a positive significant contribution. The significant negative effect of trade volume on stock returns was associated with the failure of the investor to specify the future earning and liquidity of low stocks but also was due to the existence of weak form inefficiency in the market. The study recommended reviewing capital gain tax policy also investor's decisions should rely on trading volume.

Contrary to the study of Saeed and Hassan (2018) reported that Market depth liquidity measured by turnover rate and volume of share traded was found to be positively correlated with stock returns. it was insisted that reported results were examined in both short term and long-term interaction between liquidity and expected returns of shares. Furthermore, the findings revealed that the need of considering liquidity as a measure of market development while making investment decisions in the Pakistan stock exchange. It was recommended the further study should integrate them with various indicators and observe the combined effect on stock returns.

Kuvshinov and Zimmermann (2018) analyzed 17 advanced economies from 1870 and exploring the trend and co-movement of financial and economic variables. Among the interesting finding was that the stock market size and the market capitalization to GDP ratio is a reliable indicator for stock market growth and financial development which is also influenced stock returns. Change in market capitalization was associated with the change in stock market valuation which was caused by the change of risk premium. However, a high level of market capitalization predicts low subsequent equity returns and consequently heightened the risk of stock market crashes.

The findings contradict the study of Eze (2019) who found that the market capitalization of the Nigeria stock exchange had a positive and significant impact on stock returns. comparatively, Nigeria stock exchange is in the frontier market category also the study only tested the sensitivity of the return of banking sectors. Although the findings are worthy in the context of the study, however, the scholar worried about the cross-sectional variation of stock liquidity and trading activity may result in stock market shock. Most of the studies conducted on examining the influence of market development are skewed on identifying the significant contribution of each indicator and overlooked to identify the overall strength of the market. Few of them focused on a general understanding of the stock market and draw a conclusion based on market access, stability, efficiency, and size.

Yi, Chang, Xing, and Chen (2019) revealed that the fluctuation of relative valuation efficiency of the Hong Kong stock market is less than the mainland stock market, this signified the maturity and stability of Hong Kong stock market. When the valuation level and valuation efficiency of DEA and P/E ratio are compared, the P/E values were found to be overestimated while DEA found to fit the real situation. It was further concluded that the DEA method is a reliable measure of valuation level and efficiency. Kuo, Lu, Dinh (2020) argued that the findings contradict previous studies explaining that fundamental information of listed companies is the proxies of evaluating stock market performance (Zhang, 2007; 2008). Instead, they can be used to analyze the financial strength of the companies which is again is not enough to make investment decisions unless technical analysis also conducted. For the case of China stock market, the performance is also associated with other output factor-like information asymmetry.

Dong, Zhu, Wang, Dong, and Li (2016) reported that the total productivity of china stock markets (Shanghai and Shenzhen) was observed to fluctuate over time. Although the global economic condition is considered to be the reason but also the China market is still in the development stage as the management of systematic risk, registration system, and activeness of the stock markets are associated are lagging behind. The authors further recommended completing a new stock issuing system, improve information disclosure, optimize financing structure, improve risk management mechanism, and enhance the development ability of listed companies.

Sharma (2018) concluded that the managerial efficiency measured by PTE and operational efficiency measured by SE of Indian banks show different significance levels on stock market performance. The regression results show a positive significant association between SE and market performance while PTE shows no significance. It was stressed that the operational efficiency of the Indian banks has a high contribution to stock market development. Generally, the studies conducted do not consider the variables which directly measure the stock market development as suggested by Calderon-Rossell or FSDI instead they used the inputs and outputs variables related to listed companies and draw a conclusion with the respect to the efficiency of the companies (Yi, Chang, Xing, and Chen, 2019; Dong, et.al., 2016 and Sharma; 2018).

While the recommendations of Dong, et.al. (2016) lead to improve market stability and market access which are among the FSDI, yet the indicators were not included in the model. A recent study by Kuo, Lu, Dinh (2020) concluded that the company's fundamentals cannot explain the stock market performance, other factors like information asymmetry need to be considered to improve market efficiency. Although, Sharma (2018) reported that operational efficiency computed using fundamental information of listed banks significantly explained the stock market development.

2.11 Economic Sector Performance

Among the earliest study conducted on the analysis of economic sector growth are conducted by Lewis (1954); Kuznet (1966); Chenery (1975) and Kuznet (1979) who hypothesized as a structural change involved the reallocation of capital outflow, labor, tax revenue as well as the structural term of trade across economic sectors (Hussin and Ching, 2013 and Lankauskiene and Tvaronaviciene, 2013). Generally, the indicators which are commonly used to evaluate economic sectors are growth which measures the value added by individual sector to the country economy, productivity which the ratio of value-added to labor input, profitability measured by net profit margin or return on assets, International trade measured by Revealed Comparative Advantage (RCA) or export market share, Foreign Direct Investment (FDI) measured by the ratio of inward FDI to value-added or ratio of outward FDI to value-added (Tahamipour and Mahmoudi, 2018; Lankauskiene and Tvaronaviciene, 2013; Ahmad and Malik, 2009). Various studies have been conducted to observe the variability of stock returns across different economic sectors.

Pinjaman and Aralas (2017) who analyzed the volatility of stock returns and establish causal relationship across different economic sectors in Bursa Malaysia. It was found that is the variability of stock returns across different sectors. The firms in the technology sector show the highest returns while the telecommunication sector shows the lowest returns. Also, the relationship between stock returns and economic sectors was not significant in the short run which justifies the need for diversification across different economic sectors when the investor aims to minimize risk at a given level of returns. As it was evident that the leverage effect exists in the majority of economic sectors within the market.

Contrary to the study of Tandon and Walia (2015) who conducted a sector-wise empirical analysis of risk-returns relationship in the Indian stock exchange. It was revealed that companies listed in different sectors respond differently in terms of risk and returns. The pharmaceutical sector performs better than media, finance, and metal. Companies listed on generated higher returns and low risk. However, returns of the companies listed on media, finance, and metal observer to be higher than the market returns. It is worth noted that the sectoral performance cannot be segregated with stock market performance. Different stock markets may have different sectors leading to higher returns and low risk.

The discussion note released recently by Norges Bank (2019) examined the importance of country and economic sectors in global equity returns found that mixed results over time. By applying Heston and Rouwenhorst (1994) methodology which decompose sectors and country effect into factor and regress with stock returns. It was generally concluded that in recent decades the sectors have a higher contribution to global equity returns than the country effect. The declining country effect on expected returns was also observed in an emerging market. This signified that diversification across sectors is more profitable compared to diversification across countries. Furthermore, the risk factor model was found to generate higher returns than the country-sector model.

Some studies which evaluate the sectoral effect on expected returns were conducted by segregating listed companies based on the nature of business. There are no factors that have been identified as proxies of the sectoral effect. At least Norges Bank

(2019) regret to regress sectoral factors and country factor due to the existence of perfect collinearity among regressors. Other studies managed to identify some variables which can explain the sectoral effect and evaluated them using DEA. Yet the results contradict among scholars, the context of the study, type of model used, and orientation.

Nazako and Chodakowska (2015) combined DEA and Tobit regression to evaluate the productivity of the construction sector in Europe. It was observed that there is a huge difference in the productivity of the construction sector in selected European countries. It was contended that DEA only explained managerial efficiency and excluded the impact of exogenous factors such as country economic condition. The TOBIT regression results revealed that the country's GDP is the main contributor to the productivity of the industrial sector. That country with a lower GDP also has lower productivity and vice versa. the authors concluded that failure to monitor economic condition we lead to inappropriate management decision.

Atici and Podinovski (2015) compare the efficiency of the agricultural sector from the various region in Turkey using different DEA models. The results disclosed that different DEA models produced different results, however, a conventional model which is VRS, and CRS produces poor efficiency compare to the production trade-off DEA model. The poor efficiency was associated with the discrimination power that the models possess when a number of inputs or outputs are large. The authors overcome this by considering trade-off components verified by an expert in the agricultural sector as inputs and outputs units of the conventional DEA model. It was concluded that the developed model results in significant improvement in efficiency discrimination.

Yang, Shi, Qiao, and Wanga (2017) analyzed the regional technical efficiency of the Chines iron and steel industry using DEA. The results are evidence that there are different technical efficiencies of the selected steel industry in different provinces, areas, economic zone, and country development plans. Generally, there were significant differences in technical efficiencies of the iron and steel industry located in different geographical areas whereas the eastern part is more efficient than the western part. Likewise, three economic zones which are Central Bohai, Yangtze River Delta, and Pearl River Delta were more efficient than others. Also, there was a significant improvement in technical efficiency during the period of the Eleventh Five-Year Plan compared to other country development plans. Generally, the variables used have significantly explained the technical efficiency of the steel industry.

Yannick, Hongzhong, and Thierry (2016) assessed the ability of the banks in Côte d'Ivoire to transform customer deposits into credits using both the CRS and VRS DEA model and the regression model with a volume of loan as a function of the volume of deposit. The strong positive correlation between inputs which are customer deposits and outputs which are loans offered was observed throughout. It was addressed that the owner could be among the variable influencing the efficiency in which authors overlooked to include among variables. Comparatively, banks that are private and foreign ownership are more efficient than those with local ownership. It was also found on average Ivorian commercial banks are not operationally efficient. Moreover, the study findings revealed that the efficiency score was decreased when the VRS assumption was held.

Interestingly, an economic function that all selected sectors perform is considered literally similar. It was noted that each sector has different management strategies as the financial sector observed to disrupt the suggested model. intuitively, an analysis of each economic sector needs to be conducted separately to understand its contribution to the portfolio. The reported findings of the selected studies revealed that DEA can evaluate the efficiencies of different economic sectors. The question of identifying input and output factors still raised concern among the scholars. Yannick, et. al. (2016) measured the efficiency of the banking sector found the exclusion of local and foreign ownership among input/output parameters was not an appropriate decision. Likewise, Nazako and Chodakowska (2015) forgone GDP in the initial stage while measuring the efficiency of the industrial sector result to have a false conclusion. It worth noting that, the type of DEA model used results to have unexpected results. Atici and Podinovski (2015) stressed that both CRS and VRS produced poor efficiency when they used to measure the agricultural sector in a different region in Turkey. Although was justified that mainly caused by many input variables used.

2.12 Company's Fundamentals Analysis

Analysis of company fundamentals on estimating expected returns was first introduced by Graham and Dodd (1934) who explained that selection of share is based on in-depth analysis of share, assurance of the safety of invested funds, and satisfactory expected returns (Otuteye and Siddiquee, 2015). It was stressed by Kabrt (2015) that the six main share screening criteria used in Graham and Dodd framework include Price to earnings (P/E) ratio should be less than 15, price to book value (P/BV) ratio should be less than 1.5, positive dividend yield, a current ratio greater than 2, positive earnings per share (EPS) in the last 5 years, debt to equity (D/E) less than 0.6 and market capitalization (Mcap) greater than US dollars 500million. However, the criteria used are not fixed among scholars. The study of Lee (2014) identified 10 criteria and associated them with the original version of Graham and Dodd. He was summarised that the framework has served as a stabilizing force in the financial market. It was insisted that careful fundamental analysis helps to predict the profitability and growth of the firm. It helps to understand the first moment of the company's future cash flow which is also known as a payoff and the second moment

which is referred to as the risk of the payoff.

Recent studies conducted to evaluate the influence of company fundamentals on expected returns reported different results. Mohammad and Ali (2018) used indicators such as profitability ratios, liquidity ratios, leverage ratios, and market base ratios and found that they are relevant to predict future stock returns. They insisted that profitability and market-based ratios have strong predictive power.

Ma, Ausloos, Schinckus, Chong (2018) used profitability ratios (gross profit rate, net profit rate, ROA, ROE, EPS, BVPS), liquidity determinants (cash ratio, cash maturing debt ratio, debt coverage ratio, net cash flow per share), operating capacity ratios (turnover of account receivable, inventory turnover, current assets turnover, and total asset turnover), development ability (rate of capital accumulation, the growth rate of EPS, the growth rate of ROE and net profit growth rate) solvency and risk ratios (current ratio, quick ratio, debt to assets and D/E) and found that there are many differences on correlations between ratios and stock returns in a different industry. In the media industry, the development ability shows a significant relationship with the stock price, while in the power industry and steel industry do not show any clear influence. Contrary to profitability and solvency where steel industry explains more on stock price than the power industry.

Recent studies incorporated the Graham and Dodd criteria with various DEA models to strengthen the relationship between company fundamentals and future payoff. Some of them even combined the mean-variance (MV) framework and examine the deference. Lim, Oh and Zhu (2014) considered asset utilization, liquidity, leverage, profitability, and growth and use them to evaluate expected returns base on pure DEA cross efficiency, MV-DEA cross efficiency, and market indices which are KOSPI200 and KOSI50 that correspond to Korean 200 and 50 top listed firms respectively. It was concluded that portfolio selection based on MV-DEA cross efficiency evaluation is more effective than pure DEA cross efficiency and benchmark market index. The proposed model yields the highest excess returns for 7 years, the pure cross never showed up and the market indices appeared once. Also, the Sharpe ratio revealed that there is a significant difference in the performance of the portfolios of these three categories. However, the study was limited to the parameter used and a wide range of data that made to be not enough to explain financial implication so as to be used in a real-life scenario.

Although the hybrid model was found to be effective and recommended by scholars, it was criticized by Mashayekhi and Omrani (2016) who complained that the methodology of merging MV with DEA cross efficiency was not conducted simultaneously. This means that all the constraints such as maximize portfolio returns, minimize weighted covariances of the returns, maximize portfolio efficiency, and minimize weighted covariance of the firm efficiencies need to be considered concurrently. It was explained that the stocks were selected based on DEA cross efficiency and portfolios were constructed using the MV framework. Using the same criteria used by Lim, Oh, and Zhu (2014) The study further revealed that when the merging is conducted simultaneously the portfolio performance becomes lower although it shows good diversity of the Pareto solution.

Other studies intensified on the enhancement of the DEA model and preliminary selection of shares prior to portfolio construction to maximize the portfolio returns. Jothimani, Shankar, and Yadav (2017) added valuation ratios on top of the commonly used criteria which are liquidity, leverage, asset utilization, profitability, and growth, also conducted Principal Component Analysis (PCA) to filter inputs and output factor which high explanatory power prior to DEA analysis. It was reported that the DEA-PCA model is helpful in reducing curse dimensionality which is reported as a major drawback of standard DEA. Comparatively, when standard DEA was used several inefficient firms were misclassified as efficient. Relying on standard DEA for making investment decisions will result in unnecessary loss. More importantly, PCA also transforms DEA from using subjective judgment while choosing inputs and outputs constraints. A total of 115 firms were found efficient when the standard DEA model was while only 41 remained when DEA PCA was used. Higher variability was merely caused by a large number of inputs/outputs that directly increase the dimensionality of data which cause difficulty in solving an optimization problem using standard DEA.

Edirisinghe and Zhang (2010) found that the correlation between company fundamentals such as liquidity, leverage, asset utilization, profitability, and growth with expected returns was maximized and portfolios developed were demonstrated to be superior when Expert Information (EI) is incorporated in the DEA model. Only the financial sector shows significant evidence for violating expert information in selecting input/output factors also does not show a significant marginal improvement in correlation between firm efficiency and expected returns. The use of the DEA-EI model enhances the fundamental strength of the firms. It was claimed that firms with higher predictive relative performance strength are investment worthy.

Conclusively, studies that evaluate the company fundamentals using DEA and examine their relationships with stock returns realized marginal improvement though it differs from the model used. The question of efficiency of the company fundamentals and their contribution of excess returns remains a hot discussion in the field especially in the methodology and identification of inputs and output factors.

2.13 Integration of Fundamental Components

There are two approaches that investors can use while conducting fundamental analysis which is top-down and bottom-up. The top-down approach is the one where the analysts put more emphasis on analyzing the economy of the country followed by the stock market and industry, and less emphasis on company analysis. Under the bottom-up approach, more emphasis is on company analysis followed by industry and market with little importance on analysis of the economy of the country (Navas and Bentes, 2013; Baresa, Bogdan, and Ivanovic, 2013; Li and Sulivan, 2011).

Juozapaitis and Stasytyte (2015) added a mixed approach on top of top-down and bottom-up. The mixed approach is involving the implementation of both top-down for economic activities and bottom-up for the company's activities. This means that both macroeconomic variables and company fundamentals are broadly evaluated, while other components like the stock market and economic sectors received little attention. However, the top-down approach is recommended when the investor aims to conduct geographical diversification. Where for that case, indeed must emphasize evaluating the economic condition of the countries and compare prior to making an investment decision (Navas and Bentes, 2013). Correspondingly, this study involves four countries with different economic status in which the top-down approach fit the minimum requirements.

2.14 Portfolio Diversification

The scholarly work of Harry Markowitz conducted in 1952 about portfolio selection is the steppingstone of portfolio construction. He demonstrated that the investors should allocate more funds to the assets which have maximum expected returns and vice-versa to maximize the portfolio expected returns whereas current literatures found otherwise even risk-return standard models were used. Recent literatures reported that such inconsistence may associated with investor's trading behaviour, efficiency of the listed firms and various models developed to estimate the expected returns the portfolio.

The studies conducted in Africa showed mixed results. Omran (2007) conducted analysis of the CAPM using 41 securities listed in the Egyptian Stock Market and found that the companies with positive skewness have positive risk premium and best performed portfolio are formed from construction, hotel, materials, and weaving companies. The results conflict with the study of Offiong, et.al (2016) conducted in Nigeria Stock Exchange where they found that financial sector is riskier, and investors are advised to invest in that sector for maximum returns and the efficient portfolio were observed on efficient frontier curve. Although only three top banks in Nigeria were selected for the study and the efficient sets were computed using mathematical approach. They impose mathematical constraint in the model and generate the results that can fit in efficient frontier. Nyagara, Nyagara, Ndlovu and Tyavambiza (2016) found the beta can be used to predict the stock returns in Zimbabwe Stock Exchange (ZSE) in limited time horizon, which is below six months.

They concluded that the investor needed to be very careful when using beta particularly on time horizon. Surprisingly, study of Maziviona (2013) conducted in ZSE shows different results, the stock of Security Market Line (SML) was not the same with market premium and the higher beta higher returns was not observed although SML shows linear regression. He was also found that the higher mean returns are produced by negative beta.

Limited literatures were found explained the practical application of Markowitz and CAPM in East Africa region. The study of Muiruri (2014) about the estimation of systematic risk using CAPM for 59 listed companies from 2009 to 2012 found that every sector has unique factors that influence market risk, and he stressed that beta was statistically significant in all four sectors in Nairobi Securities Exchange (NSE) however, Agricultural sector is riskier than financial sector. Different to the study of Okumu and Onyuma (2015) found that there is no direct relationship between NSE return and the returns of the listed assets, also the coefficient of determination of all stocks shows 41 percent, this result doubt on the remaining 59 percent may be contributed to other factors. Therefore, they concluded that CAPM is not significant to explain the NSE assets pricing behaviour. The study of Mayanja, at. el. (2013) conducted at Uganda Securities Exchange (USE) discussed the mathematical approach to a stock portfolio selection using Markowitz model. Although they identified “BATU” as the best share to invest when they impose the mathematical constrains during computation of portfolio optimization in which they said does not have economic or financial implication. They concluded that the study methodology was complicated and recommended to use computer application for efficient and accuracy. Similar study was conducted in Dar Es Salaam Stock Exchange (DSE) by Kaboneka, at. el (2014) on analysing the effect of diversification in DSE using

Markowitz Model and concluded that the diversification is significant when the assets are nearly correlated. Although the study was not presented on practical point of view, also the study was silent on appropriate number of assets in diversification. Bunch of research related to portfolio construction have been witnessed in Asia, Europe and America.

Ramasamy, Tat and Mohammed (2015) construct portfolio using standard Markowitz model and allocating funds based on assets returns, they found that the random approach showed better results than performance-based approach. While Moh'd, Ramasamy and Mohamed (2019) construct portfolio using standard CAPM and allocated funds based in trading frequency which are increasing trading frequency, decreasing trading frequency and random allocation. The portfolios constructed based on random allocation of funds produced maximum returns followed by increasing trading frequency where decreasing trading frequency generated minimum portfolio returns.

Lim, et. al. (2014) constructed portfolio using combined model of Markowitz DEA MV cross-efficiency and allocates funds equally. The model has the power to segregate the stocks based on returns, risk, and efficiency whereas out of 557 stocks only 30 stocks are qualified to for portfolio construction. The Sharpe ratio revealed that the proposed model is most effective for portfolio construction as it produces maximum portfolio returns compared to standard Markowitz model. Since only efficient firms were considered in portfolio construction, still there are investment opportunities on inefficient firms which have not been identified in this study. It is worth noted that, the effectiveness of the model could be widely explored when both categories of the firm were considered during portfolio construction. The DEA efficiency evaluation model attached to Markowitz provided a significant contribution on portfolio returns.

Lim and Mali (2018) used multifactor model which also includes DEA relative efficiency of the firm's stock to test whether have significant contribution on stock returns and volatility. It was confirmed that the stock of inefficient firms more volatile and generates high returns compared to efficient firms. It was insisted that investors relied on information about firm efficiency to make investment decision. Since the stock of efficient firms are less volatile, investors are likely speculating on inefficient firm. Impliedly, the findings suggested to construct portfolio using inefficiency shares to realize maximum expected returns although it was beyond the scope of the study. Therefore, still there is a room to extend the test of the influence of DEA relative efficiency to portfolio level.

Junior, Rocha, Aquila, Balestrassi, Peruchi and Lacerda (2017) constructed portfolio using standard CAPM and combined model of DEA, CAPM and entropy function. It was reported that DEA played a major role of evaluating several variables to insure low beta value was achieved that further assured the robustness of expected returns of the constructed portfolio. Portfolio performance measured by Sharpe ratio shows the portfolio constructed by proposed model outperform those constructed using standard CAPM model. The incorporation of DEA in the model shows a significant contribution in portfolio construction. It was observed that there are inconsistence of funds allocation and number of assets used between models used which disqualify the comparability. Also, the number of shares included in the portfolio are differ where as standard CAPM used all 59 shares and proposed model only used 10 share which are found efficient. In standard CAPM, funds are allocated based on returns and risk while in proposed model they are allocated based on efficiency.

Although, various studies have witnessed the significance of evaluating the efficiency of stocks before conducting portfolio construction, yet most of them are concentrated on evaluating company fundamentals and excluding other components like economic sector, stock market and country economy. Also, most of them are contested on improving the strength of DEA models and developing various hybrid models (Lim, Oh and Zhu, 2014; Jothimani, Mashayekhi and Omrani, 2016; Shankar and Yadav, 2017). There is a gap in the body of literature specifically on the linkage of DEA evaluation of country economy, stock market development and economic sectors with portfolio construction.

2.15 Portfolio Performance

There are various measures which are frequently used by fund manager to evaluate the performance of the portfolios. Recent studies of Kim, Kim, Kwon and Fabozzi, (2017); Yu, Chiou, Lee, Yi (2017) and Leon, Navarro and Nieto (2018) identified portfolio performance measures which are regularly used. Some of them are Jensen's Alpha which is the excess returns of the portfolio compared to theoretical returns computed using CAPM. Sharpe ratio which is the excess returns per unit risk measured by standard deviation of the returns. Treynor ratio which is the excess returns per unit risk measured by market beta (a regression between market returns and asset returns). Omega, Sortino or Kappa Ratio which is the excess returns per unit risk but excess returns and risk is measured relative to Minimum Accepted Returns (MAR). Value at Risk (VaR) which is the minimum level of risk expected to occur with a certain probability. Conditional Value at Risk (CVaR) which is the extension of VaR explaining the expected loss beyond the VaR level.

Broadly performance measures can be classified into different categories, there are reward-risk ratios or risk adjusted measures such as Sharpe ratio, Treynor ratio, Jensen's alpha, there are partial moment based measures which require lower partial moment defining risk as negative deviations of stock returns such as Omega or Sortino or Kappa ratios, as well as quantiles based or downside risk measure that is require to introduce two downward risk measures for the return distribution such as VaR and CVaR (Leon, Navarro and Nieto, 2018; Adcock, Areal, Cortez, Oliveira and Silva, 2019).

Leon and Moreno (2017) and Carles, Doncel and Sainz, (2018) both complained that, although the question of which performance measure can be used to evaluate various portfolios is still debated among scholars and practitioners, yet reward-risk ratios and Sharpe ratio in particular remain as a benchmark because of high level of accuracy . It is worth noted that fully compatibility of normal distribution returns is the major strength of this measure although, any existence of asymmetry and heavy tail distribution returns leads to incorrect evaluation. Carles, et.al. (2018) further concluded that managers, investor, institutions, policymakers and other agents in the financial sector can overcome the problem selecting appropriate performance measures by ranking potential investment using risk-adjusted measures.

Syed (2017) stated that the portfolio measured using reward-risk ratios which have same numerator such as Sharpe and Traynor ratio appeared to have same rank. Sharpe ratio measure both fund manager's performance and market condition which is an added advantage when making investment decision. To overcome the negative excess returns that may results negative Sharpe ratio it was advised to use absolute excess return also, to avoid the criticism of using total risk measured by variance of the returns, it was advised to estimate the performance using Treynor ratio where the risk using market beta estimated by regressing market returns and assets returns. The methodology used was helpful as the negativity of modified Sharpe ratio was significantly lowered compared to standard Sharpe ratio, although the average performance measured by Treynor ratio was lower than that of Sharpe ratio. Bodnar and Zobotoskyy (2016) demonstrated the power of Sharpe ratio on explaining optimal and minimum VaR portfolio. It was reported that although the maximum Sharpe ratio explained the most performed portfolio which is supported by various literatures, yet performed portfolio become very risky and its risk cannot be minimized by considering the risk free instead can be minimised by constructing large dimensional portfolio.

Sharpe ratio portfolio lied on the Markowitz efficient frontier in the minimum variance space without risk free asset and is basically follow the assumptions of MVCM. While Treynor ratio lied on security market line also follow the assumptions of CAPM. It was further concluded that the use of Sharpe ratio as the measure of portfolio performance in practical application need to apply in at most care otherwise will result large loss. Risk-adjusted measures particularly Sharpe and Treynor ratio continue to be recommended performance measures is various recent studies. They have high stability when multiple funds are analysed (Sheikh, Ismail, Ismail, Shahim, Mohd and Shafiai, 2019) although sometime Treynor ratio outnumbered Sharpe ratio (Benlamri and Sparer, 2017).

2.16 Portfolio Optimization

Portfolio optimization is explained as the optimal allocation of funds that investor has to apportion in different assets to achieve the reasonable trade-off between risk returns (Meghwani and Thakur, 2017; Qu, Zhou, Xiao,Liang and Suganthan, 2017; Lwin, Qu and MacCarthy, 2017). Investor can minimize variance to attain the required mean returns or maximizing mean returns to a certain level of variance (Lwin, Qu and Carthy, 2016). The nature of investors is risk averse, mostly they prefer to minimize the risks to achieve the required mean returns. Current debate is on approach to be used to identify right mix of assets that can generate required trade-off between risk and returns (Javid and Fahal-Tafti, 2019). Some of the approaches are explained below.

2.16.1 Multi-Objective Optimization (MOO)

Simple understanding of MOO is an improved version of traditional Markowitz optimization which is efficient frontier model or Single Objective Optimization (SOO). While SOO work under single objective which is either to maximize the expected returns or minimizing risks, MOO consider more than one objective like when both maximizing expected returns and minimizing risk simultaneously (Ding, Liu, Yao and Chan, 2017; Duan, 2007). Ding, et.al. (2017) further concluded that the return of MOO is slightly higher than SOO although the set of optimal portfolio are the same.

2.16.2 Stochastic dominance (SD) constraints

This is the one where investors consider the structure and behaviour of the whole investment returns distribution unlike standard mean variance dominance which only consider the first two moments which are mean of variance. SD were designed to establish returns distributions of various assets, the one which dominates considered efficient, however, SD is criticised based on assumption that the future asset returns distribution can be captured using historical returns (Liesio, Xu and Kuosmanen, 2020). Alkhazali and Zoubi (2020) mentioned that the results standard Markowitz optimization model are consistent to that of SD, although SD is more reliable because of limited assumption.

2.16.3 Ambiguity Aversion (AA)

It explains that not always the risk can be quantified in respect to assets returns distribution that gives signal to fund managers about unique prior probability of the future returns as explained under Bayesian paradigm, in some case fund managers are solely decided to avoid worst possible outcome in which the probability in unknown that referred as ambiguity (Kellerer, 2019). It was noted that the optimal portfolio selection depends on both risk eversion and ambiguity aversion. While risk eversion depends on asset returns distributions, ambiguity eversion depends on perception of uncertainty and behaviour that might affect economy and market (Agliardi, 2018). Yet the measurement of degree of the ambiguity remains crucial element in decision making.

2.16.4 Robust Optimization (RO)

It is also known uncertainty optimization approach which explained that in real world scenario the portfolio optimization problem cannot be solved only by considering asset's returns distribution, instead other unknow parameters belong to uncertainty sets need to be considered to robust the estimation (Supandi, Rosadi and Abdulrahman, 2017). The question of identifying the elements of uncertainty sets remain a setback of implementing RO approach. Geng, Tim, Craig and Olivia (2013) considered uncertainty set of Sharpe ratio which are randomly generated using Sharpe ratio estimator. They further observed that the elements are normally distributed, when VaR adjusted Sharpe ratio used was able to incorporate skewness and kurtosis of the returns distribution information which help to avoids several key assumptions about the underlying return distribution.

2.16.5 Socially Responsible Investment (SRIs)

It also knows the investor's subjective view approach, it considers Social, Environmental, or Ethical (SEE) screening criteria to make an investment decision where it can be positive or negative screening. Socially responsible investors who follow the negative screening excludes companies that are involved in controversial business such as alcohol, tobacco, gambling, military, firearms, or nuclear power, while those who follow positive screening include companies that are involved in a business that related to community, diversity, employees relation, environment, human rights and products (Maria and Jose, 2017; Amelia, Mar and Veronica, 2012). Maria and Jose (2017) stressed that SRIs results to limit the investors on diversifying to other risky investments however increases international diversification.

Overall, all approaches aim to solve the difficulties facing SOO such as maximizing returns and minimizing risk simultaneously, evaluating assets to higher moments, consideration of uncertainty with unknown probability, accommodating non-normal or asymmetric returns, the including SEE screening criteria. However, except for MOO which can capture all parameters of SOO and associated assumptions in the objective function, other approaches still facing difficulties to standardize the parameters to be used in the model, some limiting investors on diversifying on risky investments and others still contradicting on the methodology of measuring the parameters to be used in the model. These justifications convinced the researcher to opt for MOO over other optimization approaches and test its applicability in the context of this study.

Literature related to MOO used various methods to formulate optimization problems such as linear programming, Lagrange multiplier, genetic algorithm, evolutionary algorithm. Likewise, the objective function is not limited to returns and risk, other objectives like dividend, growth of sales, liquidity, portfolio returns over that of the benchmark (to be minimized), deviations from asset allocation percentage, number of stocks in the portfolio, turnover, maximum proportional weight, amount of short selling can be considered (Ding, et .al, 2017; Long, Wisitpongphan, Meesad and Unger, 2014; Radziukynienė and Zilinskas, 2008; Subbu, Bonissone, Eklund, Bollapragada and Chalermkraivuth, 2005).

Concisely, the MOO objective function of this study aimed to maximize portfolio returns and minimize portfolio risk simultaneously using a linear programming model (LP). Park, Song, and Lee (2018); Mansini, Ogryczak, and Speranza (2014) formulated a portfolio optimization problem using LP has justified that that LP is stable and computationally first even when a large number of assets were used, also it can accommodate integer variables and practical constraints. The flexibility that the LP approach has attracted many scholars to transform most of the developed into form in order to determine the optimization solution.

It was insisted by Mansini, Ogryczak, and Speranza (2014) that for the last two decades Mean Absolute Deviation (MAD) was frequently used by scholars and lead to the development of further Linear Programming (LP) models like conditional value at risk (CVaR), Mixed-integer Linear Programming (MILP) models. Gharakhani and Sadjadi (2013) implemented LP to examine the efficient allocation of funds. They incorporated the investor's view about asset pricing which was modeled using fuzzy numbers and asset returns were estimated using the Black-Litterman (BL) model. The model simply combined CAPM distribution and investor’s view. While CAPM estimate prior distribution, Bayes’s formula to estimate posterior distribution. It was concluded that the model can solve analytically and efficiently when compared with several performance criteria.

Heidari and Neshatizadeh (2018) compare the speed measured by assimilation time and accuracy measured by the variance of linear programming models which are Cardinality Constrained Mean-Variance (CCMV) and Cardinality Constrained Mean-Semi Variance (CCMSV), Firefly Algorithm (FA) as well as Imperialist-Competitive Algorithm (ICA) on solving portfolio constrained optimization problem. The results overlooked to disclose which model performs best in terms of speed and accuracy instead they compare two models. it was revealed that ICA has a smaller variance than FA and CCMV has a smaller variance than CCMSV. Similarly, ICA takes a shorter time than FA to achieve a solution while CCMSV gets a shorter time than CCMV.

Vaezi, Sadjadi, and Makui (2019) proposed an LP optimization model that maximized returns of the portfolio by considering the risk preferences of investors and budget, cardinality, lower bound and upper bounds constraints under interval uncertainty of the parameters in the objective functions and constraints simultaneously. Generally, the model was able to determine the optimal solution to the problem formulated. It is also insisted the proposed model was able to overcome most of the Markowitz limitation which related to real financial market constraints like transaction cost, CCMV, CCMSV, etc.

2.17 Portfolio Stress Test

The stress test is among the investment risk measure, it estimates the impact of an unusually severe event that may impact the listed company and market at large. It was claimed that the stress test needs to be included in the trading risk manual especially for those markets with extreme volatility. Usually, stress-testing is subjective whereas an investor or fund manager may stipulate the scenario which has interested to examine the change with respect to the portfolio constructed (Al Janabi, 2009). Developing a stress framework by considering both rare and extreme events from the range of stock markets to macroeconomy is vital for portfolio management.

Traditionally, stress testing was scenario-based, approaches such as standard scenarios, historical scenarios, or hypothetical scenario were used. The standard scenario approach is more on assessing the unexpected portfolio changes by considering possible external market condition such as stress loss happened in the various institutions at a given point of time. The historical scenario approach is more on evaluating the effect of an extreme market event such as a financial crisis and its effect on the current portfolio. The hypothetical scenario approach is based on designing scenarios by identifying possible external changes in risk factors, volatilities, correlation (Wong, Ho, and Dollery, 2003).

The study of Best and Grauer (1991) is considered among the earliest to conduct portfolio stress on equity investment. They investigated the sensitivity analysis of portfolio weight when there is a change of mean returns of individual assets using the Markowitz model subject to budget constraint. They select the assets randomly out of 958 from 1976 to 1985 in New York Stock Exchange (NYSE) and allocate fund equally in all selected assets, when they adjusted the mean returns of an individual asset by one unit results in a larger change of portfolio weight. Xiaohu (2013) impressed with the study of Best and Grauer and extended it to CAPM. He investigated the sensitivity of portfolio weight and volatilities, portfolio weight and correlation of assets and market, portfolio mean returns and volatilities, portfolio minimum variance and volatilities as well as portfolio minimum variance and correlation. His findings revealed that minimum variance portfolios, mean returns, and risk change with respect to assets correlation and volatilities. Recent literature related the stress test with modeling of uncertainty which is the most challenging exercise to investors and fund's managers.

Franco, Nicolle, and Pham (2018) demonstrated the privilege of the Bayesian learning strategy for dealing with uncertainty. The study examines the responsiveness of returns based on uncertainty level, leverage, portfolio review frequency, and portfolio rebalancing frequency. By defining different uncertainty cases from a base of 10 to 50, 100, 200, and 300 ranked lower to higher, it was revealed that when uncertainty increases the expected returns also increase without increasing the risk. Likewise, when the leverage ranked from a base of 100% to 150%, 200%, 250%, and 300%, the expected returns were observed to increase with leverage. Also, the review frequency is set from the base of 3 months to 6month, 9month, and 12month, the expected returns increase when the review frequency is below 6months. The portfolio rebalance was considered by trading bi-weekly and per month, the expected returns decreased when trading change from monthly to bi-weekly however it was not significant. The broad scope of the stress test convinced me to narrow down the specific approach to be used in this study. Uncertainty based stress test under the hypothetical scenario approach was conducted in this study to evaluate the change of portfolio expected returns, volatilities, and performance.

2.18 Conceptual Framework

Figure 2.8 represents a conceptual framework of this study. There is an independent variable formed by risk and returns as well as managerial and operational performance. Also, there are dependent variables which are portfolio construction and selection. While portfolio construction rested on diversification, portfolio selection depends on a risk-adjusted performance measure, optimal funds allocation, and stress test.

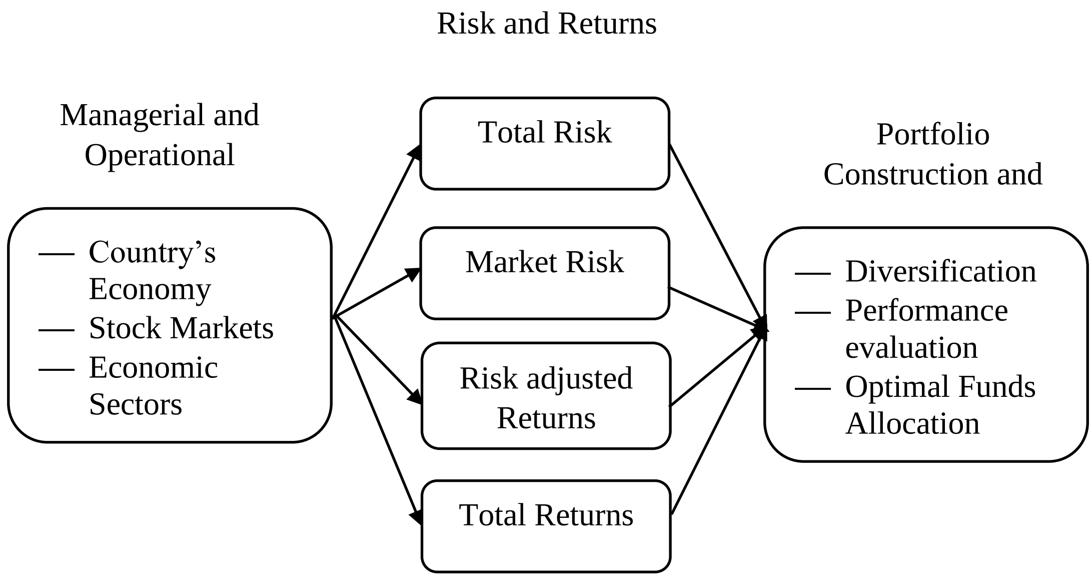


Figure 2.8 Conceptual Framework

2.18.1 Risk and Returns

Closing share prices, all share index, and T-bill rates of the shares listed in EACMs were used to compute risk and returns of various portfolios constructed using MVCM and CAPM. Since the stock price systematically raise when the closing time is approaching (Kucukkocaoglu, 2004). Recent studies associated the rising of the closing share price at the last minutes of closing time was associated with information disclosure in which the investors received (Fatluchi and Rokhin, 2017). It was stressed that the rising of closing share price leads to a significant proportion of volume shift which indicates economic importance and heightened stock volatility.

There are various indices within EACMs, there are indices which describe listed company based on size, some indices describe the specific industry, while others describe all listed companies in the market. All share index was selected to meet the requirement of the study since it describes all shares listed in each market. To use CAPM, the risk of free needs to be defined. For decades, academicians and practitioners have used the treasure bill (T-bill) as a better proxy of risk-free. It was justified that only T-bill do not have ant market risk from 1 to 5 years and even it becomes lowest over 10 years compare to other traded securities (Muherji, 2011).

2.18.2 Economic Indicators

The indicators used to evaluate a country's economic performance are government spending percentage of GDP, investment percentage of GDP, inflation, and public debt percentage of GDP. The proxies of the country's economy are different among studies, some of the recent literature considered exchange rate and oil price (Gay, 2016), T-bill, consumer price index and industrial production index (Shah, 2018), inflation, real income and money supply (Mahonye and Mandishara, 2014), GDP, unemployment, foreign direct investment, state debt, export, import, trade balance and short-term interest rate (Pilinkus, 2010).

However, for East African countries particularly Kenya, Tanzania, Uganda, and Rwanda, the GDP, inflation rate and public debt need more attention. This is because East Africa is the only region in Africa that record the highest GDP growth rate since

2017 (ADB, 2019). Also, there is a continuous increase of public debt due to the expansion of the Africa-China belt where most African countries fallen on china debt trap and Kenya is the largest lender with over 72 percent of all its foreign debt (Dhar, 2019). Furthermore, the existence of current account deficits and adoption of floating exchange rate leads to local currencies depreciation against the US dollar, and severe drought that affects Kenya and Uganda add more pressure on inflation (UNECA, 2018).

2.18.3 Stock Markets Development Indicators

Market capitalization to GDP, the ratio of the total value of share traded to GDP or ratio of the total value of share traded to market capitalization as the core measures of stock market effectiveness, all these metrics fall under the category of the size of the stock market. According to the Financial Sector Development indicators (FSDI) proposed by the World Bank (1996), another dimension like access, efficiency and stability need to be considered in analyzing the stock market development (World Bank, 2006).

Moreover, there is a newly proposed broad-based index of financial development circulated by IMF which classified FSDI into three main dimensions including depth, access, and efficiency (Svrydzenka, 2016). In the same literature, it was explained that for the equity market the dimension of depth is measured by stock market capitalization to GDP and stock traded to GDP. While access is measured by the percentage of market capitalization outside of the top 10 largest companies. Similarly, efficiency is measured by stock traded to capitalization. Some of the indicators proposed by FSDI were found suitable to measure the effectiveness of EACMs, those are listed shares, stock market capitalization, market turnover, and market index.

2.18.4 Economic Sector Growth Indicators

The key indicators of economic sector growth used in this study are the labor force of the particular sector as a percentage of total employment, value-added as a percentage of GDP, and growth rate. The selected indicators were extracted from various studies conducted (Tahamipour and Mahmoudi, 2018; Lankauskiene and Tvaronaviciene, 2013; Ahmad and Malik, 2009; Lankauskiene and Tvaronaviciene, 2013; Lee and McKibbin, 2015). The economy of Kenya, Tanzania, Uganda, and Rwanda are largely depending on agriculture, mining, and utility, construction, manufacturing, and services sectors. However, service sectors followed by agricultural sectors are dominant drivers of the economy in all countries within the region while the remaining sectors are still in the infant stage (United Nation Economic Commission for Africa (UNECA), 2018). Therefore, the sectors which have been evaluating are in this study are agriculture, service, and industry.

2.18.5 Listed Companies Performance Indicators

The indicators such as total assets, investing cash flow, revenue, net profit, financing cash flow, and operating cash flow were used to evaluate the performance of listed companies. Studies that evaluate company performance usually used financial ratios such as profitability ratios, liquidity ratios, operating capacity ratios, development ability ratios, solvency and risk ratios (Ma, Ausloos, Schinckus, Chong; 2018; Jothimani, Shankra, and Yadav; 2017; Mashayekhi and Omrani, 2016; Lim, Oh and Zhu, 2014; Edirisinghe and Zhang, 2010). The study of Wong and Deng (2017) considered the actual value of assets, loans, deposits, investments, total cost, and interest on deposit to rank the efficiency of ASEAN banks. Also, the study of

Jumanne (2018) used fixed assets, expenses, and equity as input variables as well as total sales and profit as output variables to evaluate the technical efficiency of the corporation in EAC. This study found the need for reviving the use of actual value to strengthen the literature of company analysis.

2.18.6 Portfolio Construction and Selection

Portfolio construction involved diversification across different listed shares within the market where shares are listed and share listed in different markets, also involved the shares which are efficient, inefficient and mixing of both using MVCM-DEA and CAPM-DEA models. The approaches used are the extension of the recent scholarly works which diversify on the single market and using either MVCM-DEA or CAPM-DEA (Junior, Rocha, Aquila, Balestrassi, Peruchi, and Lacerda, 2017; Mashayekhi and Omrani, 2016; Lim, et. al., 2014). While portfolio selection involved evaluation of portfolio performance using Sharpe ratio and Treynor ratio, assessing portfolio optimization using multi-objective optimization approach, also conducting portfolio stress test-based uncertainty under a hypothetical scenario.

2.19 Hypothesis Development

It is customary for the research to identify the hypothesis that can clarify and restate the problem statement on top of research objectives and questions (Emmert-Streib and Dehmer, 2019; Chigbu, 2019).

The hypothesis is a tentative explanation composed of facts that can be tested quantitively for further clarification. The hypothesis should be provided a hesitant explanation of the phenomenon, facilitate the extension of knowledge, a relational statement that can be testable in the sense that can be supported or rejected, deduced from the theory or other hypothesis (Mourougan and Sethuraman, 2017). Hypothesis can be classified into null hypothesis and alternate hypothesis. A null hypothesis is a statement state that there is no relationship between variable and is denoted as H_0 or H_N. While alternate hypothesis is a statement which suggest the expected outcome may occur and is denoted as H_1 and H_A. Null hypothesis also referred as favoured assumption and alternate hypothesis is known antithesis to null hypothesis (David and Mukamal, 2006).

Furthermore, the alternative hypothesis can either be directional where it can predict the direction of the outcome otherwise it can be non-directional. Directional can be stated that there is a positive/negative relationship between variables while non-directional can be stated as there is a mean difference between variables. The structure of this study considers the construction of various portfolios among the shares listed in EACMs using both MVCM and CAPM incorporated with DEA and conducts various portfolio analyses including performance, optimization, and stress testing.

It is well known that these two models are commonly used by scholars and practitioners for portfolio construction. Using both of them in this study provides clear understandings of the strength of each model in terms of excess returns, risk estimation, portfolio performance, and optimization under normal state as well as extreme events. Therefore, the non-directional hypothesis was found relevant in this study. The developed hypothesis are classified into four categories which are fundamental analysis hypothesis, returns and risks hypothesis, Performance hypothesis, and uncertainty hypothesis which form a total of nine hypotheses as shown below;

2.19.1 Fundamental Analysis Hypothesis

This is the hypothesis that measures the influence of combining the performance of a country's economy, stock markets, economic sectors with a company’s financial performances. The hypothesis state that.

Hypothesis 1: There is no significant difference in the performance of the companies before and after combining with the performance of other components which are country economy, stock markets, and economic sectors.

The specified hypothesis clarified the research question 1 which state that.

Research question 1: Which stocks can be selected among those listed on EACMs after evaluating the managerial and operational performance of company fundamentals, economic sector growth, development of the market listed, and economy of the country registered using DEA models?

Various literature has addressed the influences of country economic variables, stock market development, and economic sector performance on listed companies’ performance within the region although they were overlooked to demonstrate quantitively (Ndiritu and Mugivane, 2015; Page, 2016). Globally, Norges Bank (2019) demonstrated the influence of country and economic sectors development on expected returns of listed companies. However, they have tested them using a parametric regression method. There is a need for adding another component which is economic sector growth on top of the country economy and stock markets development which was ignored by Norges Bank (2019). As it was stressed by Page (2016) that the industry sector within the region is very prominent for investors particularly in Tanzania.

2.19.2 Returns and Risk Hypothesis

Two hypotheses addressing expected returns and risks of various portfolios computed using mean-variance and capital asset pricing model incorporated with data envelopment analysis were developed;

Hypothesis 2: There is no significant mean difference between mean returns calculated by MVCM-DEA and those calculated using CAPM-DEA.

Hypothesis 3: There is no significant mean difference between risk calculated by MVCM-DEA and that calculated by CAPM-DEA.

The two hypotheses mentioned above extracted the research question 2 which is stated as below.

Research question 2: Are there any variability of expected returns and risks of various portfolios constructed on selected stocks listed in EACMs using both MVCM– DEA and CAPM-DEA model?

The study which compares the two models incorporated with DEA still are limited, existing literature compares the returns and risks computed using standard MVCM and CAPM and reported the contradicting results. The study of Lee, Cheng, and Chong (2016) conducted in the Kuala Lumpur stock exchange revealed that higher returns were generated when CAPM. It was further recommended that CAPM can be used by investors for making investment decision within the region. Although the study was limited to examining the excess returns generated between the models yet overlooked to conduct statistical tests on whether the difference exists is significant.

Contrary to the study of Li and Li (2012) who argued that the MVCM is better than CAPM in estimating returns although each model has its limitation. It was also reported that the findings are based on two stock portfolios which were claimed that it has little contribution to minimizing unsystematic risk. As it is well known that the unsystematic risk will be diversified away when the number of stocks in a portfolio is increased. Likewise, the study of Clarke, Silva, and Thorley (2011) introduced that the minimum variance model generates higher excess returns than CAPM.

It was insisted by Li and Li (2012) that MVCM shows better results when it was used to estimate the risk than CAPM. The strength of the mean-variance-covariance model was associated with avoidance of unsystematic risk while computing returns volatility also limited the explanatory power of beta. Clarke, Silva, and Thorley (2011) reported that the mean-variance model has increased appreciation in risk management during extreme events contrary to market beta computed using CAPM. Since returns volatility depends on covariance of the securities while market beta depends on securities returns and market returns, this may be considered as the reason of the difference which exists between these two measures of risks.

2.19.3 Portfolio Performance Hypothesis

The performance of the portfolio constructed was measured using the Sharpe ratio and the Treynor ratio. Sharpe ratio is measured by the proportion of risk-adjusted portfolio returns to portfolio risk computed using the mean-variance model and the Treynor ratio was measured by taking the proportion of risk adjusted returns to portfolio risk computed by the capital asset pricing model. One hypothesis which compares Sharpe ratio and Treynor ratio was constructed as shown below.

Hypothesis 4: There is no significant mean difference between the Sharpe ratio and Treynor's ratio.

The defined hypothesis corresponded to research question 3 of this study which state that.

Research question 3: What is the performance of the various portfolios constructed based on the selected stocks listed in EACMs evaluated using both Sharpe ratio and Treynor ratio?

Relevant studies that compare the Sharpe ratio and Treynor ratio reported different findings. The study of Suryani and Herianti (2015) conducted in Jakarta stock exchange found that the Treynor's ratio is higher than the Sharpe ratio and both produced negative minimum ratio, although they are also varying in size the t-test conducted between these two measures shows there is no significant difference when any of these models used to measure portfolio performance.

Unexpectedly, the study of Alptekin (2009) conducted using Turkish type A mutual fund shows unpredicted results. All 22 mutual funds produce a negative Sharpe ratio and negative Treynor's ratio. The results were similar across different funds and fail to draw the conclusion on which model can be used to measure the performance of Turkish type A mutual fund. Although the further analysis was conducted to rank the performance of funds, still the study concluded that there are no differences between Sharpe ratio and Treynor's ratio without conducting any significant test.

2.19.4 Uncertainty Hypothesis

The stress was conducted to measures the influence of risk and returns of various portfolios constructed using the minimum variance model and capital asset pricing model under different levels of uncertainties. This study defined uncertainty level which is also referred to as states of the economy as good, poor, and worst. The following four hypotheses were developed based on returns and risks and the corresponding model used to compute them.

Hypothesis 5: There is no significant mean difference between sensitivity portfolio mean returns computed by MVCM-DEA in different states of the economy.

Hypothesis 6: There is no significant mean difference between sensitivity risks computed using MVC-DEA in a different state of the economy.

Hypothesis 7: There is no significant mean difference between the sensitivity of portfolio mean returns computed by CAPM-DEA in different states of the economy.

Hypothesis 8: There is no significant mean difference between the sensitivity of risks computed using CAPM-DEA in a different state of the economy.

The four hypotheses stated above which are hypothesis 5 to hypothesis 8 are all extracted from research question 5 which is.

Research question 5: What are the patterns, behaviours and directions of the various portfolios constructed will have during good times and extreme conditions?

A recent study by Franco, Nicolle, and Pham (2018) argued that portfolio returns, risk, and performance change with ambiguity. Five levels of uncertainties were stated, and the results revealed that when the uncertainty increases the portfolio returns, risk, and performance increase. It can be stated that different uncertainty level generates different returns, risk, and performance. Although the study employed a Bayesian strategy instead of mean-variance or capital asset pricing models, it was not further extended to examine the significant change between different uncertainty level.

2.20 Summary

This chapter reviewed the relevant literature related to stock selection and portfolio construction from both theoretical and empirical points of view. It provided the underpinned theories separately and collectively that end up in the development of a theoretical framework. Moreover, the reviewed literature provides scientific evidence of stock selection based on the managerial and operational performance of the country's economic, stock market, economic sectors as well as listed companies. The literature also justified the need of using MVCM and CAPM to construct various portfolios for the stock selected. Likewise, they elaborated various portfolio performance measures, optimization approaches as well as a stress test. Furthermore, the literatures guided the researcher to develop a conceptual framework and hypotheses. The following chapter discussed the complete process and procedures employed while conducting this study from the data collection process and data analysis which include hypothesis testing.

CHAPTER 3

METHODOLOGY

3.1 Introduction

This chapter explained the methods, techniques, and best practices of collecting and analyzing data. It includes the detailed information of research design, data, data collection process, population and population size, sampling and sampling technique, validity and reliability, and methods of data analysis.

3.2 Research Design

Research design explained the detail of the methods that will be used to collect, determine the sample, measurements, and analysis of the data (Sekaran and Bougie, 2016) while Kumar, Abdultalib, Ramayah (2013); Hair, Babin, Money, Samouel (2003) explained as the flow chart that shows the steps to follow to achieve the study objectives, answering research question or hypotheses developed. Research design is a structure that shows the roots of data collections and analysis by identifying the relationship between variables, filtering the presentable number of an individual that will participate in the study and mapping the context of the study and real-life (Bryman and Bell, 2007).

Various designs can be applied to answer the questions of business research. However, at any type of design, the four main characteristics including neutrality, reliability, validity, and generalization must be observed. Broadly, the research design is classified into qualitative and quantitative research design. Furthermore, it can be classified into the descriptive, experimental, correlational, diagnostic, and explanatory design (Sekaran and Bougie, 2016; Kumar, Talib and Ramayah, 2013; Hair, Celsi, Money, Samouel and Page, 2016). The efficient assessment of the questions in this study can be attained using a quantitative research design and more specifically descriptive design.

This design explains the approach of understanding the characteristics of the variables of the study in detail as various references are available to clarify the concept and the relationship of the variables exist (Sekaran, 2003). Also, it is conducted once the researcher has gathered enough information about the subject from different kinds of literature, and the source of secondary data is known since the main task of the researcher is to add more details on the subject of the research (Kumar, Abdultalib and Ramayah, 2013). More importantly, this design covers all the elements of execution, implement design phase of the basic business research process which include designing data, collecting data, checking for error, coding data and storing data which are not applicable on other designs (Hair et.al, 2003).

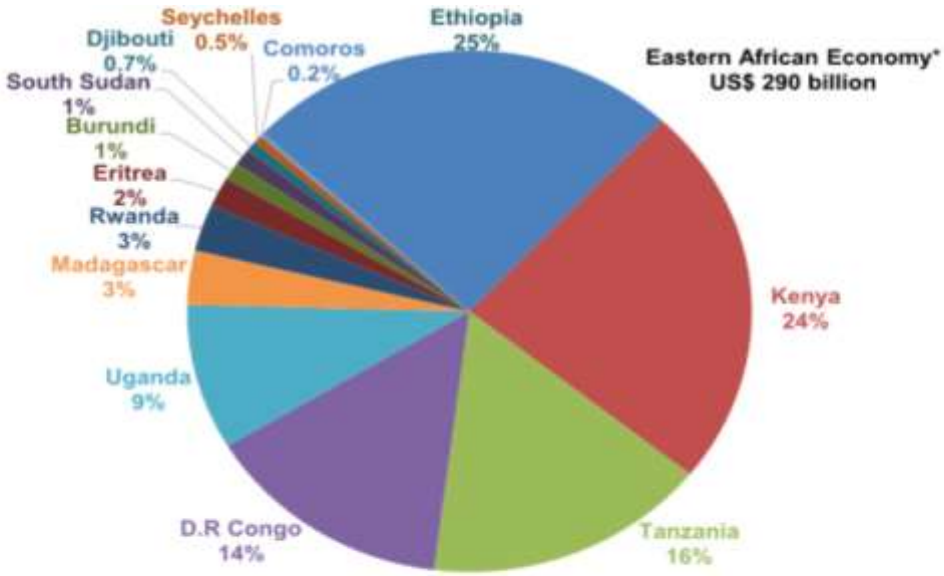
3.3 Population and Sampling

It is important to understand the population and population size to identify the sample. Since it is not viable to collect data through the entire population due to lack of time, cost, and other resources, the sample must be considered (Sekeran and Bougie, 2016). The term population is a generic word that relates to the number of people in a particular place or location. However, from a research perspective, it is narrated in a broad way that includes events or things. Various scholars defined population in the same way as the total number of people, events, things that the research intends to explore (Veal, 2006; Sekeran and Bougie, 2010; Sekeran and Bougie, 2013; Kumar at. el, 2013). The population of this study is closing share prices and market indices of all companies listed in EACMs from 2015 to 2018. While the total listed companies in all four markets are 117 with maximum trading days of 248, the population size is estimated to be 120,032.

Kothari and Gav (2014) defined sampling as the process of selecting some part of the target population. That can be either probability or non-probability sampling method which differed according to the generalization of population, the purpose of the study, time availability, or the interest of the researcher (Kumar et.al, 2013). Random sampling can be either simple, systematic, stratified, cluster, or multistage while non-random are volunteer, convenient, purposive, quota, snowball, matched or genealogy (Alvi, 2016). This study used a purposive sampling method since the markets still very young, some of the listed companies are not frequently traded and some of them do not show the price change throughout the year. It is very difficult to identify them at the very beginning, the analysis needs to be conducted to filter the companies based on the number of days that they appear in the market as well as the variability of prices of the shares.

3.4 Justification of the Study Area

The study was conducted in the East Africa region, EA. Global classification defined that the region is composed of 14 countries which Tanzania, Kenya, Ethiopia, Comoros, Seychelles, Djibouti, South Sudan, Burundi, Eritrea, Rwanda, Madagascar, Uganda, Democratic Republic of Congo, and Somalia as shown in Figure 3.1 with respective nominal GDP share as at 2016 (IMF, 2017). Six among them which Tanzania, Kenya, Uganda, Rwanda, Burundi, and South Sudan are a member of the East African Community where this study was conducted (EAC, 2020). However, Burundi and South Sudan do not have a capital market which made only four countries remained in this study. Figure 3.1 illustrated that, except Ethiopia and DRC which have GDP share of 25% and 14% respectively, the selected countries are the most dominant in term of nominal GDP in the region.



Note: (*) Somalia is not Included
Figure 3.1: East African Countries with Nominal GDP Share, 2016
Source: IMF (2017a)

Figure 3.2 show the selected countries are interconnected economically, politically, social and most important they have strong regional integrations (Irving, Schellhase and Woodsome,2017).

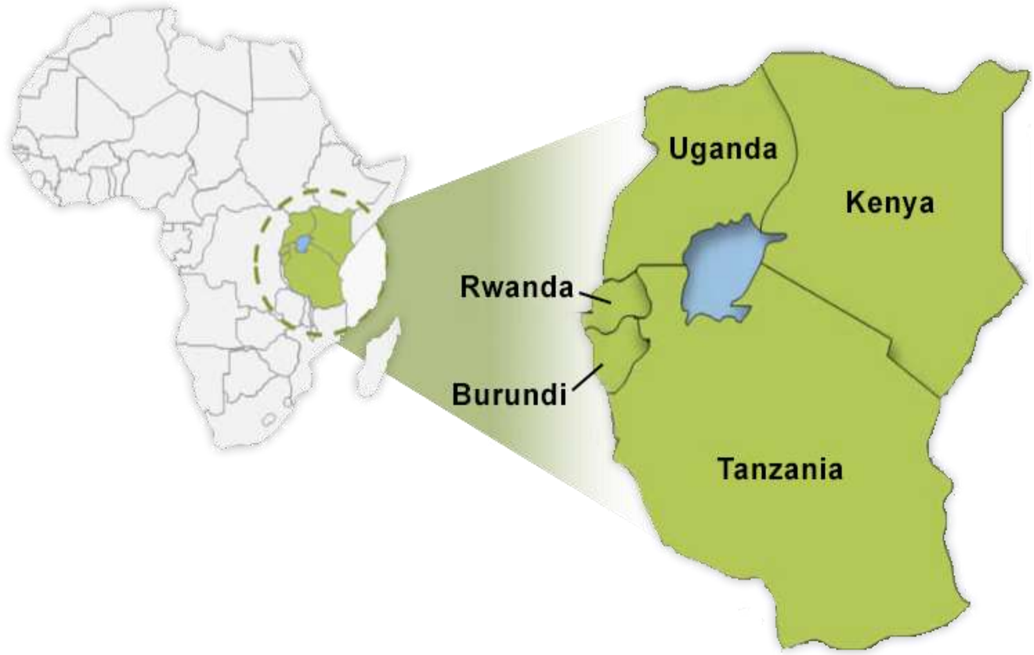


Figure 3.2: The Geography of the Selected Countries
Source: Medicopress.com

3.5 Data and Data Collection Method

There are secondary and primary data which fundamentally deferred in terms of meaning, nature of data, the process of gathering them, source, cost, collection time, and even availability. Primary data are the ones that are collected by the researcher for the first time. They are gathered through a survey, observations, experiments, questionnaires, personal interviews, etc. Contrary to secondary data which are already collected by someone else in the past. Normally, they are available in different publications, organization databases, books, journals, etc. They are cheaper and can be collected in a very short time however need to be purchased yet the cost is less than that normally incurred in primary data collection (Boslaugh, 2007).

The method of data collection is generally classified into qualitative and quantitative methods. Quantitative methods deal with numerical data that can be analyzed statistically while qualitative methods are more exploring intangible factors that cannot be quantified and analyzed using statistical procedure (Sekeran and Bougie, 2013; Kumar at. el, 2013). The nature of this study convinced to used secondary data collected quantitatively as it requires data that can be used to access and quantify the performance of the country's economy, stock market, economic sector, and Company fundamentals. Furthermore, applying quantitative techniques to constructs various portfolios.

3.6 Data Collection Process

Broadly, the secondary data collection process involved three main steps. Firstly, determine the purpose of data collection and the type of data required to meet the purpose. Secondly, understand various sources of data required. Thirdly, identify the best sources which can provide accurate and reliable data (Cheng and Philips, 2014; Johnston, 2014). However, the process of locating secondary data is not always straightforward (Boslaugh, 2007). Figure 3.1 illustrated the various steps followed by this during the data collection process.

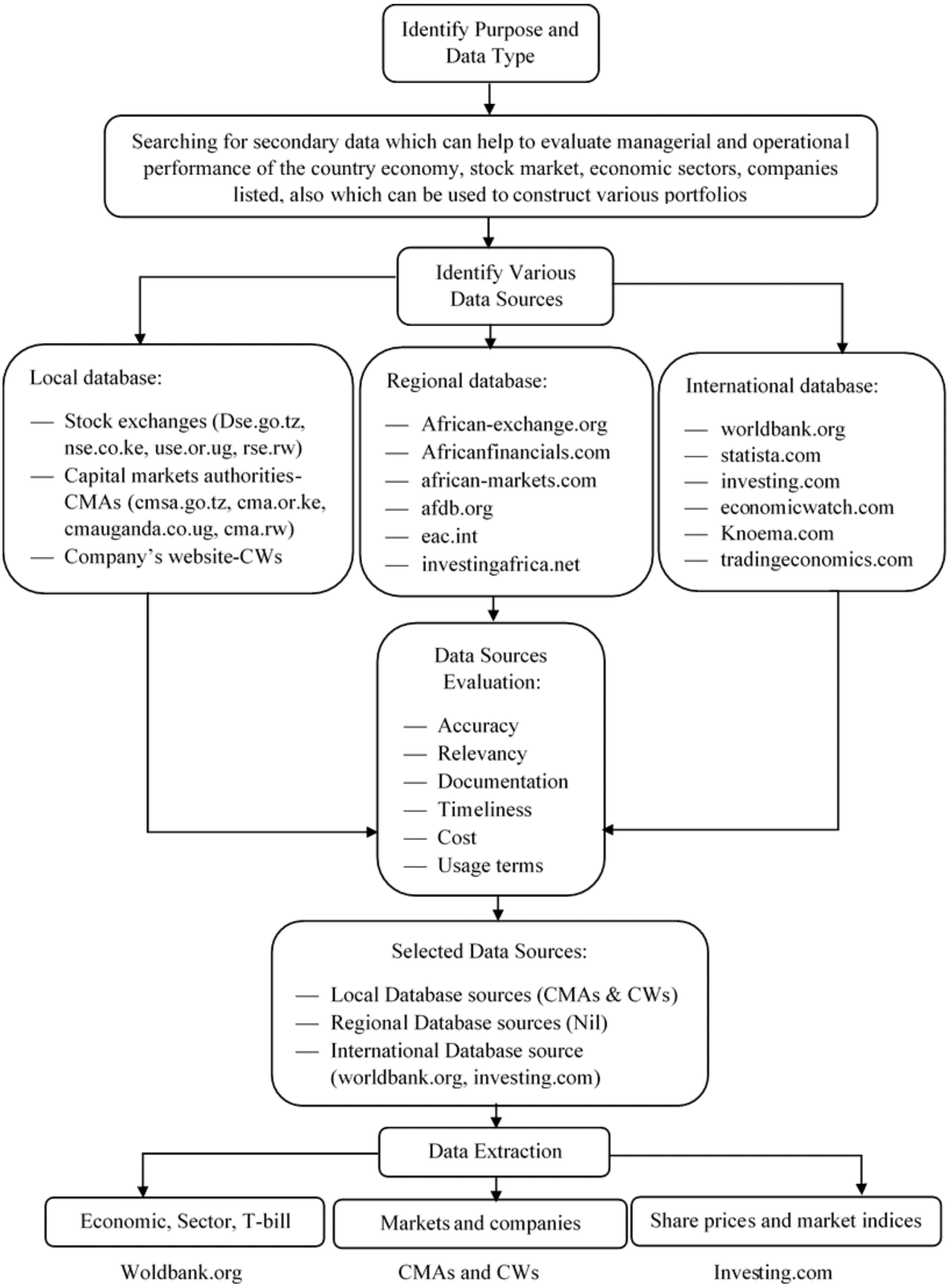


Figure 3.3 Data Collection Process Flow

3.6.1 Type of Data

Table 3.1 summarised list of data required to meet the study objective.

Table 3.1: Data Required

Variables	Components	Unit of Measure	Timeline
Government spending % of GDP	Country Economy	Ratio	2015-18
Investments % of GDP		Ratio	2015-18
Inflation rate		Ratio	2015-18
Public debt % of GDP		Ratio	2015-18
Listed shares	Market Development	Number	2015-18
Market Capitalization		USD Bill	2015-18
Market Turnover		USD Bill	2015-18
Market Index		USD	2015-18
Labour force % of total employment	Economic Sectors Growth	Ratio	2015-18
Value added % of GDP		Ratio	2015-18
Growth rate		Ratio	2015-18
Equity	Company Fundamentals	USD Mill.	2015-18
total Assets		USD Mill.	2015-18
Investing Cash flow		USD Mill.	2015-18
Revenue		USD Mill.	2015-18
Net profit		USD Mill.	2015-18
Financing cash flow		USD Mill.	2015-18
Operating cash flow		USD Mill.	2015-18
Closing share price	Others	USD	2015-18
Stock market index		USD	2015-18
T-Bill rate		Ratio	2015-18

3.6.2 Data Sources

Identification of Data sources was based on the type of data required in the context of the study. EACMs is still in the infant stage, various data sources have not started to store complete data of the markets. The searching process was classified into three zones which are local, regional, and international databases. Local or national database referred to as any data centre within the individual country such as country stock market database, country capital market database, or listed companies database. The regional database represents all data centres within the East Africa region that store consolidated data for all four counties. Also, the international database is all other databases that are not local or regional. Figure 3.3 show the various sources in each zone.

3.6.3 Data Sources Evaluation

Table 3.2 show the evaluation of data sources were conducted based on Muhen (2010) evaluation criteria.

Table 3.2: Data Sources Evaluation

Criteria	Indicator	Evaluation
Accuracy	Missing Data	Some share prices of some companies were not found in investing.com, the stock markets related data provided by eac.int are incomplete, and the economic sector related data were not reported by afdb.org.
	Report Format	The report formats for local stock exchanges are not consistent, and some of them like NSE not report closing share prices instead they report opening, high and low.
Relevancy	Data source	All regional and international databases are extracting data from local databases except afdb.org, worldbank.org, and eac.int.
	Unit of measures	All data reported in local currencies of the respective countries except the economic related data which provided by worldbank.org and afdb.org reported in USD.
	Level of aggregation	All databases report the data on the same base. Country economy data are reported country-wise, economic sectors reported sector-wise, market development reported market-wise, share prices and market indices are reported company-wise.
	Time increment	All databases report with similar time increment like the country economy, economic sectors, and market development data are reported annually, while share prices and market indices are reported daily.
	Data Format	Local and regional databases provide all annual increment data in pdf reports while international databases provide in various formats including in visual graphics. Daily data provided by investing.com are in excel format while local databases are in pdf reports.
Documentation		All database accompanied data with respective variables
Timeliness		All database reports the recent data which are required for this study
Cost		The data related to share prices and market indices provided by all local, regional, and international databases are not for free except investing.com. Also, the data related to the country's economy, economic sectors, markets are not for free except for worldbank.org, statista.com which provide in visual graphics format.
Usage terms		There are terms of usage like time frame and purpose of usage for database which require subscriptions.

Selected Data Sources

Based on the evaluation shown in Table 3.2 the shortlisted data sources are investing.com for extracting share prices and market indices, WCs for audited financial statements, CMAs database for stock markets information, and world bank for the country economy, economic sectors, and T-bill's information are shortlisted. Investing.com is only required to open an account for them to provide access to downloading daily shares and market price data in excel format, for free, with standard formats in all markets and local currency. These facilities were not observed in any of the local, regional, and other international databases.

The problem of missing data which has been observed for some listed companies was resolved by excluding them from the list. Likewise, the data provided by CMAs and CWs are from published audited reports, they are freely available on the respective websites in all years as per this study requirement. None of the remaining databases offer the required data for all markets, in the specified time frame, in a single report. For the country's economy and economic sectors and T-bill data, the study opts worldbank.org over statista.com. Although both offer the required data in a specified timeframe and both reported in USD currency and visual graphics, yet data from statista.com are also extracted from the World Bank.

3.6.4 Data Extraction

The annual audited pdf reports from CMAs and CWs databases were downloaded. The selected statements like income statement, statement of financial position, and statement of cash flow were converted to excel using online2pdf.com and only the data required were recorded. The companies with complete information based on the market listed, sector, and nature of business are summarised as shown in appendix 1. Data from worldbank.org were manually recorded from visual graphs. Since the data were very few, only four data for the country economy and three data for economic sectors in each country for each year the level of accuracy was maintained. The data from investing.com were all extracted in excel format. As these data are a lot and they are generated daily, they require the highest level of accuracy. To get then in excel format was most reliable for this study as it helps to reduce unnecessary mistakes or errors.

3.7 Data Transformation

The process of improving the compatibility of data to match with underlying assumptions during the modeling process, linearize the relationships among variables, or modify the range of values of the variables is associated with data transformation (Jones, Evans, Lipson, TI-Nspire and Casio, 2008; Leydesdorff and Bensman, 2006). There are various methods used to transform data, the most common are square, logarithmic, and reciprocal transformation. The effect of transformation depends on the methods used. Square transformation stretches the value and changes negative to positive, while logarithmic and reciprocal transformation compresses the value. A recent study by Curran-Everett (2018) reported that log transformation helps the results better satisfy the assumptions of the model used.

About this study, some companies reported negative cash flow from operations, investment, and financial as well as net profit which become unfit when incorporating them in the DEA model. Likewise, there is higher variability between data of country economy (government spending, investment, public debt, and inflation), economic sectors (labor force, value-added and growth rate) as well as listed companies fundamental (equity, revenue, and assets). Both square and logarithmic transformation were used simultaneously to remove the negativity and compress the figures. Assuming the value before transformation is P and the result is Q, therefore for square transformation, $Q = P^2$ and for log transformation, $Q = \log P$. Unfortunately, for those companies with reported figure less than one million dollars were excluded to avoid negativity after transformation as always, the logarithm of figure less than 1 is the negative number. The illustrates the transformation of the fundamentals of the companies listed in EACMs is shown in appendix 2.

3.8 Managerial and Operational Performance Evaluation

This section explained the methodology used to attempt the research question 1 for this study.

Research Question 1: Which stocks can be selected among those listed on EACMs after evaluating the managerial and operational performance of company fundamentals, economic sector growth, development of the market listed, and economy of the country registered using DEA models?

CCR and BCC models in both orientations were used to evaluate the management and operational performance of country economy, market, economic sectors, and listed companies as shown in steps below.

Identification of Inputs and outputs of all DMUs

For input and output matrix, each raw represent one DMU and each column represent one constraint. The input of $j^{th} DMU$ is defined as $X = \{x_{1j},\ x_{2j} \dots, x_{ij}\}$, the output is defined as $Y = \{y_{1j},\ y_{2j} \dots, y_{rj}\}$ where $j \in \{1, n\}$. The proportional increase of outputs is (S_r^+) and proportional decrease of input is (S_i^-). The multiplier λ_j represent a combined inputs and output weights.

Computation of Overall Efficiency

The overall efficiency is denoted by θ_j, the objective function defined as f = [zeros(1,n) -epsilon*ones(1,s) -epsilon*ones(1,m) 1] subject to only equality constraints which Aeq and beq. The equality constraints of left hand matrix, Aeq = [Y', -eye(s,s), zeros(s,m+1); -X', zeros(m,s), -eye(m,m), X(j,:)'] and equality constraints of the righthand vector is beq = [Y(j,:)';zeros(m,1)]. To solve the optimization problem, the command z = linprog(f,[],[],Aeq,beq,lb) was used. Mathematically the model can be presented as shown in the equation 3.1

$$\min_{u,v} \theta - \varepsilon\left(\sum_{i=1}^{m} S_i^- + \sum_{r=1}^{s} S_r^+\right)$$

Subject to;

$$\left.\begin{aligned} &\sum_{j=1}^{n} x_{ij}\lambda_j + S_i^- = \theta x_{io} \quad or\ i = 1,2,\ldots m \\ &\sum_{j=1}^{n} y_{rj}\lambda_j - S_i^- = y_{io} \quad for\ r = 1,2,\ldots s \\ &\lambda_j \geq 0 \qquad for\ j = 1,2,\ldots n \\ &S_i^- \geq 0\ ; \quad S_r^+ \geq 0 \end{aligned}\right\} \tag{3.1}$$

Computation of Overall Effectiveness, ϑ_j

The overall effectiveness is represented by ϑ_j, the objective function defined as f = -[zeros(1,n), epsilon*ones(1,s+m), 1] subject to only equality constraints which are Aeq and beq. The equality constraints of left hand matrix, Aeq = [-Y', eye(s,s), zeros(s,m), Y(j,:)'; X', zeros(m,s), eye(m,m), zeros(m,1)] and equality constraints of the righthand vector is beq = [zeros(s,1);X(j,:)']. The optimization problem was solved using command z = linprog(f,[],[],Aeq,beq,lb). The model used shown in the equation 3.2

$$\max_{u,v} \vartheta_j + \varepsilon\left(\sum_{i=1}^{m} S_i^- + \sum_{r=1}^{s} S_r^+\right)$$

Subject to;

$$\begin{aligned}
&\sum_{j=1}^{n} x_{ij}\lambda_j + S_i^- = \vartheta x_{io} \quad or\ i = 1,2,\ldots m \\
&\sum_{j=1}^{n} y_{rj}\lambda_j - S_i^- = y_{io} \quad for\ r = 1,2,\ldots s \\
&\lambda_j \geq 0 \qquad for\ j = 1,2,\ldots n \\
&S_i^- \geq 0\ ; \quad S_r^+ \geq 0
\end{aligned} \tag{3.2}$$

Computation of Managerial Efficiency, φ_j

The management efficiency is defined as φ_j, the objective function for IO is defined as f = [zeros(1,n) -epsilon*ones(1,s+m) 1] subject to only equality constraints which are Aeq and beq. Where the Aeq = [Y', -eye(s,s), zeros(s,m+1); -X', zeros(m,s), -eye(m,m) X(j,:)'; ones(1,n), zeros(1,s), zeros(1,m+1)]; and beq = [Y(j,:)';zeros(m,1);1]. To solve optimization problem, the command z = linprog(f,[],[],Aeq,beq,lb). The algorithm developed based on the equation 3.3.

$$\min_{u,v} \varphi_j - \varepsilon\left(\sum_{i=1}^{m} S_i^- + \sum_{r=1}^{s} S_r^+\right)$$

Subject to;

$$\left.\begin{aligned}
&\sum_{j=1}^{n} x_{ij}\lambda_j + S_i^- = \varphi x_{io} \quad or\ i = 1,2,\ldots m \\
&\sum_{j=1}^{n} y_{rj}\lambda_j - S_i^- = y_{io} \quad for\ r = 1,2,\ldots s \\
&\sum_{j=1}^{n} \lambda_j = 1 \quad for\ j = 1,2,\ldots n \\
&\lambda_j \geq 0 \qquad for\ j = 1,2,\ldots n \\
&S_i^- \geq 0\ ; \quad S_r^+ \geq 0
\end{aligned}\right\} \tag{3.3}$$

Computation of Managerial Effectiveness, ϕ_j

The PTE under OO is denoted by $\emptyset_j$, the objective function is defined as f = -[zeros(1,n), epsilon*ones(1,s+m), 1] subject to equality constraints which are Aeq and beq. The equality constraints for left hand side, Aeq = [-Y', eye(s,s), zeros(s,m), Y(j,:)'; X', zeros(m,s), eye(m,m), zeros(m,1); ones(1,n), zeros(1,s+m+1)] and that of right hand side beq = [zeros(s,1);X(j,:)';1]. The optimum solution is obtained using the command z = linprog(f,[],[],Aeq,beq,lb). The equation 3.4 was used to develop the algorithm.

$$\min_{u,v} \phi_j + \varepsilon\left(\sum_{i=1}^{m} S_i^- + \sum_{r=1}^{s} S_r^+\right)$$

Subject to;

$$\left.\begin{array}{l} \displaystyle\sum_{j=1}^{n} x_{ij}\lambda_j + S_i^- = \phi x_{io} \quad or\ i = 1,2,\dots m \\ \displaystyle\sum_{j=1}^{n} y_{rj}\lambda_j - S_i^- = y_{io} \quad for\ r = 1,2,\dots s \\ \displaystyle\sum_{j=1}^{n} \lambda_j = 1 \quad for\ j = 1,2,\dots n \\ \lambda_j \geq 0 \qquad\qquad for\ j = 1,2,\dots n \\ S_i^- \geq 0\ ; \quad S_r^+ \geq 0 \end{array}\right\} \qquad (3.4)$$

Computation of Operational Efficiency, $\emptyset_j$

The operational efficiency which is represented by $\emptyset_j$ is formulated by dividing overall efficiency with management efficiency which are θ_j and φ_j respectively, as shown in the equation 3.5

$$\emptyset_j = \frac{\theta_j}{\varphi_j} \qquad (3.5)$$

Computation of Operational Effectiveness, ϱ_j

The operational effectiveness which is denoted by ϱ_j can be computed by dividing overall effectiveness with management effectiveness which are ϑ_j and ϕ_j respectively, as shown in the equation 3.6

$$\varrho_j \quad = \quad \frac{\vartheta_j}{\phi_j} \tag{3.6}$$

Computation of Managerial Performance, ξ_j

The Managerial performance which is denoted by ξ_j is computed by multiplying management efficiency φ_j and management effectiveness ϕ_j as shown in the equation 3.7

$$\xi_j \quad = \quad \varphi_j \times \phi_j \tag{3.7}$$

Computation of Operational Performance, ς_j

The Operational performance which is denoted by ς_j is computed by multiplying operational efficiency $\emptyset_j$ and operational effectiveness ϱ_j as shown in the equation 3.8

$$\xi_j \quad = \quad \emptyset_j \times \varrho_j \tag{3.8}$$

Combined Evaluation

The performance score of each component (economy, market, sector, and companies) were combined together. Four steps were involved during the combination process top-down approach

- The DMUs of the company analysis which are the listed companies were considered as the reference.
- The scores of each component were assigned in respect to listed company arranged column-wise.

- The component's matrix was developed with column of listed companies and rows of component's scores.
- The combined score of each DMUs is computed by summing up the scores of each component weighted by top-down ($w_e > w_m > w_s > w_c$). The basic assumptions of weight generation, $\sum_i w_i = 1$ and $w_i \geq 0$, where $i = 1,2 \ldots n$ were held. Therefore, the formulation of the combined score can be presented using the equation 3.9

$$S_T = w_e S_e + w_m S_m + w_s S_s + w_c S_c \qquad (3.9)$$

Whereas S_T is the combined score or total score, S_e is the economy score, S_m is the market score, S_s is the sector score and S_c is the company score.

Existing studies emphasised on either top-down or bottom-up approach (Navas, 2013; Grimn, 2012; Gregory-Allen, Shawky and Stangl, 2008) though, they oversight on incorporating them quantitatively.

3.9 Rationale Selecting Companies

The short-listed companies are those which are performed equally or above minimum average out of all four years in all three measures which are overall, managerial, and operational. The stated rationale was the reflation of the study Cooper et al. (2006): Sherman and Zhu (2006) who explained that the higher the ratio indicates the better the performance of the company. Likewise in the recent study of Curtis, Hanis, Kourtis and Kourtis (2020) highlighted that the company with highest relative performance can be considered under the group which ranked number 1 among the other companies in the pool.

3.10 Conversion of Non-stationery data to Stationery

This section explained the methodology used to attempt the research question 2 and research question as stated below.

Research question 2: Are there any variability of expected returns and risks of various portfolios constructed on selected stocks listed in EACMs using both MVCM– DEA and CAPM-DEA model?

Research question 3: What is the performance of the various portfolios constructed based on the selected stocks listed in EACMs evaluated using both Sharpe ratio and Treynor ratio?

The stationary data are those data where its statistical properties like mean, variance and covariance are not change over time. The graphs of stationery data are roughly horizontal, with constant variance and irregular pattern. Yang and Shahabi (2005) demonstrated that stationery data have characteristic of jumping away and returns to its mean and create irregular movement, if the data show some trend, it is definitely non-stationery. According to Baumöhl and Lyócsa (2009) the y_t referred as stationery when the value of mean $E(y_t)$, variance $V(y_t)$, and covariance $Cov(y_t, y_{t+n})$ between time t and $t + n$ depend only on the distance n (lag) between the two period and not definite time t. They also stressed that if the data have different statistical properties, it is refereed as non – stationery.

The study of Yang and Shahabi (2005) and Baumöhl and Lyócsa (2009) both reported that, it is difficult to proceed with analysis if the series are non-stationery and therefore advised to transform them to stationery. While Baumöhl and Lyócsa (2009) insisted that continuing to analyse non – stationary data will result to spurious regression, Yang and Shahabi (2005) explained that the trend in non-stationery data can be removed by taking the difference of $(y_t - y_{t-1})$. Which is simply can be expressed in mathematical form using the equation 3.10

$$\Delta y_t = y_t - y_{t-1} \tag{3.10}$$

Where Δy_t is called first difference or integration order one $I(1)$ which correspond to $n = 1$, for a series of non-stationary that has $n = 1, \dots p$, will have p differences or integration order p $I(p)$.

Baumöhl and Lyócsa (2009) insisted that before differencing is advised to take natural logarithm to avoid non – linear movement data as shown in equation 3.11

$$\Delta lny_t = lny_t - lny_{t-1} = ln\frac{y_{t-1}}{y_t} \tag{3.11}$$

The closing share price and market index are non – stationary, therefore, the same approach was used to transform the share closing share prices of selected companies and corresponding market indices. For this study, a total of 52 shares from all EACMs were evaluated and only 11 shares that are qualified were transformed to non-stationery. Appendix 3 presented 11 shares prices (top) which are non-stationery and 11 share returns (down) which are stationery used for portfolio construction.

3.11 Portfolio Construction

Mean Variance Covariance Model (MVCM) was used to construct various portfolio of various shares based on managerial and operational performance and Sharpe ratio was used to evaluate the constructed portfolio. The detail procedures were explained below.

3.11.1 Computation of Share returns

Geometric return formula shown in equation 3.12 was used to convert all share prices to returns. By using the command "r1 = price2ret (x (1: n, :))", the prices have converted to geometrical returns in MATLAB.

$$r \quad = \quad ln\frac{P_t}{P_{t-1}} \tag{3.12}$$

Where, P_t is the share price of second day, P_{t-1} is the share price of previous day and r is the daily share returns. The returns r_{ik} for shares $i = 1, \dots n$ in time $k = 1, \dots m$ will be presented in matrix form as follow;

$$r \quad = \quad \begin{bmatrix} r_{11} & \cdots & r_{1m} \\ \vdots & \ddots & \vdots \\ r_{n1} & \cdots & r_{nm} \end{bmatrix} \tag{3.13}$$

3.11.2 Computation of Mean Returns

The mean returns of shares, $\bar{r}$ was calculated by dividing the total equity returns, r_i with number of returns, n as shown in the equation 3.14. The command "xmean = mean(r1)" will be used to compute the mean returns of shares.

$$\bar{r} \quad = \quad \frac{1}{n} \sum_{i=1}^{n} r_i \tag{3.14}$$

3.11.3 Computation of Standard Deviation

The standard deviation, σ was be calculated by sum up the square of the differences between share returns with mean returns computed in equation 3.12 and 3.14 respectively, and divide them with total number of returns as shown in the equation

3.15 and the command “xsd = std(r1)” was used to compute the standard deviations of the mean returns.

$$\sigma \quad = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(r_i - \bar{r})^2} \tag{3.15}$$

3.11.4 Computation of Sharpe Ratio of Shares

The Sharpe ratio of shares, sr was calculated by dividing the difference between share mean returns and risk free returns, r_f with standard deviation of the share returns as shown in equation 3.16 and the command “shr1 = pr1/psd1” was used to compute the Sharpe ratio.

$$sr \quad = \quad \frac{\bar{r} - r_f}{\sigma} \tag{3.16}$$

3.11.5 Sorting of Share Sharpe Ratio

Sorting of Sharpe ratio in descending order means the company with higher Sharpe ratio at the top and lower company at the bottom. The list of Sharpe ratio arranged in descending order with the corresponding index (xin) was developed. by writing the command “[xsr xin] = sort(xmean(1:m-1). / xsd(1:m-1), 'descend')”.

3.11.6 Sorting of Share Returns

The returns of data loaded were random with index number (xin) from 1 to n. Sorting was conducted based on Sharpe ratio. the returns with higher Sharpe were at the top and that will lower wer at the bottom. The command “r2 = r1(:, xin)” was used to sort them. The sorted returns matrix also was developed by writing the command “ [ro co] = size(r2)”.

3.11.7 Sorting of Share Mean Returns

The mean returns of shares were sorted based on Sharpe ratio, the shares mean returns correspond to higher Sharpe ratio were at the top and the those correspond to lower Sharpe ratio were at the bottom. The command "xmean = xmean(:, xin)" was used to sort them.

3.11.8 Sorting of Standard Deviation of Share Mean Returns

The standard deviation of share mean returns were also sorted based on Sharpe ratio, the standard deviation that produce higher Sharpe ratio were at the top and the standard deviation that have low Sharpe ratio were at the bottom. The command "xsd = xsd(:, xin)" were used to sort them.

3.11.9 Weight Generation and Sorting

The weights of shares were generated by taking the proportion of index to the total number of index of the sorted returns matrix using the command "wi= linspace (i,1, i)". and the weight vector was developed in equation 3.17

$$w_i = [w_1 \quad \cdots \quad w_n] \tag{3.17}$$

3.11.10 Computation of Portfolio Mean Returns

The mean returns of portfolio, $\bar{r}_p$ were calculated multiplying the matrix of share mean returns with weight matrix as shown in equation 3.18.

$$\bar{r}_p = \sum_{i=1}^{n} w_i \bar{r}_i \tag{3.15}$$

the command “pr1 = xmean (1: i) * w'”. this imply that the mean returns were multiplied to inverse matrix which is w^{-1} as shown in 3.16

$$\bar{r}_p = \begin{bmatrix} w_1 \\ \cdot \\ \cdot \\ \cdot \\ w_n \end{bmatrix} \times [\bar{r}_i \quad \dots \quad \bar{r}_i] \tag{3.18}$$

3.11.11 Computation of Standard Deviation of Portfolio Mean Returns

The Standard deviation of the portfolio, σ_p^2 was calculated using equation 3.19. To incorporate the formula in the MATLAB the following steps were follows;

$$\sigma_p^2 = \sum_{i=1}^{n} \sum_{j=1}^{n} \sigma_i \sigma_j w_i \, w_j \, \rho_{i,j} \tag{3.19}$$

Firstly, the covariance matrix, xco for the returns was computed using the command “xco = cov (r2(:1: i)) as shown in equation 3.20

$$xco = \begin{bmatrix} \rho_{11} & \cdots & \rho_{1m} \\ \vdots & \ddots & \vdots \\ \rho_{n1} & \cdots & \rho_{nm} \end{bmatrix} \tag{3.20}$$

Secondly, the weighted Covariance have computed, the matrix 3.18 was multiplied with weight vector 3.17 as presented in the equation 3.21. The command “t1 = xco. *w1. *w2” was used.

$$t1 = \begin{bmatrix} \rho_{11} & \cdots & \rho_{1m} \\ \vdots & \ddots & \vdots \\ \rho_{n1} & \cdots & \rho_{nm} \end{bmatrix} \times [w_1 \quad \dots \quad w_n] \tag{3.21}$$

Thirdly, both weighted covariance and covariance were added together and standard deviation was computed by taking the square root of the summation using the command “psd1 = sqrt(t3)”.

3.11.12 Computation of Portfolio Sharpe Ratio

The portfolio Sharpe ratio, sr_p was computed by dividing the difference of the portfolio returns (equation 3.18) and risk-free returns with portfolio standard deviation (equation 3.19) as shown in the equation 3.21. The command “shr1 = (pr1-rf)/psd1” will be used for computation.

$$sr_p = \frac{\bar{r}_p - r_f}{\sigma_p} \tag{3.21}$$

3.12 CAPM Portfolio Construction

3.12.1 Risk Free Returns

The risk-free rate was identified by taking the annual lending rate issued by the central bank and converted them to daily since the share returns are daily. The command “rf = lr/365” will be used.

3.12.2 Computation of Market Mean Returns

The mean market returns, $\bar{r}_m$ was calculated through the returns of market index, r_m using the equation 3.22. The command “rm = mean (r (: end))” was used to compute the market mean returns.

$$\bar{r}_m = \frac{1}{n}\sum_{i=1}^{n} r_m \tag{3.22}$$

3.12.3 The Computation of Share's Beta

The share beta, β_i is computed as a regression coefficient between market returns and shares returns. Also, equation 3.23 can be used to compute the share beta. The command "beta = regress (r1, [ones(n,1) r (1: n, end)])" was be used to compute them.

$$\beta_i \quad = \quad \frac{\rho m,i}{\sigma_m^2} \tag{3.23}$$

Where $\rho m, i$ is the Covariance of Share i and market index and σ_m^2 is the variance of market index. The vector of share's beta from $i = 1, \dots n$, will be formed as shown in 3.24.

$$\beta_i = [\beta_1 \quad \cdots \quad \beta_n] \tag{3.24}$$

3.12.4 The computation of Mean Returns of Share

The mean returns of shares $\bar{r}_i$ will be calculated using equation 3.25. similar equation will be composed in MATLAB using command "RR= (rf + beta (2) *(rm - rf))"

$$\bar{r}_i = r_f + \beta_i(\bar{r}_m - r_f) \tag{3.25}$$

The share mean returns vector for $i = 1, 2 \dots . n$, will be formed as presented in equation 3.26

$$\bar{r}_i = [\bar{r}_1 \quad \cdots \quad \bar{r}_n] \tag{3.26}$$

3.12.5 The Computation of Share Treynor's Ratio

The Treynor's ratio, tr was calculated by dividing the difference of share returns and risk free returns with share beta as shown in equation 3.27. the command "itr = xrr. / bt" was used to calculate the share Treynor's ratio in MATLAB.

$$tr = \frac{\bar{r}_i - r_f}{\beta_i} \tag{3.27}$$

3.12.6 Sorting of Share Treynor's Ratio

Sorting the shares Treynor's ratio was in descending order, the shares with higher Treynor's ratio were at the top and lower Treynor's ratio were at the bottom. The sorting command "[itr xin] = sort(itr,'descend')" was used.

3.12.7 Sorting of Mean Returns of Shares

Share mean returns were sorted based on Treynor's ratio, the share mean returns that produce higher Treynor's ratio were at the top and those produce lower Treynor's ratio were at the bottom. The command " xrr = xrr(:, xin)" was used for sorting.

3.12.8 Sorting of Share's Beta

The share's beta with correspond to higher Treynor's ratio were listed at the top and those betas which correspond to lower Treynor's ratio were listed at the bottom. The command "bt = bt(:, xin) was used to arrange beta.

3.12.9 Weight Generation and Sorting

Similar method used in Markowitz portfolio for weight generation and sorting was used in CAPM, the same command was used and the same results of weight matrix as shown 3.6 was obtained.

3.12.10 Computation of Portfolio Beta

The portfolio beta β_p was calculated by multiplying the beta vector (equation 3.24) with weight transpose vector (equation 3.17) as shown in the equation 3.28. The command "pb1 = bt (1: j) *w' was used for computation.

$$\beta_p = \begin{bmatrix} w_1 \\ \cdot \\ \cdot \\ \cdot \\ w_n \end{bmatrix} \times [\beta_1 \quad \dots \quad \beta_n] \tag{3.28}$$

3.12.11 Computation of Portfolio Mean Returns

The portfolio mean returns, $\bar{r}_p$ was calculated by multiplying the share mean returns vector (equation 3.26) with weight transpose vector (equation 3.17) as shown 3.29. the command "pr1 = xrr (1: j) *w'" was used for computation.

$$\bar{r}_p = \begin{bmatrix} w_1 \\ \cdot \\ \cdot \\ \cdot \\ w_n \end{bmatrix} \times [\bar{r}_1 \quad \dots \quad \bar{r}_n] \tag{3.29}$$

3.12.12 Computation Portfolio Treynor's Ratio

The portfolio Treynor ratio, tr_p was computed by dividing the difference between portfolio mean returns and risk-free returns with portfolio beta as shown in equation

3.30. The portfolio returns computed in the equation 3.29 and portfolio beta computed in the equation 3.28. The command “ter1 = pr1/pb1” was applied for computation.

$$tr_p \quad = \quad \frac{\bar{r}_p \; - \; r_f}{\beta_p} \tag{3.30}$$

3.13 Computation of Portfolio Optimization

This section presents the methodology used to attempt the research question 4 of this study which sate that.

Research question 4: Which are the preferred portfolios among the portfolio constructed by the selected stocks listed in EACMs when multi-objective optimization approach was used?

Multi-objective optimization approach was applied to compute optimal portfolios for both domestics and international. The approach was tested in both MVCM-DEA and CAPM-DEA as shown below.

MVCM-DEA

When MVCM-DEA model was used, the optimal portfolio was computed with the objective of minimizing variance or standard deviation and maximizing mean return subject to required portfolio Sharpe ratio is attained, total of weight equal to 1 and the weight assigned in each share must be greater than or equal to 0. The linear programming model is as follows.

$$\left.\begin{array}{l} Min\sigma_p^2 \quad and\ Max\bar{r}_p \\ \quad \text{Subject to;} \\ \quad \sum_{i=1}^{n} w_i = 1 \\ \quad\quad w_i \geq \ 0 \quad and\ i = 1, \ldots n \\ \left(\frac{\bar{r}_p - r_f}{\sigma_p}\right) \geq \ \alpha \end{array}\right\} \tag{3.31}$$

The investor required Sharpe ratio α as shown in constraint was assigned the command " shrp >= α" incorporated in a while loop. The random weight was generated and number of iterations will be running to find the required Sharpe ratio.

CAPM-DEA

The optimal portfolio was determined with the objective of maximizing portfolio beta and portfolio returns subject to required Treynor's ratio is attained, sum total of weight equal to 1 and the weight assigned in each share must be greater than or equal to 0. The linear programming model is as follow;

$$\left.\begin{array}{ll} \text{Maximize} & \beta_P \ and\ \bar{r}_p \\ & \quad \text{Subject to;} \\ & \quad \sum_{i=1}^{n} w_i = 1 \\ & w_i \geq 0 \quad and\ i = 1, \ldots n \\ & \left(\frac{\bar{r}_p - r_f}{\beta_p}\right) \geq \ \omega \end{array}\right\} \tag{3.32}$$

The investor required Treynor's ratio ω was assigned the command " trr >= ω incorporated in a *while loop*. The random weight was generated, and number of iterations run to find the required Treynor ratio.

3.14 Stress Testing

This section presents the methodology used to answer the research question 5 of this study as stated below.

Research Question 4: What are the patterns, behaviours and directions of the various portfolios constructed will have during good times and extreme conditions?

The stress testing was conducted according to state of economy. There are three states of economy considered which are worst, poor, and good which is also referred as the current state. The weights were allocated based on the state of economy and the portfolios were constructed. Both good and poor, the weights were generated by taking the proportion of average of the index numbers generated during sorting the shares using the MATLAB command “bi= linspace (1, i, i); w = bi. / sum(bi);”.The fund will be allocated based on the share returns. In good state, more funds were allocated in best shares than bad shares while in poor state the allocation was vice-versa. Contrary to worst state where the random weights were generated using MATLAB command “bi= randn (1, i); w = bi. / sum(bi)“and allocated them randomly.

3.15 Hypothesis Testing

Hypothesis testing is the method used to determine the probability of occurrence of an observed event (Allua and Thomson, 2013). It involves deducing the consequences that should be observed if the hypothesis is correct (Mourogugan and Sethuraman, 2017). It is used to decide on whether a data sample is typical or atypical compared to a population (Emmert-Streib and Dehmer, 2019). One of two types of error may occur while concluding hypothesis testing results. It can be either concluded that there is difference between the groups while actual there is no which is called type one error (α) or conclude that there no difference between group while there is which is known as type two error (β) (Allua and Thomson, 2013). Table 3.3 shows the truth and possible decision that the researcher may make.

Table 3.3: Type I and Type II Error

		Truth	
		H_0	H_1
Decision	H_0 (Accept H_0)	Correct (1- $\alpha = p$)	Type I ($\beta = p$)
	H_1 (Reject H_0)	Type II ($\alpha = p$)	Correct (1- $\beta = p$)

Any of the two errors can happen while doing the research, yet researcher aims is to minimize α or β. It is required to state the significant level to accept α or β otherwise the decision of accepting or rejecting H_0 will be far from reality, the benchmark of α or β is selected among 0.05 or 0.01 (Allua and Thomson, 2013). It can be observed from the Table 3.3 that the H_0 can be accepted on when $p = 1 - \alpha$ and rejected when $p = 1 - \beta$.

The computation of p-value is based on sampling distribution which is a probability distribution and estimated test statistics t_n (Emmert-Streib and Dehmer, 2019). The p-value is the sum of cumulative probability of t-value from negative infinity to $-t_n$ and from positive infinity to $+t_n$. If the calculation involves both ends is called two tailed test and when involve on one end is called one tail. One tail testing is used for directional hypothesis otherwise two tail is used. Test statistics are broadly classified into two main categories which are parametric and non-parametric test (Niroumand, Zain and Jamil, 2013; Ruxton and Neuha¨user, 2010).

While non-parametric is distribution free, the parametric test is subjected to the assumption of normal distributed sample, independent and equal variance. Most common parametric test are t-test and Analysis of Variance (ANOVA) and non-parametric are Wilcoxon test, Mann-Whitney test, and Kruskal-Wallis test. Since the data use in this study are characterised by the basic assumption of parametric test, that is, $X_i \sim N(\mu, \sigma)$, therefore t-test and ANOVA were used. More specifically, t -test is classified as independent sample t-test, dependent sample-test and one sample t-test. All of them compare the mean difference of the two group, independent sample t-test compare two group which are unrelated, dependent sample t-test compare the groups which are related and one sample t-test compare group with predefined mean (Gerald, 2019).

Likewise, ANOVA can be classified into one way, two way and highway ANOVA. When the groups are compared based on one factor is called one way ANOVA, when groups are compared two factors is referred as two way ANOVA and when the groups are compared by more than two factors the analysis called higher way ANOVA. Some of the hypothesis developed in this study compares the mean deference of two groups which are unrelated, therefore the independent t-test was used. Also, some of the hypothesis compare more than two groups based on single factor, therefore one way ANOVA was used. The details of these statistical tests are explained below.

3.15.1The Independent Sample t Test

This test is used when the mean of one group does not depend on the mean of another group. This means that if any value selected from one group does not affect the mean of the other group (Gerald, 2019). The significance of this test is to determine whether the value of these two groups generated from the same population. It aims to test the significant mean difference between two groups e.g between Sharpe ratio and Treynor ratio, standard deviation and beta, total returns and risk-adjusted returns, etc. The test can be computed by taking the ratio of mean difference and standard error of the mean difference.

3.15.2 One Way ANOVA

This statistical test is an advanced version of the t-test used to measure the difference by assessing the variance that exists when there are more than two groups are related. It compares the relative size of variance size among groups mean to the average size of variance within groups (Kim, 2014). It is simply the ratio of between-groups variance to within groups variance. This test aims to examine the existence of a significant difference between the groups which are compared, e.g this study compares the mean difference between three states of the economy which are good, poor and worst in term of portfolio mean returns, volatility, and sensitivity. In this study, both tests were conducted using excel solver.

For the independent sample t-test, the data was transferred into excel and the independent t-test was conducted to test whether there is a significant mean difference between the two samples. From the Data Analysis function available in Excel, the "t-Test: Two-Sample Assuming Equal Variances" was selected and both the range M_1 and range M_2 of data was selected and labelled. The 0.05 significant level was selected, and the table of output was generated and analysed. For one way ANOVA which was conducted to measure the significant mean deference which are exist between three states of economy. Single factor ANOVA was selected from Data Analysis function available in excel, all the data transferred in excel was selected together and labelled. The 0.05 level of significant was assigned and table of outputs was generated for analysis.

3.16 Data Analysis Process Flow

Figure 3.4 show the process flow of data analysis, it combines the DEA model and risk-returns framework

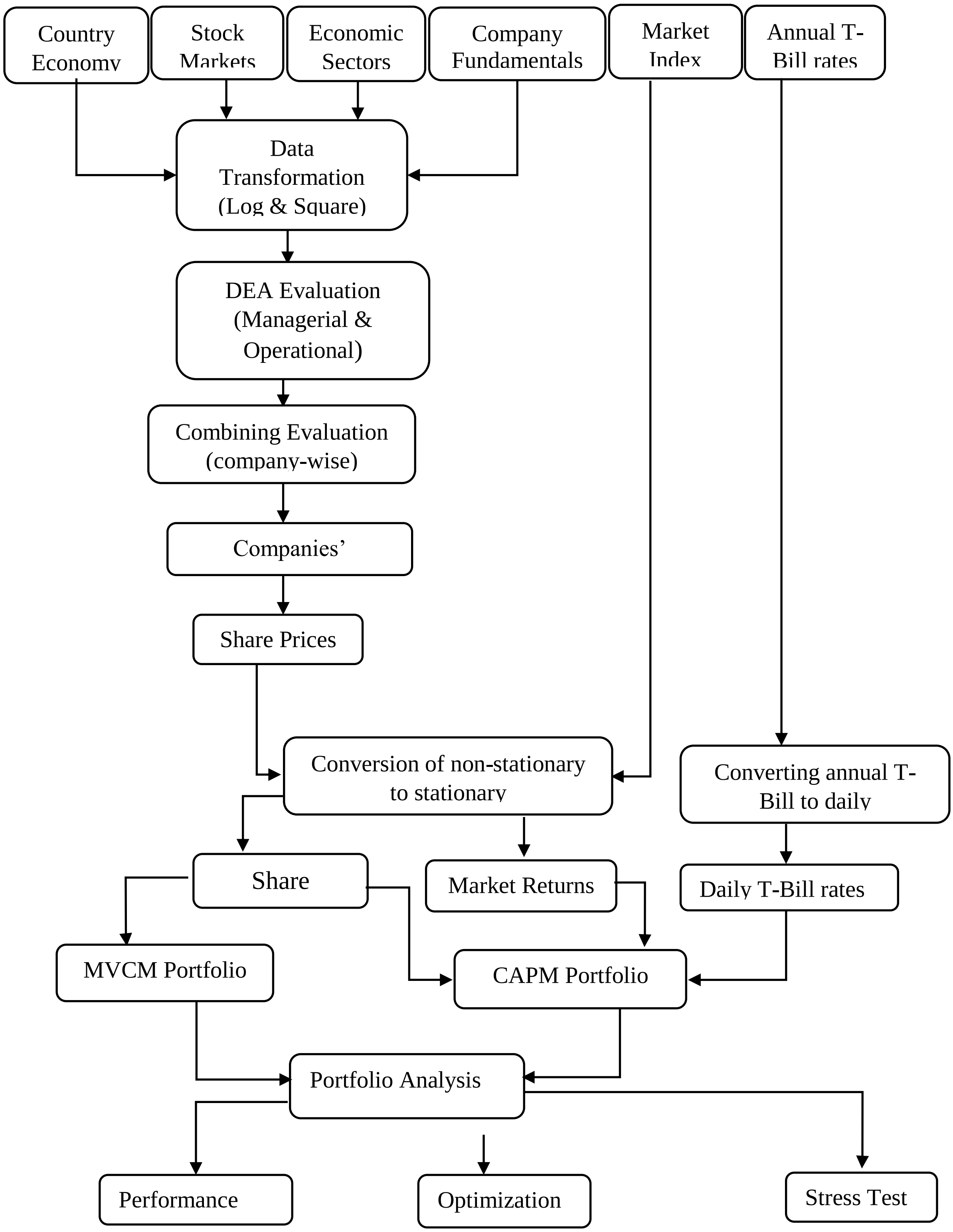


Figure 3.4: Data Analysis Process Flow

3.17 Summary

This chapter provided the overall process and procedures for the collection and analysis of the data. The validity and reliability of the sources which provide data related to economic, market, economic sectors, and companies listed in EACMs were evaluated based on accuracy, relevancy, documentation, currency, and timeliness, cost usage terms as well. Non-linear data were transformed using square and natural logarithm, also non-stationary time series data were converted to stationary to avoid spurious results. The study adopts a non-parametric DEA method to assess the performance stocks listed in EACMs which are further incorporated with MVCM and CAPM to construct various portfolios. MATLAB algorithms used for analysis were presented step wise in each part of analysis from stock selection, portfolio construction, optimization, and stress testing.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Introduction

This chapter presents and discusses the results of the data analysed based on thematic areas which are in line with the study objectives and hypotheses. The outputs of DEA for the country economy, stock market, economic sectors, and listed companies of EACMs as well as the combination of all four components which lead to share selection. Portfolio construction of selected shares based on MVCM and CAPM also, the portfolio performance is measured by the Shape ratio and Treynor ratio. Portfolio optimization is based on the required Sharpe ratio and Treynor ratio as a constraint of the objective functions. Stress testing is based on different states of the economy which are current, poor, and worst states. The results were presented in figures and table with detail textual presentation.

4.2 Analysis of Managerial and Operational Performance of Fundamental Components

This section presented the results and discussion related to research question one which is also correspond to hypothesis one of this study as stated below.

Research question 1: Which stocks can be selected among those listed on EACMs after evaluating the managerial and operational performance of company fundamentals, economic sector growth, development of the market listed, and economy of the country registered using DEA models?

Hypothesis 1: There is no significant difference in the performance of the companies before and after combining with the performance of other components which are country economy, stock markets, and economic sectors.

4.2.1 Degree of development Country Economy

Table 4.1 presents the managerial, operational, and overall performance of the four countries under EAC which are Kenya, Tanzania, Uganda, and Rwanda from 2015 to 2018.

Table 4.1: Development Degree of EAC States

Year	Country	Performance		
		Overall	Managerial	Operational
2015	Kenya	1.00	1.00	1.00
	Tanzania	1.00	1.00	1.00
	Uganda	0.98	1.00	0.98
	Rwanda	0.32	0.54	0.60
2016	Kenya	1.00	1.00	1.00
	Tanzania	1.00	1.00	1.00
	Uganda	1.00	1.00	1.00
	Rwanda	1.00	1.00	1.00
2017	Kenya	1.00	1.00	1.00
	Tanzania	1.00	1.00	1.00
	Uganda	0.92	1.00	0.92
	Rwanda	1.00	1.00	1.00
2018	Kenya	1.00	1.00	1.00
	Tanzania	1.00	1.00	1.00
	Uganda	0.85	0.90	0.95
	Rwanda	0.46	0.64	0.72

Generally, the development degree of the country's economy among EAC members is inconsistent. The results from Table 4.1 show that Kenya and Tanzania are fully performed in all three measures with a score of 1 which corresponded to 100 performances. This signified that the government of Kenya and Tanzania have enough capability of managing and identifying ideal expenditures and investments to maintain the required rate of inflation and balance of the public debt. This builds confidence in existing and prospective investors both within and outside these countries while making an investment decision. The full performance of Kenya was associated with the huge investment of China-Kenya's Nairobi-Mombasa railway, which was completed in 2016, although the consequence was expected on public debt. Contrary to Tanzania, the full performance was associated with strengthening domestic resource mobilization via enhancing tax administration and collection (United Nations Economic Commission for Africa, 2018). While the performance of the other two countries which are Uganda and Rwanda fluctuated throughout 2015-2018. Comparatively, Uganda records higher managerial performance all the time equivalent to 100 percent, 100 percent, 100 percent, and 90 percent while Rwanda reports 54 percent, 100 percent, 100 percent, and 64 percent from 2015 to 2018 respectively. Likewise, Uganda accounts for higher operational performance for the years 2015 and 2018 equivalent to 98 percent and 95 percent respectively compared to Rwanda which was 60 percent and 72 percent respectively. Generally, Uganda and Rwanda were suffered from the managerial and operational capability of recognizing the optimal level of government expenditure and investment to minimize inflation and public debt.

Only during the year 2017 found Uganda is lagging Rwanda with an operational performance of 92 percent while Rwanda was 100 percent. This was the continuation of operational transformation for Rwanda which started in 2016 which is also recorded 100 percent operational performance. Various tax reforms including enhancing tax collection, avoid tax evasion, and increase the efficiency of public spending are among the reasons which are associated with considerable performance. ADB report (2018) addressed that 65 percent of Rwanda's' 2016 budget was funded by the domestic tax, non-tax revenue, and domestic financing. Correspondingly, government expenditure reported hitting 12.9 percent which is the second after Tanzania which record 15.8 percent.

4.2.2 EACMs Performance Trends

Four EACMs which are NSE, DSE, USE, and RSE were evaluated from 2015 to 2018 and the performance score was summarised in Table 4.2.

Table 4.2: East African Capital Markets Development

Year	Country	Performance		
		Overall	Managerial	Operational
2015	NSE	0.51	1.00	0.51
	DSE	1.00	1.00	1.00
	USE	0.52	0.79	0.65
	RSE	0.33	1.00	0.33
2016	NSE	1.00	1.00	1.00
	DSE	1.00	1.00	1.00
	USE	0.55	0.97	0.56
	RSE	0.29	1.00	0.29
2017	NSE	1.00	1.00	1.00
	DSE	1.00	1.00	1.00
	USE	0.59	0.84	0.71
	RSE	0.24	1.00	0.24
2018	NSE	1.00	1.00	1.00
	DSE	1.00	1.00	1.00
	USE	0.79	1.00	0.79
	RSE	0.28	1.00	0.28

The results in Table 4.2 show that only DSE record full performance in all measures throughout from 2015 to 2018 while NSE record full performance for the last three year from 2016 to 2018 and the year 2015 only management records full performance, other measures like overall and operational both performed only for 51 percent. USE performance of all measures was bumpy throughout while in RSE at least management was fully performed from 2015 to 2018 and other measures were varied from time to time. An interesting observation was found in 2018 where all four stock exchanges record 100 percent management performance. This show that, the management of DSE and NSE can manage and detect the optimal number of listed companies and market capitalization required to meet the required level of stock turnover and market returns.

Contrary to USE where both management and operation were unable to achieve and spot the ideal volume of listed companies and a market capitalization that can generate the required market turnover and returns. Except for DSE, the overall performance of EACMs is not impressive, although management of individual stock exchanges shows exemplary performance yet the operationally not convincing investors to make an immediate decision. The findings are in line with the study of Biau (2018) reported that the individual markets are very small with few numbers of listed shares also illiquid with small market capitalization. It was further suggested to speed-up the EACMs integration process solve the existing problem. Likewise, Bright Africa (2018) insisted that asset allocation within the region is dominated by fixed income allocations mostly local bonds, alternative investment opportunities are still very limited. Similarly, the performance of EACMs also associated with high requirements and cost associated with new entrants, lack of investors' confidence and risk appetite, weak local currencies, policies are changed drastically (Raubenheimer, 2018).

4.2.3 Economic Sectors Growth

Overall, the management and operational performances of agriculture, industry, and service sector in each country from 2015 to 2018 are summarised in Table 4.3. The results indicate that only the industry sector in Tanzania records 100 percent performance overall, managerial, and operational throughout from 2015 to 2018. While Uganda and Rwanda both records 100 percent managerial performance in the service sector for the last three years from 2016 to 2018. Surprisingly, no sector in Kenya which is fully performed in any measure, only the industry sector reports a considerable score where maximum overall performance is 43 during 2015 while managerial and operational performance hit a maximum of 66 percent and 67 performances during 2015 and 2016 respectively. Although more than half of the total workforce is employed in the agricultural sector, the efficiency and productivity of labor forces on increasing the country's GDP and promoting the growth of the sector are unsatisfactory. At least Kenya the agricultural sector performance reaches 3 percent, the rest of the countries are within one percent.

Weak infrastructure, such as transportation networks, access to energy, irrigation system, and stock holding facilities are the main setbacks that slowdown agricultural sector performance (OECD/FAO, 2016; African capacity-building foundation, 2017, AfDB, 2019).

Generally, the industry and services sectors are the most promising sectors in the region in recent years. Apart from structural change which made most of the skilled labor forces shift from the agricultural sector to industry and service sectors, most of the country within the region fails to reach an optimal level, especially in the industrial sector. The exemplary performance of the industry sector in Tanzania was associated with new government policies which are among them is to make Tanzania as an industrialized country

Table 4.3: Economic Sectors Performance from 2015 to 2018 for EAC member states

Date	Country	Economic Sector	Overall Performance	Managerial Performance	Operational Performance
2015	Kenya	Agriculture	0.02	0.11	0.17
		Industry	0.43	0.66	0.66
		Service	0.13	0.59	0.22
	Tanzania	Agriculture	0.01	0.07	0.17
		Industry	1.00	1.00	1.00
		Service	0.17	0.55	0.32
	Uganda	Agriculture	0.01	0.04	0.18
		Industry	0.55	0.59	0.93
		Service	0.35	0.59	0.59
	Rwanda	Agriculture	0.01	0.08	0.16
		Industry	0.51	0.64	0.79
		Service	0.28	0.53	0.53
2016	Kenya	Agriculture	0.02	0.13	0.16
		Industry	0.40	0.60	0.67
		Service	0.12	0.56	0.22
	Tanzania	Agriculture	0.01	0.08	0.15
		Industry	1.00	1.00	1.00
		Service	0.16	0.56	0.29
	Uganda	Agriculture	0.01	0.05	0.17
		Industry	0.58	0.73	0.79
		Service	0.34	1.00	0.34
	Rwanda	Agriculture	0.01	0.09	0.15
		Industry	0.27	0.48	0.58
		Service	0.27	1.00	0.27

Table 4.3 Continue…

Date	Country	Economic Sector	Overall Performance	Managerial Performance	Operational Performance
2017	Kenya	Agriculture	0.03	0.17	0.16
		Industry	0.37	0.59	0.64
		Service	0.11	0.47	0.23
	Tanzania	Agriculture	0.01	0.10	0.14
		Industry	1.00	1.00	1.00
		Service	0.16	0.48	0.33
	Uganda	Agriculture	0.01	0.05	0.18
		Industry	0.58	0.75	0.78
		Service	0.35	1.00	0.35
	Rwanda	Agriculture	0.02	0.13	0.13
		Industry	0.25	0.46	0.55
		Service	0.27	1.00	0.27
2018	Kenya	Agriculture	0.03	0.21	0.15
		Industry	0.33	0.56	0.59
		Service	0.11	0.47	0.22
	Tanzania	Agriculture	0.01	0.09	0.16
		Industry	1.00	1.00	1.00
		Service	0.16	0.51	0.31
	Uganda	Agriculture	0.01	0.05	0.16
		Industry	0.51	0.70	0.73
		Service	0.34	1.00	0.34
	Rwanda	Agriculture	0.01	0.08	0.16
		Industry	0.44	0.66	0.66
		Service	0.27	1.00	0.27

Contrary to the finding of Page (2016) who reported that the rising star of Tanzania on economic growth is not reflected in industrial sectors as far as an international benchmark is concerned. However, when African economies are considered as a benchmark, the industry sector in Tanzania is growing faster than the economy as a whole. It was insisted that Tanzania records the most rapid growth in manufactured exports compare to other EAC member states. The main reasons are the growth in formal manufacturing has been above the average rate of economic growth, although not as rapid as a services business. Also, a large number of micro and small enterprises have entered manufacturing since 2005.

4.2.4 Listed Companies Performance

The results presented in Table 4.4 show the performance score of the listed companies in different measures from 2015 to 2018. Generally, the listed companies have a different level of performance when either evaluated in overall, managerial or operational capacity. Five companies which are BAT, FTGH, KQ, SCOM, and BOBU records 100 percent overall, managerial, and operational performance in all four years consecutively. Only MSC maintains full performance for three years consecutively from 2015 to 2017 in all performance measures while TPCC maintains for two years which are 2017 and 2018. Out of 13 companies that were fully performed in the year 2015 alone, most of them were underperformed for the rest of the years. The performance scores of the rest of the companies were not predictable. however, some were sported with full managerial performance. Astonishing capabilities listed companies within the region to manage and optimize the shareholders' funds, company's assets, and investments to generate the required revenue, profits as well cash required for operation and financing activities are associated with a foreign professional which hold the highest management position in most of the listed companies. This was also observed by Jumanne (2018) when compared the performance between foreign and local owned companies and it was revealed that there is a significant difference in performance between these two categories.

Although the listed companies are working hard to safeguards shareholders interest, other scholars pinpoint the challenges which are beyond to company's management. Ndiritu and Mugivane (2015) addressed various factors that lead to the poor performance of the listing companies in the region including institutional factors, environmental factors, regulatory factors, historical factors, and information factors. Generally, all the factors were associated with the stock market and country economic development proxies. It was stressed that there is a lack of well-trained professionals in the market and the interest rate yield is always high and unstable in all countries within the region. Investors considered the deposit rate is too low and the landing rate is too high, this is directly discouraged both domestic saving and investment. It is worth noted that all the countries within the region share a common problem for years. Since the study of Onyuma, Mugo, and Karuiya (2012) addressed that the cross-listing within EACMs was not helpful to boost listed companies' performance. Low improvements in firm performance in term of liquidity and profitability have been observed which were also not significant.

Table 4.4: Performance of various listed companies From 2015 to 2018

	2018			2017			2016			2015		
Shares	Overall	Mgt	Opt	Overall	Mgt	Opt	Overall	Mgt	Opt	Overall	Mgt	Opt
BAMB	0.53	0.58	0.91	0.66	0.71	0.92	0.75	0.87	0.86	0.79	0.86	0.92
BAT	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
BERG	0.99	1.00	0.99	0.82	0.85	0.97	0.89	1.00	0.89	1.00	1.00	1.00
BOC	0.78	1.00	0.78	0.31	0.48	0.64	0.31	0.46	0.68	0.33	0.42	0.79
BRIT	0.50	0.55	0.92	0.57	0.58	0.97	0.57	0.61	0.93	0.56	0.57	0.97
CFC	0.97	1.00	0.97	0.47	0.56	0.83	0.66	0.76	0.86	1.00	1.00	1.00
CIC	0.66	0.69	0.96	0.57	0.59	0.97	0.60	0.66	0.91	0.59	0.60	0.99
COOP	0.78	0.84	0.93	0.48	0.65	0.75	0.63	0.76	0.82	0.71	0.78	0.91
DTK	0.90	1.00	0.90	0.43	0.57	0.76	0.63	0.71	0.88	0.82	1.00	0.82
FTGH	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
HFCK	1.00	1.00	1.00	0.52	0.56	0.93	0.62	0.64	0.97	0.75	0.77	0.98
I&M	0.55	0.87	0.63	0.53	0.61	0.88	0.58	0.68	0.86	1.00	1.00	1.00
JUB	0.34	0.37	0.91	0.54	0.57	0.94	0.54	0.63	0.86	0.55	0.59	0.92
KCB	0.57	1.00	0.57	0.42	0.64	0.66	0.64	0.86	0.75	0.62	0.80	0.77
KNRE	0.89	0.97	0.92	0.50	0.53	0.95	0.56	0.58	0.95	0.55	0.59	0.94
KUKZ	0.45	0.51	0.89	0.45	0.60	0.74	0.46	0.56	0.82	0.52	0.57	0.92
NIC	0.59	0.62	0.96	0.45	0.57	0.79	0.60	0.72	0.83	0.81	0.82	0.99
NMG	0.90	0.94	0.96	0.50	0.58	0.87	0.77	0.78	0.99	0.83	0.84	0.99
SCAN	0.70	0.72	0.97	0.75	0.78	0.96	0.78	0.89	0.87	0.53	0.69	0.78
SGL	0.62	0.67	0.92	0.69	0.70	0.98	0.72	0.74	0.97	0.71	0.75	0.94
TCL	0.55	0.61	0.89	0.54	0.56	0.96	0.58	0.66	0.88	0.88	0.89	0.98
TOTL	1.00	1.00	1.00	0.88	1.00	0.88	0.89	1.00	0.89	1.00	1.00	1.00
TPSE	0.42	0.45	0.93	0.45	0.53	0.85	0.46	0.52	0.88	0.38	0.42	0.90
EQTY	0.74	0.81	0.92	0.79	1.01	0.78	0.92	1.00	0.92	1.00	1.00	1.00
KEGN	0.96	1.00	0.96	0.45	0.54	0.83	0.63	0.72	0.87	0.91	1.00	0.91
KPLC	1.00	1.00	1.00	0.67	0.77	0.88	0.70	1.00	0.70	0.92	1.00	0.92

Table 4.4 Continue

	2018			2017			2016			2015		
Shares	Overall	Mgt	Opt	Overall	Mgt	Opt	Overall	Mgt	Opt	Overall	Mgt	Opt
MSC	0.80	0.82	0.98	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
PORT	1.00	1.00	1.00	0.45	0.50	0.89	0.71	0.73	0.97	1.00	1.00	1.00
UNGA	1.00	1.00	1.00	0.85	0.87	0.98	0.79	0.88	0.91	1.00	1.00	1.00
EABL	0.93	0.96	0.97	0.97	1.01	0.96	1.00	1.00	1.00	1.00	1.00	1.00
KAPC	0.64	0.75	0.85	0.40	0.52	0.78	0.44	0.56	0.79	0.30	0.35	0.85
KQ	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
SCOM	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
SASN	0.40	0.48	0.84	0.22	0.32	0.67	0.28	0.33	0.82	0.31	0.34	0.91
C&G	0.83	0.84	0.99	1.00	1.00	1.00	0.74	0.84	0.89	0.86	0.87	0.98
CARB	0.29	0.62	0.47	0.23	0.41	0.55	0.60	1.00	0.60	0.44	0.57	0.77
CRDB	0.55	0.77	0.71	0.56	0.70	0.80	0.57	0.65	0.89	0.61	0.69	0.87
DCB	1.00	1.00	1.00	0.45	0.55	0.82	0.74	1.00	0.74	0.43	0.60	0.71
NMB	0.64	0.66	0.96	0.70	0.85	0.83	0.56	0.59	0.95	0.73	0.74	0.98
SWIS	0.72	1.00	0.72	0.68	0.78	0.87	0.92	1.00	0.92	1.00	1.00	1.00
TBL	0.84	0.85	0.99	0.79	0.80	0.99	0.94	1.00	0.94	0.92	0.92	1.00
TCC	0.87	0.87	1.00	0.82	0.84	0.97	0.86	0.88	0.98	1.00	1.00	1.00
TCCL	0.67	0.72	0.94	0.48	0.50	0.97	0.42	0.47	0.90	1.00	1.00	1.00
TOL	0.47	1.00	0.47	0.25	0.39	0.64	0.41	0.58	0.71	0.65	1.00	0.65
TPCC	1.00	1.00	1.00	1.00	1.00	1.00	0.79	0.82	0.96	0.83	0.83	0.99
BOBU	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
DFCU	0.93	1.00	0.93	0.74	0.86	0.86	0.67	0.72	0.93	0.60	0.66	0.90
UMME	0.77	0.79	0.97	1.00	1.00	1.00	0.96	0.98	0.98	0.74	0.75	0.99
NVL	0.80	1.00	0.80	0.60	0.83	0.72	1.03	1.03	1.00	0.80	1.00	0.80
BOK	0.37	0.44	0.84	0.41	0.42	0.97	0.44	0.46	0.97	1.00	1.00	1.00
BRL	0.70	0.77	0.91	0.73	0.75	0.98	0.80	0.81	0.99	0.82	0.83	0.99

4.2.5 Combined Performance Evaluation

Table 4.5 shows the company's combined score for overall, managerial, and operational performance from 2015 to 2018. The results show that, when the performance of the country's economy, stock market, and economic sectors are considered, the combined score of the listed companies in various measures are unpredictable. This signified that, although the financial statements portrayed that companies are well performed yet not guarantee investors to select the company as a prospective investment. Parallel to the recommendations drawn by Grimm (2012) that comprehensive analysis needs to be conducted to increase assurance margin of safety. The findings are partially in line with the observations reported by Ndiritu and Mugivane (2015) that the decreasing performance of listed companies in EACMs was associated with among other factors the country's economic status and stock market development. This is because the companies that report full performance were underperformed and vice versa when the country's economy, stock market, and economic sector performance are combined with company performance using a top-down approach. Giant companies within the region were most affected when the economic, market, and economic sector growth are incorporated in the model compared to companies with moderate financial performance.

Companies such as BAT, FTGH, KQ, SCOM, and BOBU records 100 percent overall, managerial and operational performance in all four years consecutively before combination, all of them were underperformed after combination. Similarly, MSC which records full performance for three years consecutively observed to decline due to the country's economic performance, stock market, and economic sector. Only, TPCC which was full performed in all measures for two years consecutively which is

2017 and 2018 before the combination maintains the same after combination also the performance of all measures have increased in other years which is 2015 and 2016.

Surprisingly, TOL which was among the least performed shares with a minimum overall performance score of 25 percent during 2017 shot to the list of most performed shares with a minimum overall performance score of 92 percent in the same year. Generally, the companies from Tanzania particularly from the industry sector found to perform well. This may be associated with the well-performed economic condition, stock market, and industry sector. The results are in line with the study of Page (2016) that Tanzania is among the leading stars of the 'African growth miracle' also, the growth of the industry sector is faster than the economy as a whole. Page (2016) He was further instated that the manufacturing industry in Tanzania show rapid growth compare to neighbouring countries which in turn influence the firm performance.

Table 4.5: Combined Performance Score of Listed Companies

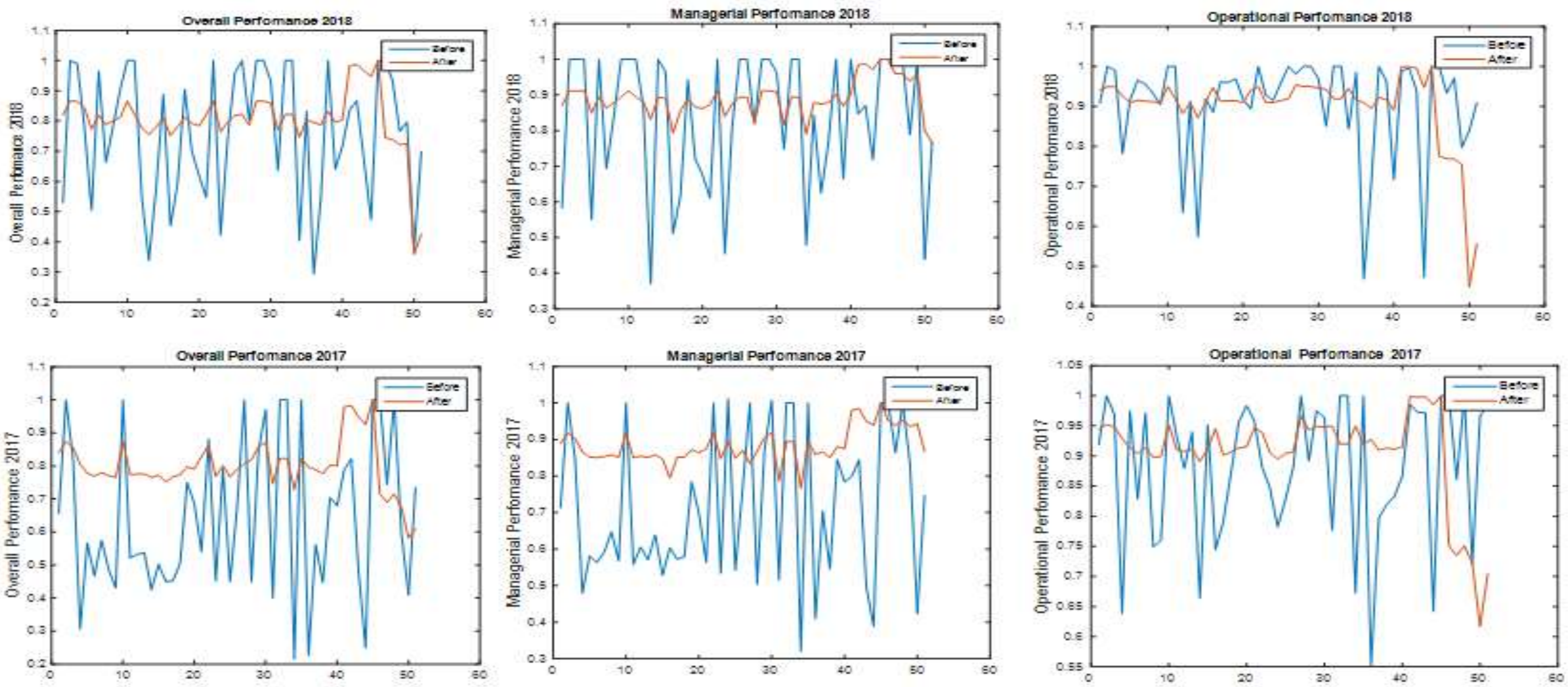
	2018			2017			2016			2015		
share	Overall	Mgt	Opt	Overall	Mgt	Opt	Overall	Mgt	Opt	Overall	Mgt	Opt
BAMB	0.82	0.87	0.94	0.84	0.89	0.94	0.85	0.91	0.94	0.72	0.92	0.78
BAT	0.87	0.91	0.95	0.87	0.92	0.95	0.88	0.92	0.96	0.74	0.93	0.79
BERG	0.87	0.91	0.95	0.86	0.90	0.95	0.87	0.92	0.94	0.74	0.93	0.79
BOC	0.84	0.91	0.93	0.80	0.87	0.93	0.81	0.87	0.94	0.67	0.87	0.77
BRIT	0.77	0.85	0.91	0.78	0.85	0.91	0.78	0.87	0.89	0.63	0.88	0.73
CFC	0.82	0.89	0.92	0.77	0.85	0.90	0.79	0.89	0.89	0.68	0.92	0.74
CIC	0.79	0.86	0.91	0.78	0.85	0.91	0.78	0.88	0.89	0.64	0.88	0.73
COOP	0.80	0.88	0.91	0.77	0.86	0.90	0.79	0.89	0.89	0.65	0.90	0.73
DTK	0.81	0.89	0.91	0.77	0.85	0.90	0.79	0.88	0.89	0.66	0.92	0.72
FTGH	0.87	0.91	0.95	0.87	0.92	0.95	0.82	0.92	0.90	0.74	0.93	0.79
HFCK	0.82	0.89	0.92	0.77	0.85	0.91	0.79	0.88	0.90	0.65	0.90	0.73
I&M	0.78	0.88	0.88	0.78	0.85	0.91	0.78	0.88	0.89	0.68	0.92	0.74
JUB	0.76	0.83	0.91	0.78	0.85	0.91	0.78	0.87	0.89	0.63	0.88	0.72
KCB	0.78	0.89	0.87	0.76	0.86	0.89	0.79	0.90	0.88	0.64	0.90	0.71
KNRE	0.81	0.89	0.91	0.77	0.85	0.91	0.78	0.87	0.90	0.63	0.88	0.72
KUKZ	0.75	0.79	0.95	0.75	0.79	0.95	0.75	0.78	0.96	0.61	0.78	0.78
NIC	0.78	0.86	0.91	0.77	0.85	0.90	0.78	0.88	0.89	0.66	0.90	0.73
NMG	0.81	0.89	0.91	0.77	0.85	0.91	0.80	0.89	0.90	0.66	0.90	0.73
SCAN	0.79	0.87	0.91	0.80	0.87	0.91	0.80	0.90	0.89	0.63	0.89	0.71
SGL	0.78	0.86	0.91	0.79	0.86	0.92	0.80	0.89	0.90	0.65	0.89	0.73
TCL	0.82	0.87	0.94	0.83	0.87	0.95	0.84	0.89	0.95	0.73	0.92	0.79
TOTL	0.87	0.91	0.95	0.86	0.92	0.94	0.87	0.92	0.94	0.74	0.93	0.79
TPSE	0.76	0.84	0.91	0.77	0.85	0.91	0.77	0.86	0.89	0.62	0.86	0.72
EQTY	0.80	0.88	0.91	0.80	0.90	0.89	0.82	0.91	0.90	0.68	0.92	0.74
KEGN	0.82	0.89	0.91	0.77	0.85	0.90	0.79	0.88	0.89	0.67	0.92	0.73
KPLC	0.82	0.89	0.92	0.79	0.87	0.91	0.79	0.91	0.87	0.67	0.92	0.73

Table 4.5: Combined Performance Score of Listed Companies (cont)

	2018			2017			2016			2015		
share	Overall	Mgt	Opt	Overall	Mgt	Opt	Overall	Mgt	Opt	Overall	Mgt	Opt
MSC	0.79	0.82	0.95	0.81	0.83	0.97	0.80	0.83	0.97	0.66	0.82	0.80
PORT	0.87	0.91	0.95	0.82	0.87	0.94	0.85	0.89	0.95	0.74	0.93	0.79
UNGA	0.87	0.91	0.95	0.86	0.90	0.95	0.86	0.91	0.95	0.74	0.93	0.79
EABL	0.86	0.91	0.95	0.87	0.92	0.95	0.88	0.92	0.96	0.74	0.93	0.79
KAPC	0.77	0.82	0.94	0.75	0.79	0.95	0.75	0.78	0.96	0.59	0.76	0.78
KQ	0.82	0.89	0.92	0.82	0.89	0.92	0.82	0.91	0.90	0.68	0.92	0.74
SCOM	0.82	0.89	0.92	0.82	0.89	0.92	0.82	0.91	0.90	0.68	0.92	0.74
SASN	0.75	0.79	0.94	0.73	0.77	0.95	0.73	0.76	0.96	0.59	0.76	0.78
C&G	0.81	0.88	0.92	0.82	0.89	0.92	0.80	0.90	0.89	0.66	0.91	0.73
CARB	0.80	0.87	0.91	0.80	0.86	0.93	0.84	0.92	0.91	0.68	0.89	0.77
CRDB	0.79	0.88	0.90	0.79	0.87	0.91	0.79	0.88	0.90	0.79	0.88	0.90
DCB	0.83	0.90	0.92	0.78	0.85	0.91	0.81	0.91	0.88	0.78	0.87	0.89
NMB	0.80	0.87	0.92	0.80	0.88	0.91	0.79	0.87	0.90	0.81	0.88	0.91
SWIS	0.80	0.90	0.89	0.80	0.87	0.91	0.82	0.91	0.90	0.83	0.91	0.92
TBL	0.98	0.98	1.00	0.98	0.98	1.00	0.99	1.00	0.99	0.99	0.99	1.00
TCC	0.99	0.99	1.00	0.98	0.98	1.00	0.99	0.99	1.00	1.00	1.00	1.00
TCCL	0.97	0.97	1.00	0.95	0.95	1.00	0.94	0.95	1.00	1.00	1.00	1.00
TOL	0.95	1.00	0.95	0.92	0.94	0.99	0.94	0.96	0.98	0.97	1.00	0.97
TPCC	1.00	1.00	1.00	1.00	1.00	1.00	0.98	0.98	1.00	0.98	0.98	1.00
BOBU	0.75	0.96	0.78	0.72	0.95	0.75	0.73	0.99	0.74	0.72	0.86	0.84
DFCU	0.74	0.96	0.77	0.69	0.94	0.73	0.70	0.96	0.73	0.68	0.82	0.83
UMME	0.72	0.94	0.77	0.72	0.95	0.75	0.73	0.99	0.74	0.69	0.83	0.83
NVL	0.72	0.96	0.75	0.67	0.94	0.72	0.74	0.99	0.74	0.70	0.86	0.82
BOK	0.36	0.80	0.45	0.58	0.94	0.62	0.59	0.95	0.62	0.38	0.72	0.53
BRL	0.43	0.76	0.56	0.61	0.87	0.70	0.62	0.88	0.71	0.41	0.73	0.57

4.2.6 Company's Performance before and after combination

Figure 4.1 illustrate variability of performances of 51 companies listed in EACMs before and after combination with other components which country economic performance, market listed and economic sector for 2015, 2016, 2017 and 2018.



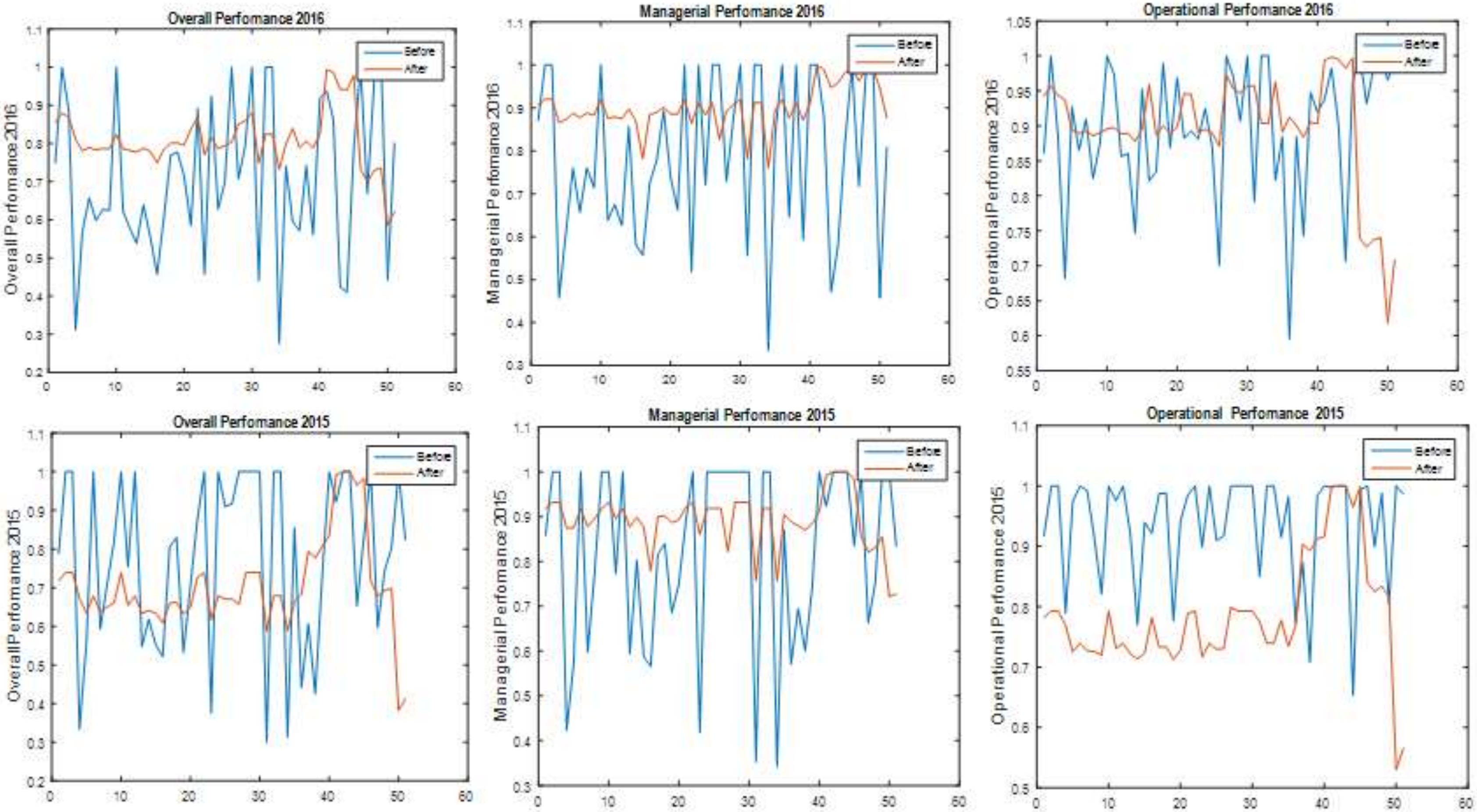


Figure 4.1: Company Performances Before and After Combination, 2015-2018

A significant mean difference can be observed when the performance of the various companies before and after combination with other components are compared. Table 4.6 summarised the independent t-test conducted in all three measures from 2015 to 2018. The combined effect of fundamental components found to decrease when approaching to 2018. Only during 2015 were the combined effect of economic development, stock market, and economic sector growth the performance of listed companies was observed. There was a significant difference in the overall, managerial, and operational performance of listed companies before and after considering the performance of other components equivalent to $p = 0.017, p \leq 0.05$, $p = 0.014, p \leq 0.05$ and $p = 0.00, p \leq 0.001$ respectively.

Some inconsistences have been observed in the rest of the years which is 2016, 2017 and 2018. During 2016 and 2017 the overall and managerial performance of the listed companies has been significantly affected by the country's economy, stock market, and economic sectors transformations that took place within the region while operational performance was not affected. Contrary to 2018 where both overall and operational performance remains stable and managerial performances of listed companies were significantly interrupted by the changes that took place in the country economy, stock markets, and economic sectors equivalent to $p = 0.02, p \leq 0.05$

An interesting observation was found on the variability of the performance scores before and after combination. The variances of the average performances have minimized and even approach zero when other components were included in the model. It is worth saying, the country's economy, stock markets, and economic sector performance play a major role to normalize the listed companies' performance. Technically, this will increase confidence to investors and scope of selecting shares to be included in the portfolio.

Table 4.6: Independent t-test of Company Performance before and After Combination

Year	Performance Measure	Before		After		P-value	Decision
		Mean	Variance	Mean	Variance		
2018	Overall Performance	0.76	0.05	0.80	0.010	0.090	Not Significant
	Managerial Performance	0.83	0.03	0.89	0.003	0.020**	Significant
	Operational Performance	0.90	0.02	0.90	0.010	0.430	Not Significant
2017	Overall Performance	0.64	0.06	0.80	0.006	0.000***	Significant
	Managerial Performance	0.71	0.04	0.88	0.002	0.000***	Significant
	Operational Performance	0.88	0.01	0.90	0.006	0.114	Not Significant
2016	Overall Performance	0.71	0.04	0.81	0.006	0.000***	Significant
	Managerial Performance	0.78	0.04	0.90	0.006	0.000***	Significant
	Operational Performance	0.89	0.01	0.89	0.006	0.473	Not Significant
2015	Overall Performance	0.78	0.05	0.70	0.010	0.017**	Significant
	Managerial Performance	0.83	0.04	0.89	0.004	0.014**	Significant
	Operational Performance	0.93	0.01	0.79	0.01	0.000***	Significant

***Significant at 0.01 level (2-tailed)

** Significant at 0.05 level (2-tailed)

4.2.7 Selected Companies

The minimum average performance after combination for each measure from any year shown in Table 4.6 was used as a benchmark of identifying shares that can be used for portfolio construction. Therefore, the qualified shares are all shares with an overall performance score of 70 percent and above, a managerial performance score of 88 percent and above as well as an operational performance score of 79 percent and above throughout from 2015 to 2018. However, the selection criteria are more tolerable compared to that of Jothiami, et., al. (2017) who strictly consider the shares with 100 percent performance throughout for the period of 8 years as a potential candidate for asset selection whereas out of 523 stocks only 41 stocks were qualified. Table 4.7 summarised the selected shares which meet the minimum required criteria.

Table 4.7: Summary of Selected Companies

Sn	Code	Company	Market	Country	Business	Sector
1	BAT	BAT Kenya	NSE	Kenya	Cigarette	Industry
2	BERG	Berge Paint	NSE	Kenya	Paints	Industry
3	FTGH	Flame Tree Group Limited	NSE	Kenya	Plastic	Industry
4	TOTL	Total Kenya	NSE	Kenya	Oil	Industry
5	UNGA	Unga Group Plc	NSE	Kenya	Food	Industry
6	EABL	East African Breweries	NSE	Kenya	Beer	Industry
7	TBL	Tanzania Breweries Plc	DSE	Tanzania	Beer	Industry
8	TCC	Tanzania Cigarette Company	DSE	Tanzania	Cigarette	Industry
9	TCCL	Tanga Cement Company	DSE	Tanzania	Cement	Industry
10	TOL	TOL Gas Limited	DSE	Tanzania	Gas	Industry
11	TPCC	Tanzania Portland Company	DSE	Tanzania	Cement	Industry

Generally, all companies from Uganda and Rwanda and all companies from the service and manufacturing sectors in the region were underperformed therefore were disqualified for further analysis. Only some companies that fall under the industry sector in Kenya and Tanzania were shortlisted as they meet the minimum requirements. Out of 11 companies, 6 are from Kenya which is equivalent to 16 percent of the total companies, and 5 from Tanzania which is equivalent to 56 percent of the total companies evaluated from Kenya and Tanzania respectively.

4.3 Portfolio Construction

This section presented the analysis related to second research question which correspond to second and third hypothesis as stated below.

Research question 2: Are there any variability of expected returns and risks of various portfolios constructed on selected stocks listed in EACMs using both MVCM– DEA and CAPM-DEA model?

Hypothesis 2: There is no significant mean difference between mean returns calculated by MVCM-DEA and those calculated using CAPM-DEA.

Hypothesis 3: There is no significant mean difference between risk calculated by MVCM-DEA and that calculated by CAPM-DEA.

The portfolios were constructed using MVCM and CAPM. Eleven shares were mixed, and nine portfolios were constructed starting from three shares portfolio to eleven shares portfolio. The MATLAB program was developed, and the weights were generated accordingly. The weights are allocated based on share returns arranged in descending order as shown in Table 4.8. The best shares are most left and the worst shares are most right. The best shares received more weight than the worst shares.

Table 4.8: Weight Allocation Based on Share Returns - Descending

No. Shares	Portfolio Size	1	2	3	4	5	6	7	8	9	10	11
A3	P1	0.50	0.33	0.17								
A4	P2	0.40	0.30	0.20	0.10							
A5	P3	0.33	0.27	0.20	0.13	0.07						
A6	P4	0.29	0.24	0.19	0.14	0.10	0.05					
A7	P5	0.25	0.21	0.18	0.14	0.11	0.07	0.04				
A8	P6	0.22	0.19	0.17	0.14	0.11	0.08	0.06	0.03			
A9	P7	0.20	0.18	0.16	0.13	0.11	0.09	0.07	0.04	0.02		
A10	P8	0.18	0.16	0.15	0.13	0.11	0.09	0.07	0.05	0.04	0.02	
A11	P9	0.17	0.15	0.14	0.12	0.11	0.09	0.08	0.06	0.05	0.03	0.02

Note: 1) TPCC, 2) UNGA, 3) TOTL, 4) BERG, 5) TCC, 6) TBL, 7) TCCL, 8) BAT, 9) FTGH, 10) TOL, 11) EABL

4.3.1 MVCM Portfolios

Table 4.9 show presents 9 portfolios constructed using MVCM and corresponding portfolio returns and risk from 2015 to 2018. The results revealed that all the portfolio constructed during 2015 generates a loss range between 0.15 to 0.17 percent and a high-risk range between 2.49 to 3.30 percent. Likewise, during 2016 where the loss range between 0.07 to 0.10 percent, and the risk range between 2.27 to 2.85 percent. Both risks and returns of the portfolios in 2016 are smaller than in 2015. While in 2017 all the portfolio constructed generates profits range between 0.01 to 0.12 percent and the risk range between 1.89 to 2,46 percent. Moreover, during 2018 the portfolios constructed generates a loss of 0.05 to 0.07 percent and a corresponding risk range between 1.97 to 3.33 percent.

Table 4.9: Returns and Risk of Portfolios Constructed Using MVCM from 2015 to 2018

No. of Shares	Portfolio Size	2015		2016		2017		2018	
		Returns	Risk	Returns	Risk	Returns	Risk	Returns	Risk
A3	PI	-0.16	2.49	-0.07	2.27	0.12	1.89	-0.06	1.97
A4	P2	-0.17	2.78	-0.08	2.51	0.10	2.15	-0.07	2.27
A5	P3	-0.17	3.00	-0.09	2.65	0.09	2.29	-0.07	2.42
A6	P4	-0.16	3.13	-0.09	2.74	0.08	2.37	-0.06	2.49
A7	P5	-0.16	3.20	-0.10	2.79	0.06	2.41	-0.05	2.64
A8	P6	-0.16	3.24	-0.10	2.81	0.04	2.43	-0.05	2.84
A9	P7	-0.16	3.27	-0.10	2.83	0.03	2.44	-0.05	3.04
A10	P8	-0.16	3.29	-0.10	2.84	0.02	2.45	-0.05	3.20
A11	P9	-0.15	3.30	-0.09	2.85	0.01	2.46	-0.05	3.33

Note: All values of returns and risks presented in the Table 4.9 are converted into percentage. This is because the values were very small in such a way that cannot be seen when were rounded in two decimal point

The correlation analysis was conducted to examine the relationship between Portfolio returns and risks in different in different years. The results in the Table 4.10 revealed that there are significant positive correlation between portfolio returns and risks during 2018 with $r = 0.734, p \leq 0.05$. Also, there are strong negative correlation during 2016 and 2017 with $r = -0.863, p \leq 0.01$ and $r = -0.925, p \leq 0.01$ respectively. While during 2015, there was no correlation observed between returns and risk of different portfolio constructed. The inconsistence of correlation between returns and risks across different year within EACMs associated with market rationality and investors trading behaviour. The study of Lukanima (2014) found that the trading activity within DSE still inactive and illiquid. Investors preferred on dividends than returns on share trading. Comparison across different years revealed that the markets are in transformation phase and investors started to engage on share trading. The claim of MPT about the relationship between return and risk which is the higher the risk the higher the returns has been observed from 2018.

Table 4.10: Correlation Analysis Between Returns and Risks from 2015 to 2018

	Ret15	Ret16	Ret17	Ret18	Ris15	Ris16	Ris17	Ris18
Ret15	1							
Ret16	-0.22	1						
Ret17	-0.64	.772*	1					
Ret18	.801**	-0.64	-.799**	1				
Ris15	0.45	-.924**	-.901**	.670*	1			
Ris16	0.41	-.925**	-.886**	0.64	.999**	1		
Ris17	0.37	-.924**	-.863**	0.60	.994**	.998**	1	
Ris18	0.61	-.742*	-.993**	.734*	.895**	.881**	.861**	1

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

On another side, the negative correlation observed during 2016 and 2017 is associated with heterogeneous beliefs among investors within the region. Barberis, et., al. (2015) reported that when the market comprises both investors who are the speculative and rational assumption of MPT could not be realized. Considering the finding of Liu, Shi, Wu, and Guo (2020) who reported the existence of non-correlation in the short run. Although, they considered stocks with a monthly interval in constructing portfolios while this study using daily returns. Yet, only during 2015, there was a non-correlation between returns and risk. Another interesting finding is when more shares are added to the portfolios the returns decreases and risk increases which give doubt on observing diversification benefit. Since in this study all shares used to construct all 9 portfolios are from the same sector which is the industry sector it could be the reasons. Other sectors should be considered to realize the maximum benefits of diversification. However, the shares listed in the industry sector in EACMs are only shares found actively traded. According to Aliu, Pavelkova, and Dehning (2017) concluded that more diversification benefit is attained when the shares forming portfolio are selected from different sectors as different sectors have different diversification benefits. Other scholars associated diversification benefits with optimum portfolio size and investor risk tolerance. Alexeev and Tapon (2013) were insisted on limiting portfolio size for achieving the most diversification benefit. For investors concerned with extreme risk need to choose a small number of shares to form a portfolio to achieve diversification benefits. Comparing to the findings of this study, the risk-averse investor only can choose P1 in any time frame from 2015 to 2018 which has a limit of 3 shares. They were concluded that the average stock to hold in the US IS 49, the UK is 43, Japan is 39, Canada is 40 Australia is 38. While for Nairobi Securities Exchange reported the optimal number of stocks to lie between 18 to 22 (Kisaka, Mbithi, and Kitur, 2015). The study of Chong and Philips (2013) highlighted that the benefits of diversification can be realized based on the criterion used to judge the adequacy of diversification including start date to avoid timing bias, time of holding stock, and mode of funds allocation such as naïve, random or based on returns. This can be understood that even if the shares are selected from different sectors an optimal size might not be attained. As in this study, the funds were allocated based on Share returns, other allocation models should be considered to examine the influences. Generally, the trends of the portfolio returns are inconsistence for all four years. Figure 4.2 and 4.3 illustrated the trends of returns and risk in all four years from 2015 to 2018. It can be observed that the risk of the portfolio returns is more sensitive with portfolio size during the first three years. A small increase in the number of shares in the portfolio results in a large increase of portfolio risks. Only during 2018 where the portfolio risks behave almost linearly with portfolio size and even concave when the portfolio of 3 to 7 share was constructed.

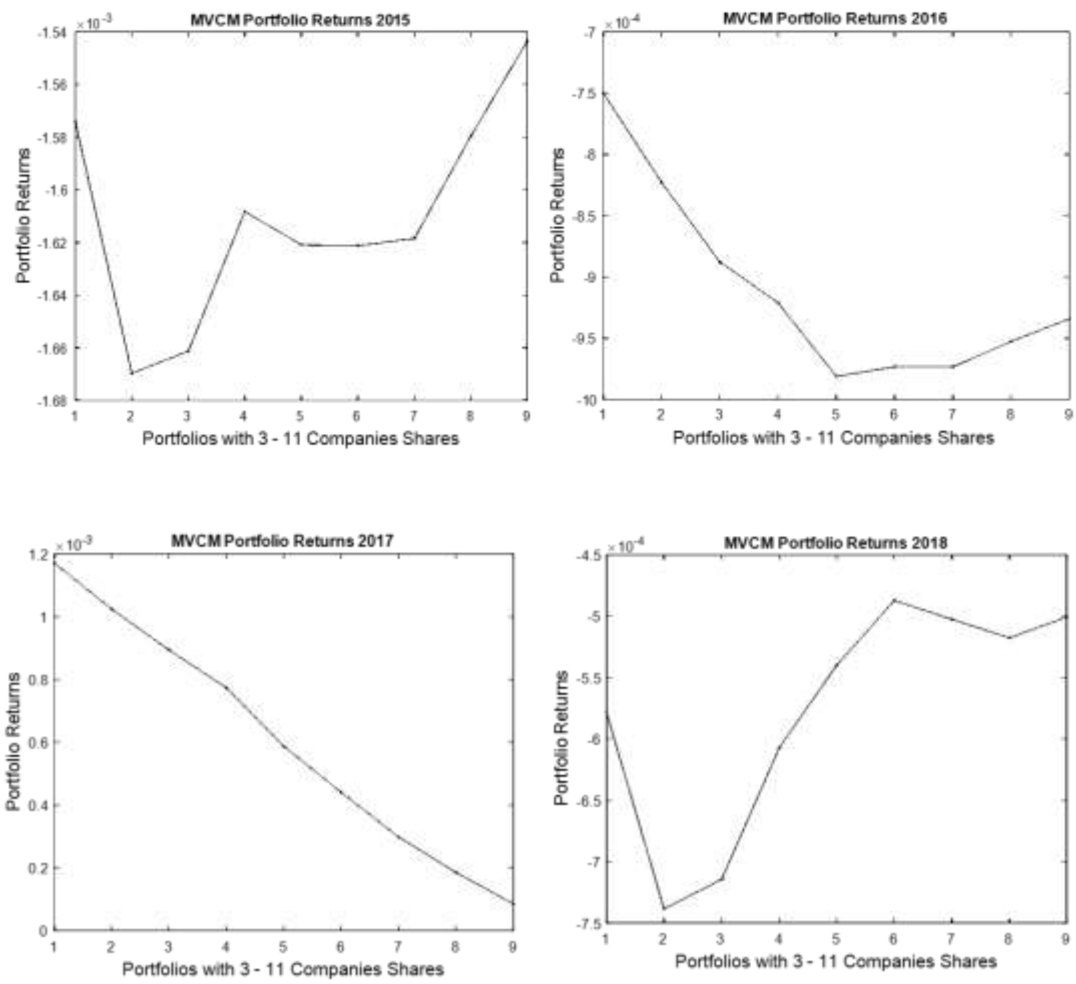


Figure 4.2: The Trend of Returns

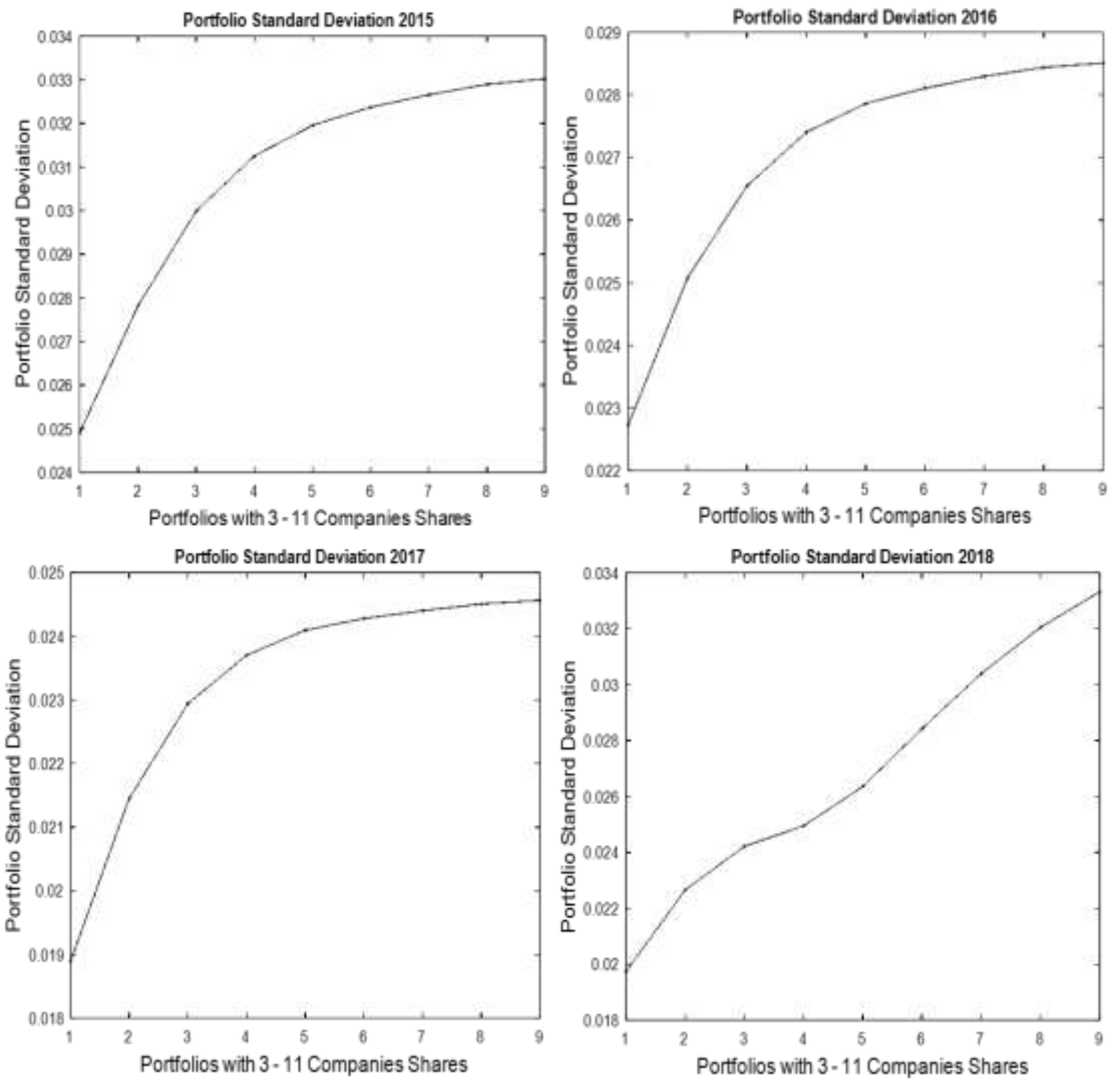


Figure 4.3: The Trend of Risk

4.3.2 CAPM Portfolio

Table 4.11 shows the portfolio constructed using CAPM and corresponding portfolio returns and portfolio beta for the years 2015 to 2018. The results from Table 4.11 the portfolio returns decrease when portfolio size increases in all four years from 2015 to 2018 while portfolio beta increases with portfolio size. Minimum portfolio returns and maximum portfolio beta were found during 2015 equivalent to -0.04 percent and 50.57 percent when 11 share portfolios were constructed.

Table 4.11: Returns and Risks of CAPM portfolios from 2015 to 2018

No. of Shares	Portfolio Size	2015		2016		2017		2018	
		Returns	Beta	Returns	Beta	Returns	Beta	Returns	Beta
A3	PI	0.01	22.93	0.04	3.71	0.05	1.54	0.04	5.23
A4	P2	0.00	28.60	0.04	4.86	0.05	2.24	0.04	6.08
A5	P3	-0.01	34.13	0.04	6.44	0.05	3.33	0.04	7.73
A6	P4	-0.01	38.19	0.04	8.11	0.05	4.48	0.03	9.62
A7	P5	-0.02	41.29	0.04	9.65	0.05	5.61	0.03	11.42
A8	P6	-0.03	44.80	0.04	11.05	0.05	7.15	0.03	13.04
A9	P7	-0.03	47.57	0.03	12.57	0.05	8.81	0.03	14.53
A10	P8	-0.03	49.86	0.03	14.18	0.05	10.75	0.02	14.57
A11	P9	-0.04	50.57	0.03	15.04	0.05	11.88	0.03	13.71

Note: All values of returns and risks presented in the Table 4.10 are converted into percentage. This is because the values were very small in such a way that cannot be seen when were rounded in two decimal point

On contrary, maximum portfolio returns and minimum beta were found during 2017. There was a negligible change in portfolio returns even when the portfolio size increases in the year 2017. The returns oscillated at 0.05 percent while beta continues to increase from 1.54 percent for 3 shares portfolio to 11.88 percent for 11 share portfolios. The slight changes in portfolio returns were also observed during 2016 where the first 6 portfolios generate returns of 0.04 percent, and the last 3 portfolios generate returns of 0.03 percent. The slight inconsistencies were experienced during 2018 where the first 3 portfolios record 0.4 percent while the remained portfolios produced 0.03 percent except for the 10 shares portfolio which shows 0.02 percent. The trend of portfolio returns, and beta are illustrated in Figure 4.4 and 4.5 respectively.

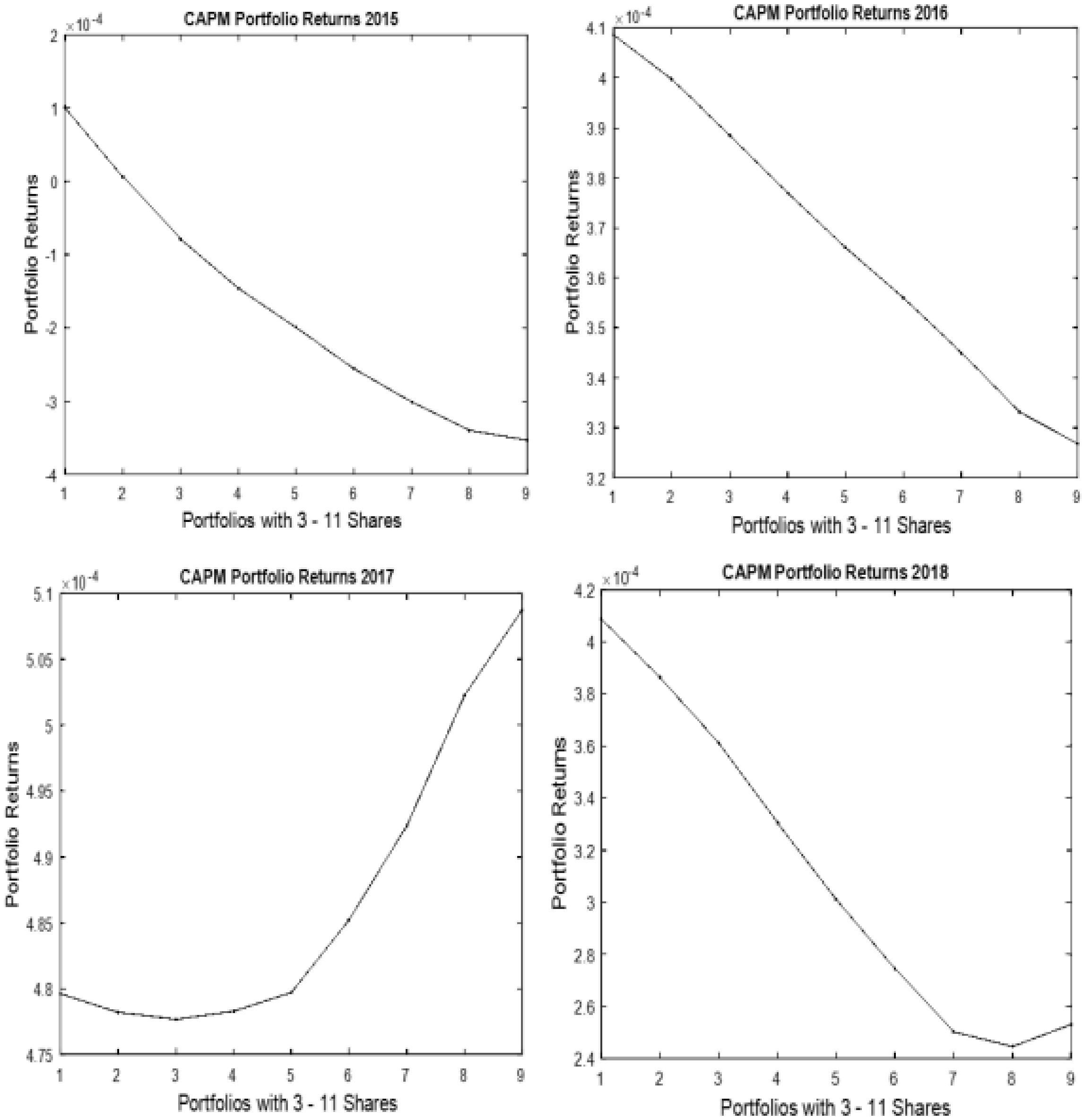


Figure 4.4: Trend of CAPM Portfolio Returns

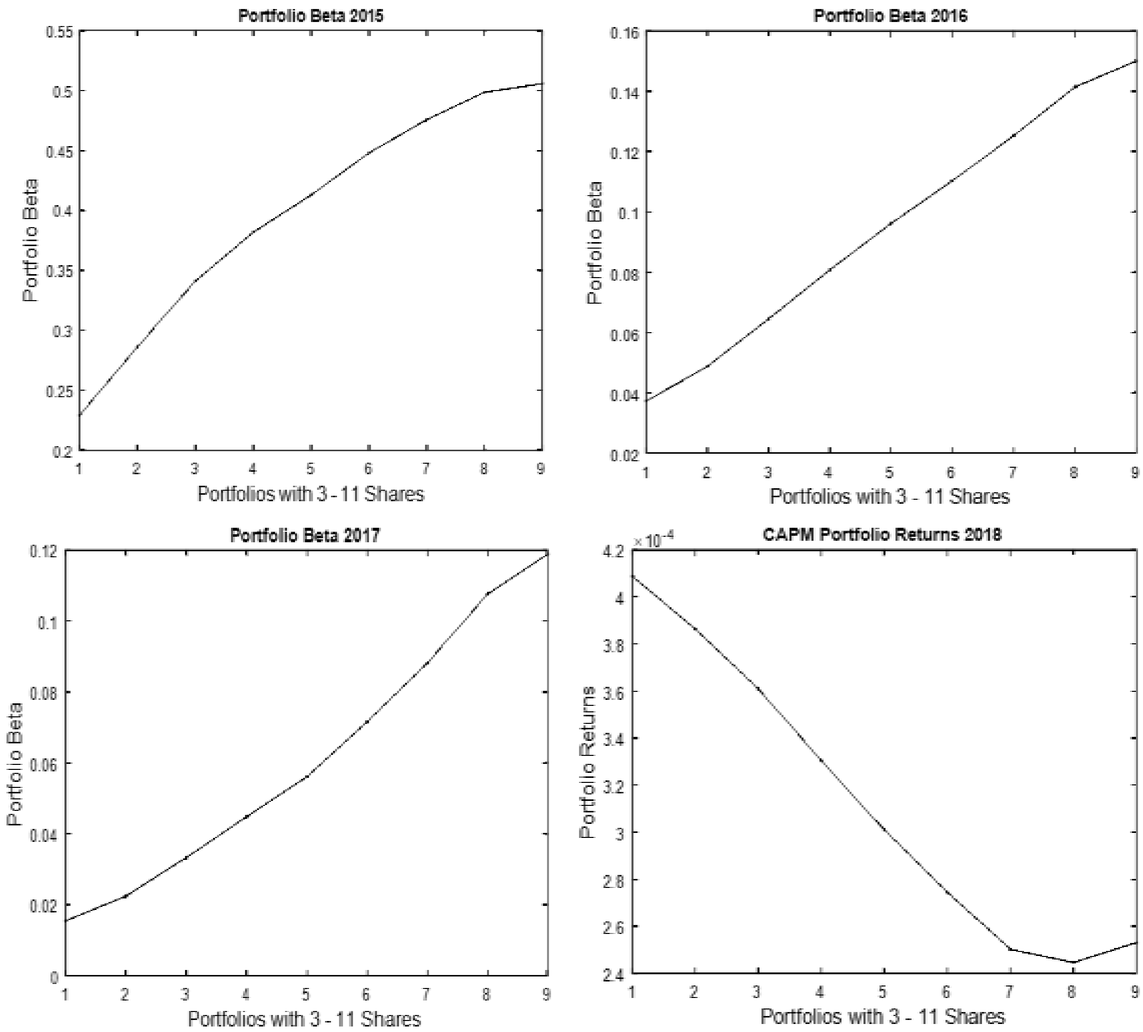


Figure 4.5: Trend of CAPM Portfolio Beta

The results in the Table 4.12 show correlation analysis conducted between CAPM returns and beta. It was confirmed that confirmed the existence of strong negative correlation between CAPM returns and Beta during 2015, 2016, 2017 and 2018 with $r = -1, p \leq 0.00), r = -1.00, p \leq 0.00$and $r = -0.99, p \leq 0.00)$ respectively. Only during 2017 where the expected returns and beta become positive correlated with , $r = 0.92, p \leq 0.00$.

Table 4.12: Correlation Analysis between CAPM returns and Beta

	Ret15	Ret16	Ret17	Ret18	Bet15	Bet16	Bet17	Bet18
Ret15	1							
Ret16	.986**	1						
Ret17	-.772*	-.865**	1					
Ret18	.990**	.980**	-.764*	1				
Bet15	-1.000**	-.984**	.768*	-.990**	1			
Bet16	-.984**	-1.000**	.867**	-.980**	.983**	1		
Bet17	-.955**	-.991**	.925**	-.949**	.953**	.991**	1	
Bet18	-.981**	-.969**	.739*	-.998**	.981**	.968**	.934**	1

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

The negative relationship between portfolio returns and portfolio beta is against the hypothesis of Capital Market Theory and Capital Asset Pricing Model (CAPM) introduced by Treynor (1962); Sharpe (1964); Lintner (1965) and Mossin (1966). While the CAPM hypothesis claimed a direct positive linear relationship between returns of shares and market returns, studies testing the hypothesis in frontier and infant stock markets show different results. Mazviona (2013) reported a negative linear relationship between returns of shares and returns of the index of the stocks traded in the Zimbabwe stock exchange between 2009 and 2012. Matteev (2004) found that the relationship between share returns, and market returns was flat in the Bulgaria stock exchange for the stocks traded between 1998 and 2002. Iqbal & Brooks (2007) pointed out that the relationship between share returns and market returns is non-linear for the stocks traded in the Karachi stock exchange between 1992 and 2006, although the market performance was backed with a high level of liquidity and trading activities. The study of Mensah (2013) and Mensah (2015) both highlighted that portfolio beta decreased with the increase in portfolio size. Similarly, portfolio returns increased with the increase of portfolio size to the maximum of seven shares out of ten shares used. The complex behavior of beta in frontier and infant markets confused interpreting the CAPM, and this has further led to the conclusion that the CAPM is inapplicable in these infant markets. In a recent study of African stock markets by Essingone & Diallo (2019) in West Africa, Economic and Monetary Union Regional Exchange of Securities, Asymmetric Response Model (ARM) was considered as an alternative model for CAPM in estimating risk. However, the asymmetric nature of the risk was still existed due to the lack of attractiveness of shares listed in, lack of speculative behavior among investors, the tendency of holding the stock for long, and fear of getting lost. It was stressed by Asad, Khan, & Faiz (2018) that in developing countries, investors were more sensitive to price volatility. Most potential investors preferred to invest in riskless financial assets due to the expected profit in the share invested. However, the scholars overlooked to demonstrate quantitatively the relationship between the behaviour of holding a stock with expected gain or loss as well as the risk of getting that loss. Experience gained from developed markets showed that the investors who traded frequently generated higher returns than infrequently traded investors (Busse, Tong-Lin, Tong-Qing, & Zhang-Zhe, 2019). But the results may prove different in frontier and infant markets due to the low liquidity of the shares traded.

4.3.3 Comparison between MVCM and CAPM Portfolio Returns

Figure 4.6 compare the trends of portfolio returns computed using MVCM and that computed using CAPM for 2015, 2016, 2017 and 2018. It is clearly observed that portfolio returns generated using MVCM are differ to that generated by CAPM in any time frame. CAPM portfolio returns are appeared to the top during 2015, 2016, 2018 in any portfolio size constructed and in 2017 when portfolio size is above 8 shares. MVCM portfolios reported highest returns only during 2017 when portfolio size is below 8 shares.

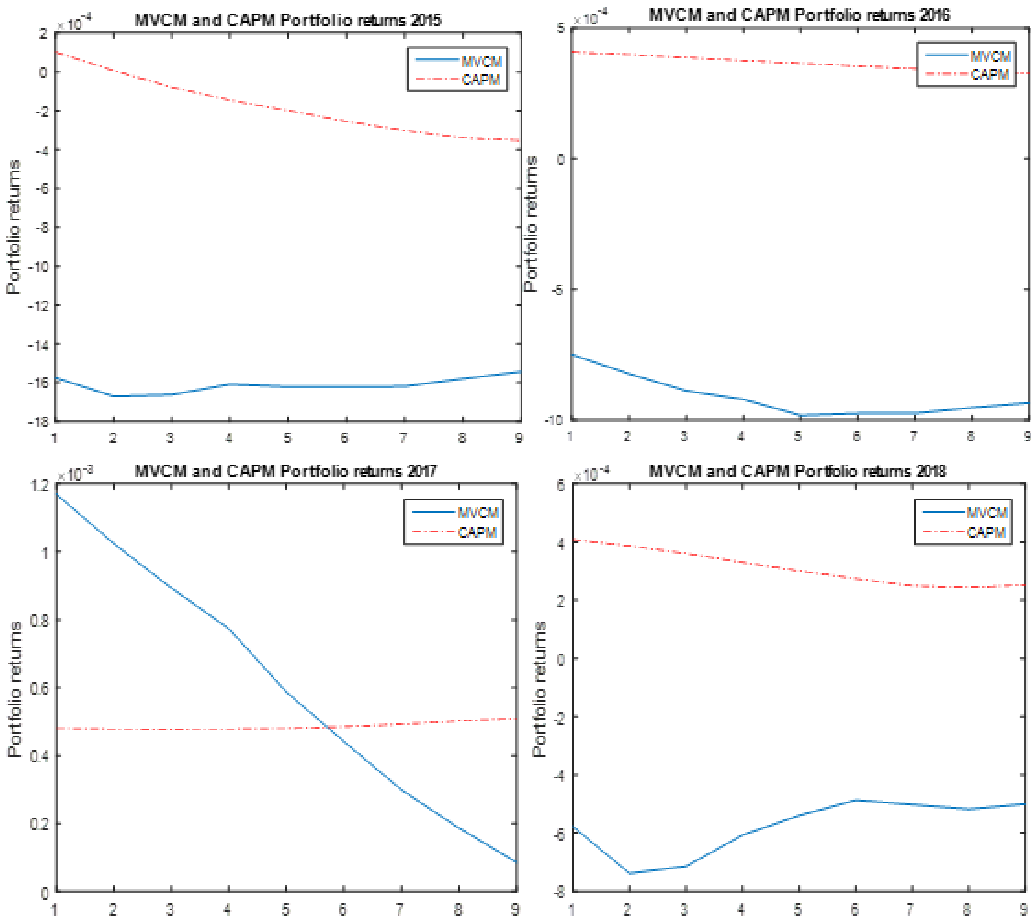


Figure 4.6: Comparison between MVCM and CAPM portfolio returns

Table 4.13 shows the independent t-test conducted to examine whether the mean difference of the portfolio returns computed using MVCM and CAPM is significant. The results revealed that there is a significant mean difference between the returns of the portfolio constructed using MVCM and that of CAPM from 2015 to 2018. In all four years, the average portfolio returns produced by CAPM was higher than that produced by MVCM except in 2017. The maximum average returns reported in 2017 under MVCM equivalent to 0.06 percent while CAPM reported 0.05 percent. It was also noted that MVCM produced negative average returns for three years 2015, 2016, and 2018 while CAPM produced positive average returns in the same time frame.

Table 4.13: Independent t test for MVCM and CAPM Portfolio returns

Year	MVCM		CAPM		P-value	Decision
	Mean	Variance	Mean	Variance		
2015	-0.16	0.00	-0.02	0.00	0.00***	Significant
2016	-0.09	0.00	0.04	0.00	0.00***	Significant
2017	0.06	0.00	0.05	0.00	0.00***	Significant
2018	-0.06	0.00	0.03	0.00	0.00***	Significant

*** Significant at 0.01 level (2-tailed)

The findings are in line with the study of Lee, Cheng and Chong (2016); Li and Li (2012) both concluded that CAPM mean returns are always higher than that produced by MVCM. It was further recommended that is better to investor to use CAPM in making investment decision that MVCM. Although, in this study MVCM – DEA was used yet was outnumbered by CAPM – DEA. This signified that always MVCM is lugging behind the CAPM when the same extension is added in both models. In the recent study of Hafsal and Durai (2019) who considered different versions of beta such as fundamental beta and bubble beta introduced by Anderson and Brook (2014) in CAPM and compare them MVCM during portfolio construction concluded that CAPM with fundamental beta perform better than the others. Only the study of Clarke, Silva and Thorley (2011) concluded that MVCM generates excess returns over CAPM.

4.3.4 Comparison between MVCM and CAPM Portfolio risks

Figure 4.7 illustrated the trends of standard deviation and beta of 9 portfolios constructed in each year from 2015 to 2018. It can be observed that the portfolio betas are always higher in any portfolio size for the year 2015, 2016 and 2018, also during 2017 when the portfolio size is above 4 shares. Similarly, portfolio betas are more sensitive with portfolio size.

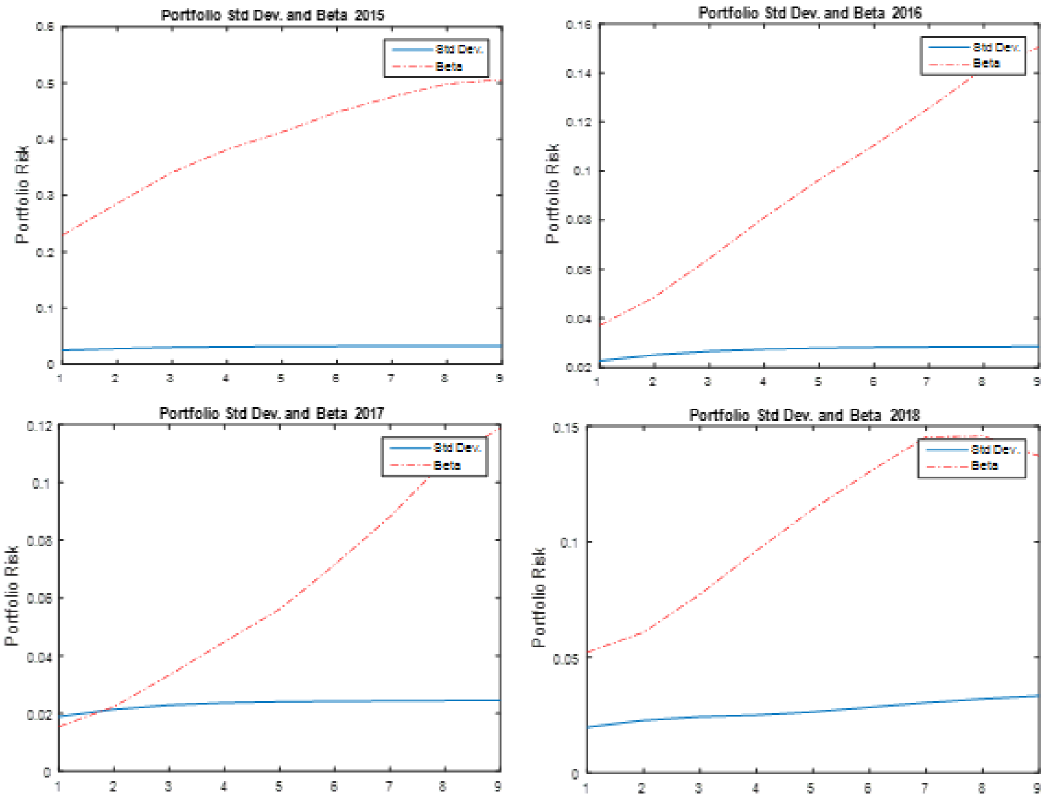


Figure 4.7: Trend of Standard Deviation and Beta of 9 portfolios

When single share is added in the portfolio beta increased more than one point. While the trend of portfolio standard deviation is almost stationary even when portfolio size increases to the maximum. Comparatively, the trends betas and standard deviation are different throughout. The results of independent t test shown in Table 4.14 revealed that the mean differences exist between standard deviation and beta are significant with $p = 0.00 (p \leq 0.00)$ in all four years.

Table 4.14: Independent t test for Portfolio Standard Deviation and Beta, 2015 to 2018

Year	Std Deviation		Beta		P-value	Decision
	Mean	Variance	Mean	Variance		
2015	3.08	0.08	39.77	93.69	0.00***	Significant
2016	2.70	0.04	9.51	16.34	0.00***	Significant
2017	2.32	0.04	6.20	13.71	0.00***	Significant
2018	2.69	0.20	10.66	13.24	0.00***	Significant

Note: *** Significant at 0.01 level (2-tailed)

In all four years the risk measured by beta were higher in average than that measured by standard deviation of the portfolio mean returns. maximum average beta was 39.77 percent while maximum average standard deviation was 3.08 percent both reported during 2015. The minimum average beta was 6.20 percent and minimum standard deviation was 2.32 percent both generated in 2017. Likewise, the variability of average beta across different portfolio in a year was higher than that of standard deviation. From 2015 to 2018, the variability of average beta oscillated with two digit and maximum variance was 93.69 that was observed in 2015. Contrary to that of standard deviation, which was less than subunit throughout, and the maximum variance found in 2018 which was equal to 0.20.

4.4 Portfolio Performance Evaluation

This section presented the analysis related to third research question and fourth hypothesis of this study as listed below.

Research question 3: What is the performance of the various portfolios constructed based on the selected stocks listed in EACMs evaluated using both Sharpe ratio and Treynor ratio?

Hypothesis 4: There is no significant mean difference between the Sharpe ratio and Treynor's ratio.

Two portfolio performance measurements which are Sharpe ratio and Treynor ratio were conducted under this analysis. Both measures were computed with respect to portfolio mean returns generated by MVCM and CAPM respectively.

4.4.1 Sharpe Ratios

From the Table 4.15 there is clear direct relationship between portfolio returns and Sharpe ratio. The higher Sharpe ratio correspond to higher portfolio mean returns and lower Sharpe ratio produce lower portfolio mean returns for the portfolios generated positive returns. This can be observed during 2017 where the highest return was 0.12 percent produced highest Sharpe ratio equivalent to 6.20 percent. Similarly, lowest return was 0.01 percent corresponds to lowest Sharpe ratio equal to 0.35 percent. Likewise, for the portfolios which generated negative returns produces negative Sharpe ratio. The negativity of Sharpe ratio become higher when the portfolio losses increase

Table 4.15: Sharpe Ratios of MVCM Portfolio Returns from 2015 to 2018

No. of Shares	Portfolio Size	2015		2016		2017		2018	
		Returns	SR	Returns	SR	Returns	SR	Returns	SR
A3	PI	-0.16	-6.32	-0.07	-3.30	0.12	6.20	-0.06	-2.93
A4	P2	-0.17	-6.00	-0.08	-3.28	0.10	4.78	-0.07	-3.26
A5	P3	-0.17	-5.54	-0.09	-3.34	0.09	3.90	-0.07	-2.95
A6	P4	-0.16	-5.15	-0.09	-3.36	0.08	3.26	-0.06	-2.43
A7	P5	-0.16	-5.07	-0.10	-3.52	0.06	2.44	-0.05	-2.05
A8	P6	-0.16	-5.01	-0.10	-3.46	0.04	1.82	-0.05	-1.71
A9	P7	-0.16	-4.96	-0.10	-3.44	0.03	1.22	-0.05	-1.65
A10	P8	-0.16	-4.80	-0.10	-3.35	0.02	0.76	-0.05	-1.62
A11	P9	-0.15	-4.67	-0.09	-3.28	0.01	0.35	-0.05	-1.50

The trend and sensitivity of the Sharpe ratio against portfolio size can be observed in Figure 4.8. Generally, Sharpe ratios are more sensitive with portfolio size and sensitivity becomes higher when portfolios are poorly performed. This can be observed in Sharpe ratio 2015 and 2018 where the graphs were bowed from the second portfolio. Contrary to the outperformed portfolio where Sharpe ratios are less linear with portfolio size. When one share is added to the portfolio results in approximately one unit decrease of Sharpe ratio as appeared in the graph of Sharpe ratio 2017. A surprising observation was found on the trend and sensitivity of the Sharpe ratio of 2016 with portfolio size. The negativity of Sharpe decreases with the increase of portfolio size from P2 up to P5, thereafter increase continuously.

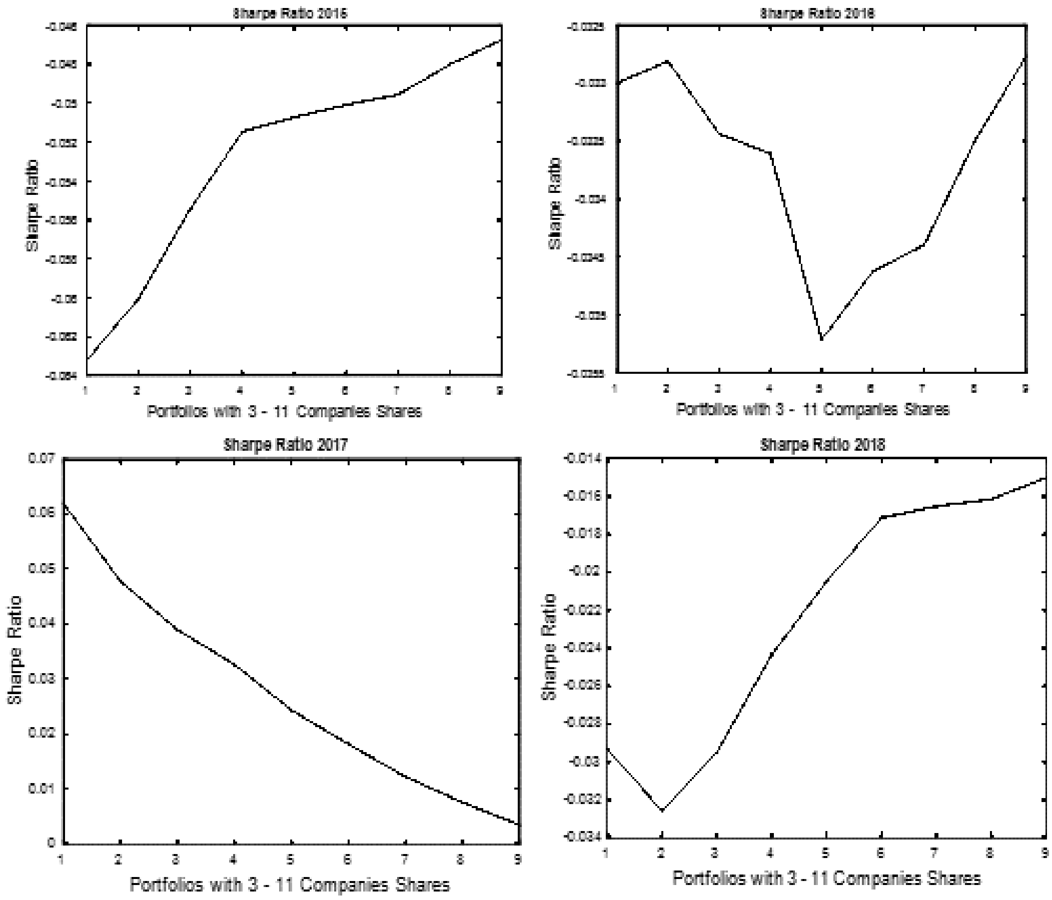


Figure 4.8: Sensitivity of Sharpe ratio with Portfolio size

4.4.2 Treynor Ratio

The linear relationship between portfolio returns and Treynor's ratio was observed across various portfolios constructed using CAPM from 2015 to 2018 as shown in the Table 4.12. Although not always the same portfolio size with equal returns produced equal Treynor ratio. For instance, P1, P2, P3, P7 and P9 produced equal returns in 2016 and 2018 yet they generated different Treynor ratios. Therefore, not only portfolio returns and portfolio size, the inconsistence of Treynor ratio may also be due to market risk which is the function stock market development and country economy. Overall, Treynor ratios found to be more sensitive with portfolio returns and portfolio size throughout from 2015 to 2018.

Table 4.16: Treynor Ratios of the CAPM portfolios from 2015 to 2018

No. of Shares	Portfolio Size	2015		2016		2017		2018	
		Returns	TR	Returns	TR	Returns	TR	Returns	TR
A3	PI	0.01	0.04	0.04	1.10	0.05	3.11	0.04	0.78
A4	P2	0.00	0.00	0.04	0.82	0.05	2.14	0.04	0.64
A5	P3	-0.01	-0.02	0.04	0.60	0.05	1.44	0.04	0.47
A6	P4	-0.01	-0.04	0.04	0.46	0.05	1.07	0.03	0.34
A7	P5	-0.02	-0.05	0.04	0.38	0.05	0.86	0.03	0.26
A8	P6	-0.03	-0.06	0.04	0.32	0.05	0.68	0.03	0.21
A9	P7	-0.03	-0.06	0.03	0.27	0.05	0.56	0.03	0.17
A10	P8	-0.03	-0.07	0.03	0.23	0.05	0.47	0.02	0.17
A11	P9	-0.04	-0.07	0.03	0.22	0.05	0.43	0.03	0.18

Figure 4.9 illustrated that small change of portfolio size led to greater change on portfolio performance. In all four years, the Treynor ratios observed to decrease sharply with the increase of portfolio size.

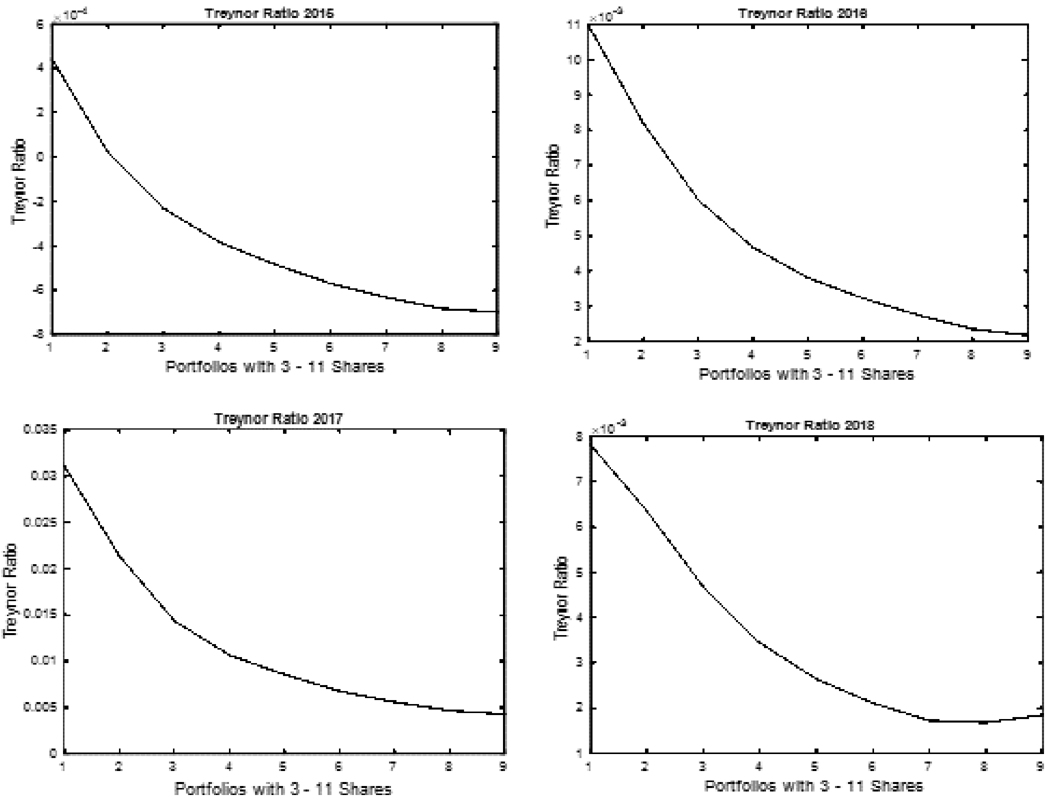


Figure 4.9: The Sensitivity of Treynor Ratio Against Portfolio Size

4.4.3 Comparison Between Sharpe Ratio and Treynor Ratio

Figure 4.10 shows the comparison between the portfolio Sharpe ratio and the Portfolio Treynor ratio for 2015 to 2018. It can be observed that the two performance measures differ in all four years. Treynor ratios appeared to be higher than Sharpe ratios for three years are 2015, 2016, and 2018 while the Sharpe ratio was on top of the Treynor ratio only during 2017. The trends of the Treynor ratio and Sharpe ratio are opposing. The Treynor ratio was found to decrease with the increase of portfolio size while the Sharpe ratio increase with the increase of portfolio size except during

2017. Treynor ratio is less sensitive with portfolio size as most of its curves have shallow slopes while that of Treynor ratio is steeper in all years except 2016.

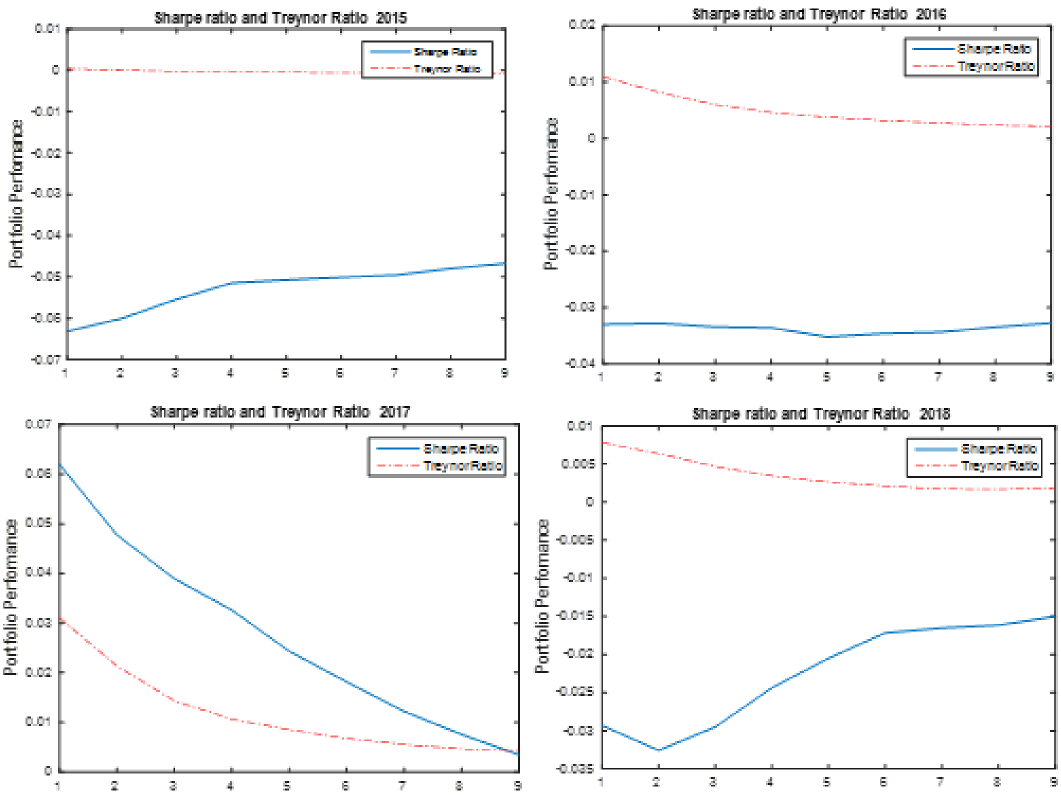


Figure 4.10: Comparison Between Sharpe Ratio and Treynor Ratio

Table 4.17 present the independent t test conducted to examine the existence of significant mean difference between the two performance measures. The results indicated that for 2015, 2016 and 2018 the mean difference between Sharpe ratio and Treynor is significant with $p = 0.00$ $(p \leq 0.00)$. While in 2017 the mean difference was significant with $p = 0.02(p \leq 0.05)$. Furthermore, the average Sharpe ratios were higher than Treynor ratio. Except during 2017, the Treynor ratio produced are always subunit while Sharpe ratios were always greater than 1. Highest average Sharpe ratio was reported in 2017 which was equal to 2.75 percent while the lowest average Sharpe ratio was -5.28 percent on 2015.

Table 4.17: Independent t test between Sharpe Ratio and Treynor Ratio

Year	Sharpe Ratio		Treynor Ratios		P-value	Decision
	Mean	Variance	Mean	Variance		
2015	-5.28	0.31	-0.04	0.00	0.00***	Significant
2016	-3.37	0.01	0.49	0.09	0.00***	Significant
2017	2.75	3.82	1.19	0.82	0.02**	Significant
2018	-2.23	0.46	0.36	0.05	0.00***	Significant

*** Significant at 0.01 level (2-tailed)

Although, there were higher variability of average Sharpe ratio across different portfolio size compared to average Treynor ratio in all years except in 2016. The highest variability of Sharpe ratio was recorded during 2017 which was equivalent to 3.82 percent while the highest variability of Treynor ratio observed in 2016 and was equal to 0.09 percent.

4.5 Portfolio Optimization

This section presented the analysis of fourth research question of this study as stated below.

Research Question 4: Which are the preferred portfolios among the portfolio constructed by the selected stocks listed in EACMs when multi-objective optimization approach was used?

The unbiased random weights were generated using the MATLAB algorithm. The program runs seven different alterations and produced different weights which are allocated in different shares arranged in descending order of individual mean returns. Both MVCM and CAPM were used to the constructed optimum portfolio from 2015 to 2018. The weight generated based on Sharpe and Treynor ratios required to be attained in each year. The required ratios were identified based on the incremental process starting from 0. Initially, the weight allocation of all seven iterations was generated in a single run (1 epoch) and the patterns of all iterations were not uniform.

When the ratios were slowly increased, the number of epochs was also increased, and all seven iterations started to show a similar pattern. The minimum ratios which produced a comparable trend of weight allocations among different shares in all seven iterations were considered as a benchmark. Since the portfolio returns distributions are different in all four years from 2015 to 2018, the benchmark ratios which results in similar trends of funds allocations in various iterations were also different

4.5.1 MVCM Optimization

Figure 4.11 and 4.12 show the patterns of funds allocations across 11 before and after identifying the benchmark Sharpe ratio respectively.

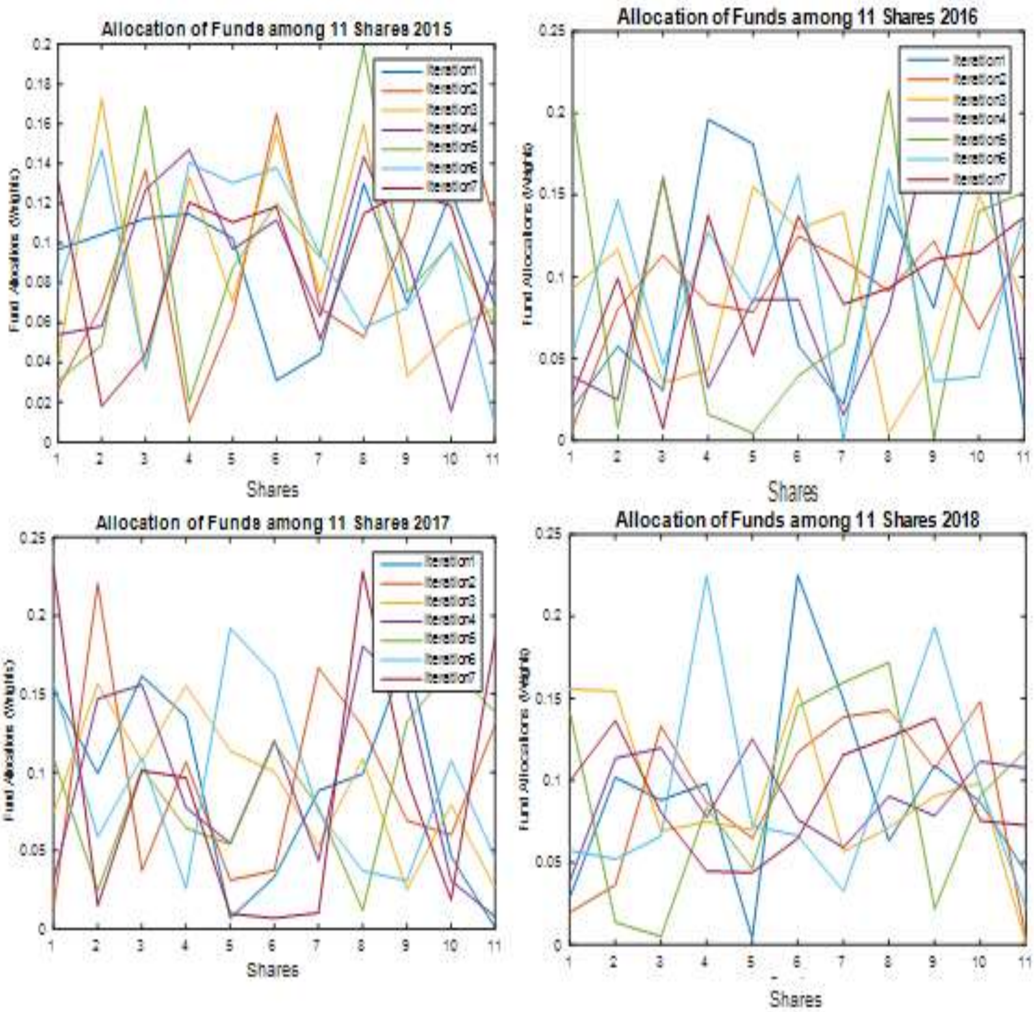


Figure 4.11: Patterns of Fund Allocation before identifying benchmark Sharpe Ratio

The benchmark Sharpe ratio was 6.72, in 2016 was 14.90, in 2017 and 2018 both was 11.15. Initially, the patterns of funds allocation of all iterations were rough and was difficult to trace. However, when the Sharpe ratio increased to benchmark the co-movement was observed as shown in the Figure 4.12

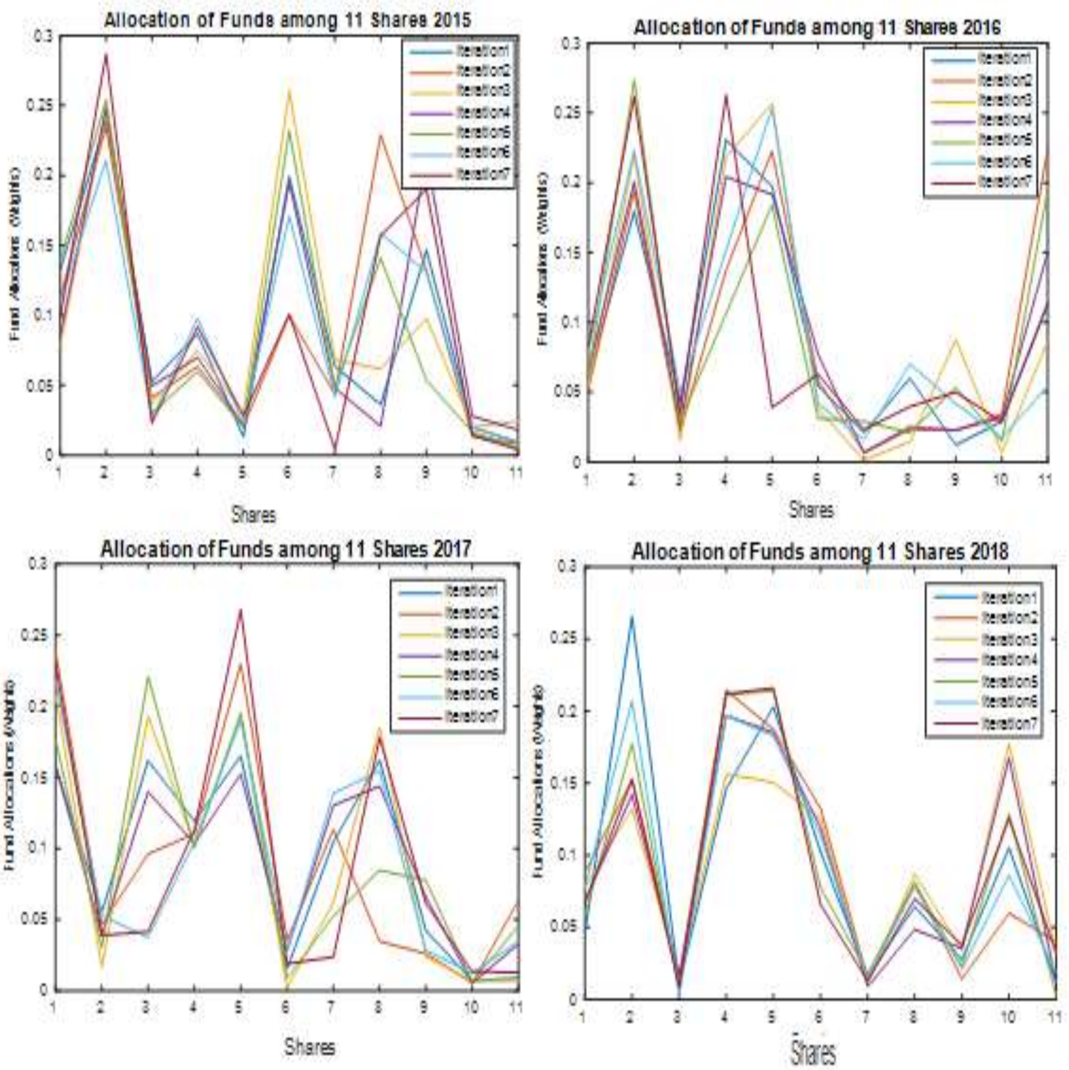


Figure 4.12: Patterns of Fund Allocation After identifying benchmark Sharpe Ratio

Table 4.18 presented the weight used to construct an optimal portfolio among 11 shares for all four years. The results revealed that the shares which received more weights were not the same in all years. UNGA is the only share that received maximum weights in all iteration except the third iteration during 2015. In the first iteration, more than 50 percent of funds were allocated on two shares whereas UNGA received 30 percent and FTGH received 24 percent which is the highest allocation compared to other shares.

Table 4.18: Optimal Allocation of Funds for MVCM Portfolios from 2015 to 2017 of the Selected Companies

Year	Iteration	TPCC	UNGA	TOTL	BERG	TCC	TBL	TCCL	BAT	FTGH	TOL	EABL
2015	1	0.10	0.30	0.04	0.11	0.04	0.09	0.04	0.02	0.24	0.02	0.01
	2	0.11	0.26	0.04	0.05	0.02	0.26	0.06	0.09	0.09	0.00	0.01
	3	0.13	0.20	0.05	0.07	0.03	0.24	0.06	0.14	0.05	0.00	0.02
	4	0.09	0.29	0.04	0.07	0.02	0.18	0.02	0.09	0.13	0.04	0.02
	5	0.12	0.29	0.06	0.12	0.03	0.15	0.05	0.06	0.07	0.03	0.01
	6	0.13	0.24	0.05	0.09	0.01	0.20	0.06	0.04	0.15	0.02	0.01
	7	0.11	0.24	0.04	0.06	0.02	0.10	0.04	0.23	0.13	0.01	0.01
2016	1	0.06	0.18	0.04	0.23	0.20	0.05	0.02	0.06	0.01	0.03	0.11
	2	0.05	0.19	0.02	0.14	0.22	0.06	0.01	0.03	0.02	0.03	0.22
	3	0.05	0.22	0.02	0.22	0.26	0.04	0.00	0.01	0.09	0.01	0.09
	4	0.06	0.20	0.03	0.20	0.19	0.08	0.01	0.02	0.02	0.03	0.15
	5	0.06	0.27	0.03	0.11	0.18	0.03	0.03	0.02	0.05	0.01	0.20
	6	0.08	0.22	0.05	0.15	0.25	0.04	0.02	0.07	0.04	0.02	0.05
	7	0.08	0.26	0.04	0.26	0.04	0.06	0.02	0.04	0.05	0.03	0.11
2017	1	0.16	0.06	0.16	0.12	0.17	0.02	0.10	0.16	0.04	0.01	0.01
	2	0.24	0.05	0.10	0.11	0.23	0.04	0.11	0.03	0.03	0.01	0.06
	3	0.21	0.02	0.19	0.10	0.19	0.00	0.06	0.19	0.02	0.01	0.01
	4	0.16	0.04	0.14	0.10	0.15	0.03	0.13	0.14	0.07	0.01	0.03
	5	0.18	0.03	0.22	0.10	0.20	0.01	0.05	0.08	0.08	0.01	0.05
	6	0.22	0.05	0.04	0.10	0.19	0.03	0.14	0.15	0.03	0.01	0.03
	7	0.23	0.04	0.04	0.11	0.27	0.02	0.02	0.18	0.06	0.01	0.01
2018	1	0.05	0.27	0.01	0.15	0.20	0.10	0.02	0.06	0.03	0.11	0.01
	2	0.09	0.15	0.02	0.21	0.19	0.13	0.01	0.08	0.01	0.06	0.04
	3	0.08	0.13	0.02	0.16	0.15	0.13	0.01	0.09	0.03	0.18	0.03
	4	0.07	0.14	0.02	0.20	0.19	0.12	0.01	0.05	0.04	0.17	0.01
	5	0.06	0.18	0.01	0.21	0.21	0.08	0.02	0.08	0.02	0.13	0.00
	6	0.08	0.21	0.00	0.20	0.18	0.11	0.01	0.08	0.02	0.09	0.02
	7	0.07	0.15	0.01	0.21	0.22	0.07	0.01	0.07	0.04	0.13	0.03

Likewise, in the second iteration where UNGA and TBL each received 26 percent. From the fourth iteration onward, only UNGA remains the leading share with maximum weight. Unexpectedly, TOL was excluded from the portfolio in the second and third iteration. Excluding BERG, BAT, and FTGH, the remaining shares received the weight of less than 10 percent in all iterations. Generally, at least two shares in each iteration received weight from 15 percent and above in the year 2015. During 2016, UNGA and TCC received more weight in a different iteration. While TCC was leading in first, second, third, and sixth iteration with 20, 22, 26, and 25 percent respectively. UNGA received maximum weight in fourth, fifth, and seventh equivalent to 20, 27, and 26 percent respectively. Only TCCL was not considered among shares forming optimal portfolios in the third iteration. Group of 6 shares including TOL, FTGH, BAT, TBL, TOTL, and TPCC received the maximum weight of 9 percent and below. However, in every iteration, there is a minimum of three shares with weight from 15 percent and above except in the seventh iteration. Among shares that have got maximum weights from 15 percent and above in the optimal portfolios constructed for all iterations during 2017 are TPCC and TCC.

Some other shares like TOTL received 16, 19, and 22 percent in first, third, and fifth iteration respectively, and BAT which received 16, 19, 15, and 18 percent in first, third, sixth, and seventh iteration respectively. While TBL was not considered among efficient shares in the third iteration, shares including FTGH, TOL, and EABL received the weight of 8 percent and below. Only in 2017 where UNGA was not found to be among the most preferred shares to form optimal portfolios in any iteration. Overall, shares which are always received more weight and that which have less weight in each year are more or less the same. The first six shares always are among the most weighted shares while the last five shares are among the least weighted shares. unexpectedly, during 2018 TOTL was excluded among the shares forming optimal portfolio in the sixth iteration. While UNGA, BERG, and TCC continued to be among the most weighted shares in various iterations. TCCL, BAT, EFGH, and EABL remained as least weighted shares included in the optimal portfolios constructed.

The optimized returns, risk, and Sharpe ratios of the 9 portfolios constructed are summarised in Table 4.19. The results show that in 2015 the maximum optimal portfolio mean returns generated in the first iteration are equivalent to 2.12 and the minimum was 1.65 produced in the seventh iteration. Also during the year 2016, the maximum optimal portfolio mean returns were 1.48 generated in the sixth iteration and the minimum was 0.93 produced in the third iteration. Likewise, in 2017 the maximum optimal portfolio mean returns which were equal to 1.19 was generated in the sixth iteration and the minimum was 0.66 produced in the third iteration. While for 2018 the maximum optimal portfolio mean return was 1.24 generated in the second iteration and the minimum was 0.91 produced in the first iteration. In each year the variability of risks in different iterations is very small, this signified that the algorithm able to reduce the influence of risk to attain an optimal solution. The results also revealed that the maximum portfolio returns not always correspond to a maximum number of the epoch. This can be only observed during 2017 and 2018 where the maximum returns of 1.19 and 1.24 generated after 154293 and 927804 times respectively while the maximum epoch was 333932 times in 2017 and 6398460 times in 2018. Also, the portfolio returns are more sensitive than portfolio risk in different optimum funds allocations which correspond to the solution of the MOO problem.

Table 4.19: MVCM Optimal Portfolio Returns and Risks in Different Iteration

Year	Required SR	Iteration	Epoch	returns	Risk	SR
2015	6.72	1	1278527	2.12	0.32	6.72
		2	204950	1.79	0.26	6.80
		3	528184	1.75	0.26	6.77
		4	731779	1.78	0.26	6.79
		5	484973	1.92	0.29	6.73
		6	879452	1.81	0.27	6.73
		7	524051	1.65	0.24	6.74
2016	14.90	1	9330	1.30	0.09	14.98
		2	86801	1.00	0.07	15.29
		3	904000	0.93	0.06	15.06
		4	770121	1.19	0.08	14.95
		5	230401	1.19	0.08	15.03
		6	1030438	1.48	0.10	14.99
		7	21442	1.45	0.10	15.00
2017	11.15	1	143351	1.10	0.10	11.18
		2	18019	1.15	0.10	11.18
		3	63425	0.66	0.06	11.20
		4	211275	1.04	0.09	11.30
		5	24945	0.84	0.07	11.18
		6	154293	1.19	0.11	11.22
		7	333932	1.03	0.09	11.20
2018	11.15	1	6398460	0.91	0.08	11.22
		2	927804	1.24	0.11	11.22
		3	4481768	1.14	0.10	11.18
		4	1125342	1.05	0.09	11.18
		5	856187	0.97	0.09	11.21
		6	332313	1.08	0.10	11.20
		7	120229	1.02	0.09	11.17

As it was stated that the objective function was to maximize portfolio returns and minimize portfolio risk subject to required Sharpe ratio was attained. Equal portfolio risks have been observed in different iterations in the same year although the corresponding portfolio returns, and Sharpe ratio are different. This can be observed in 2015 from second to the fourth iteration, in 2016 from fourth to seventh iteration, 2017 in the first and second iteration as well as in 2018 in the fourth and fifth iteration. Figure 4.13, 4.14 and 4.15 illustrated the trend of portfolio returns, risk, and Sharpe ratio in all iterations.

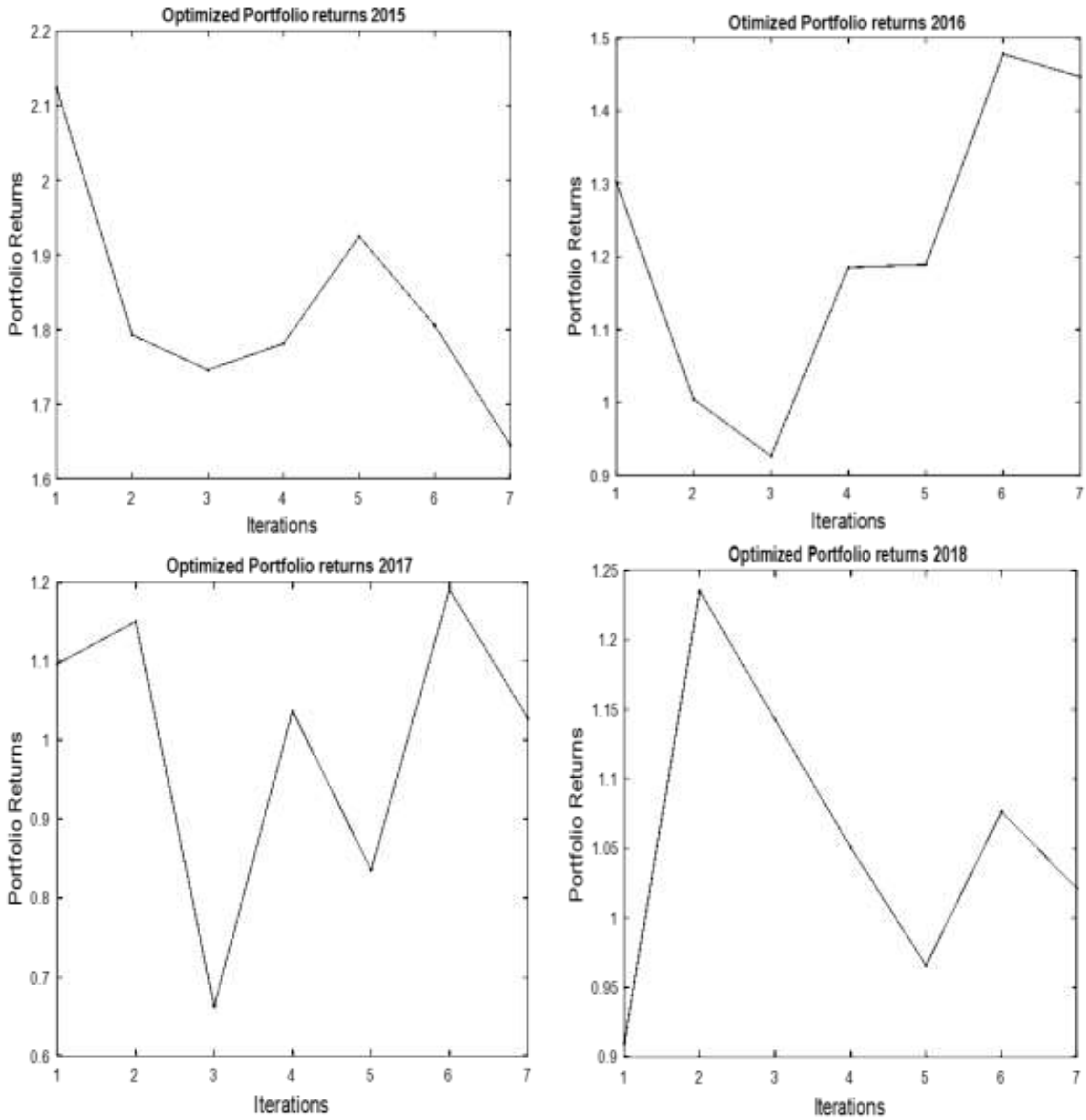


Figure 4.13: The Trend of Optimized MVCM Portfolio Returns in 7 Iterations

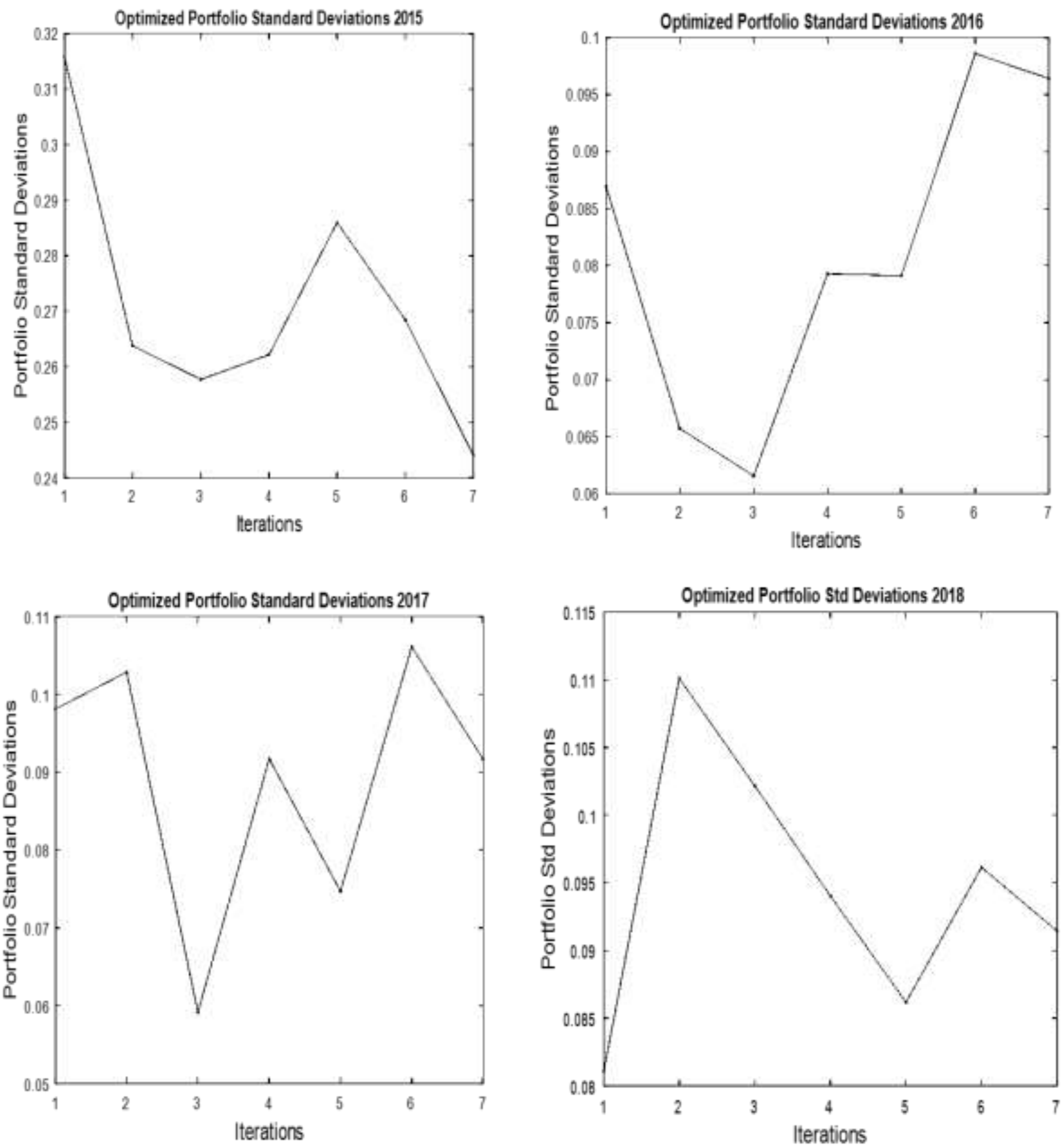


Figure 4.14: The Trend of Optimized Portfolio Risks in 7 Iterations

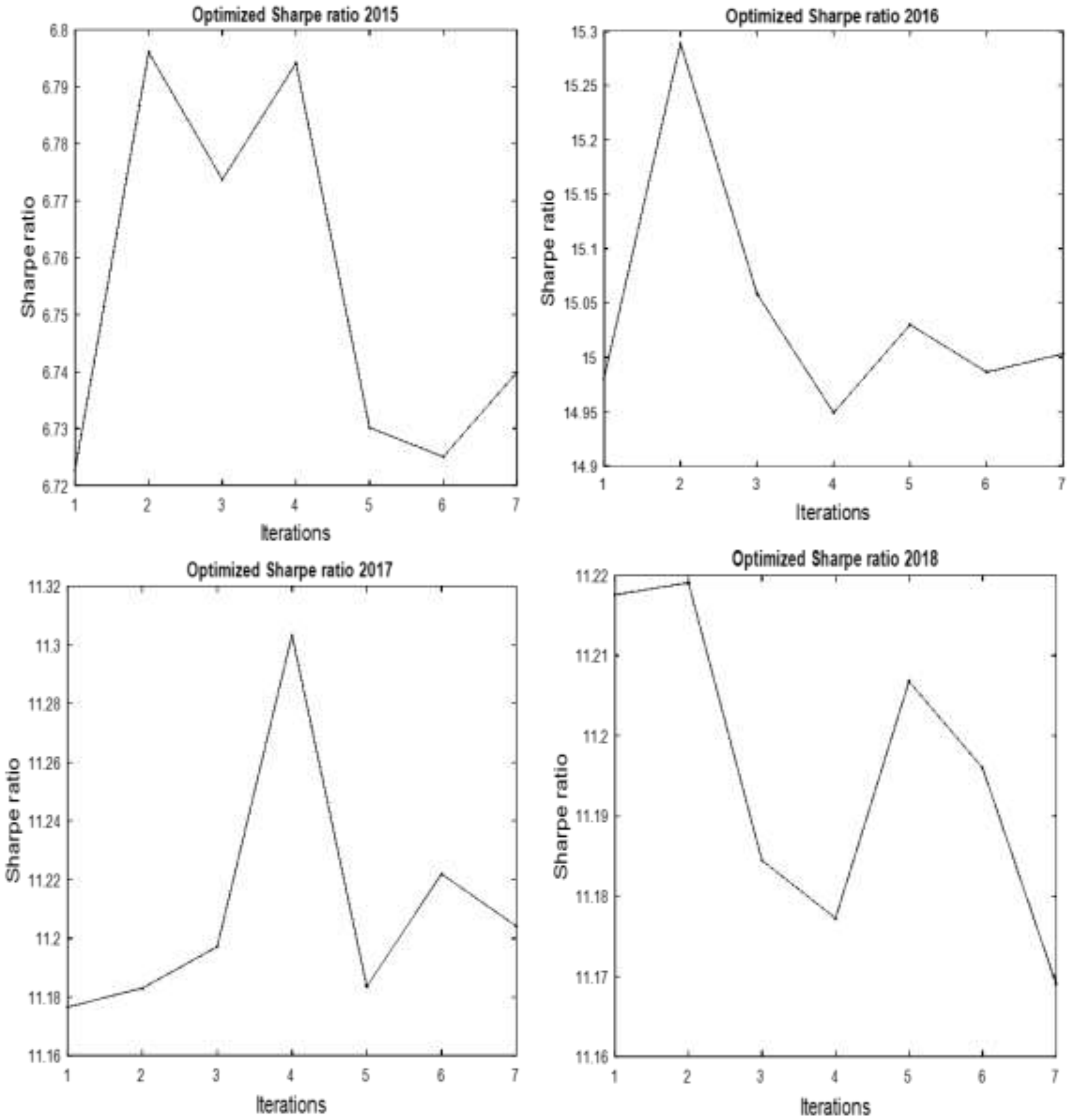


Figure 4.15: The Trend of Optimized Portfolio Sharpe ratio in 7 Iterations

4.5.2 CAPM Portfolio Optimization

Figure 4.16 and 4.17 illustrated the patterns of funds allocations across 11 before and after identifying the benchmark Treynor ratio.

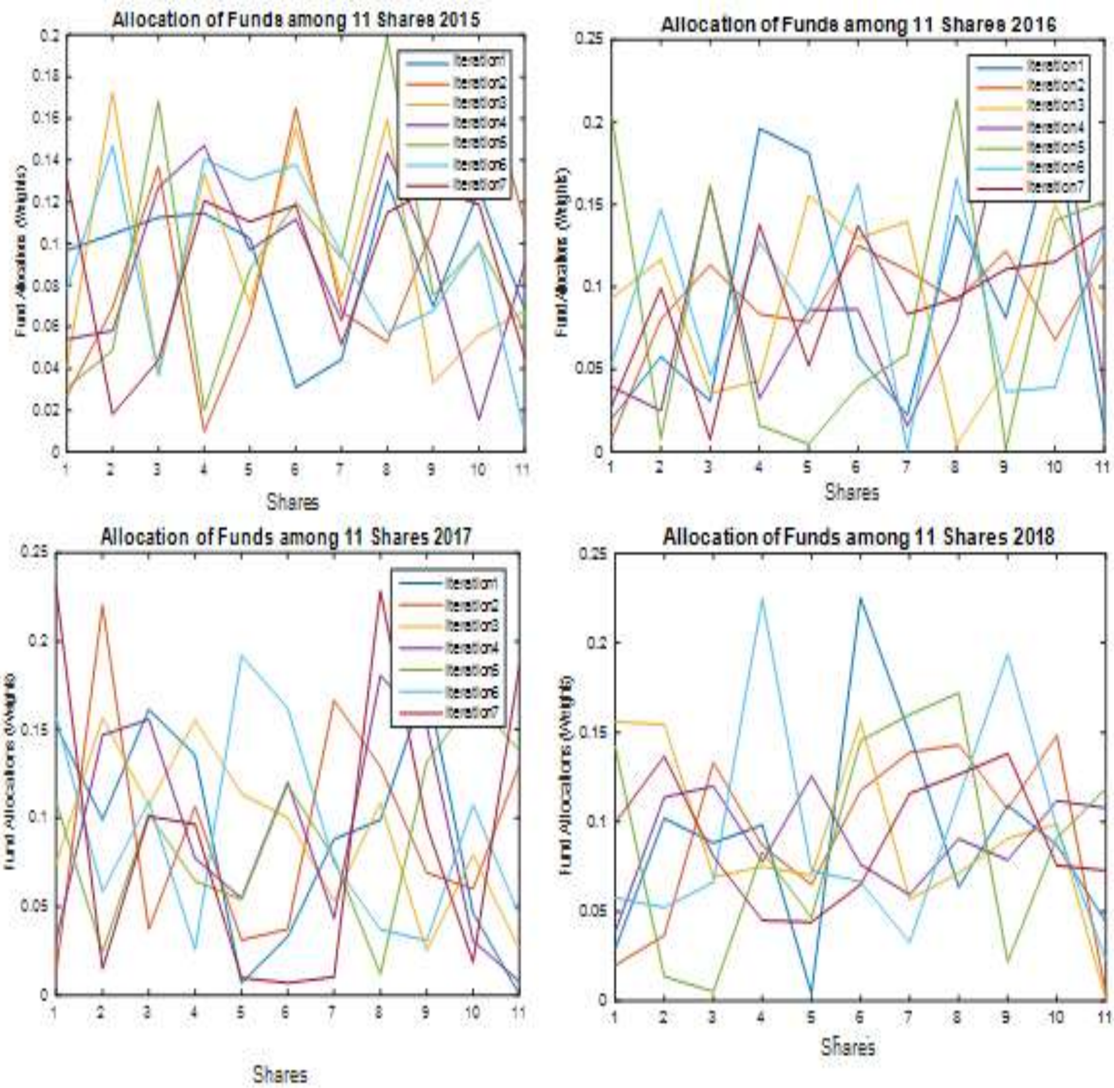


Figure 4.16 Funds Allocation before Achieving Benchmark TR

The rough patterns of funds allocation have been observed before achieving the minimum required Traynor ratio in all years. Only when it reaches certain minimum level which was 0.01 for 2015, 0.70 for 2016, 5.50 for 2017 and 3.98 for 2018 the pattern started to show similar trend.

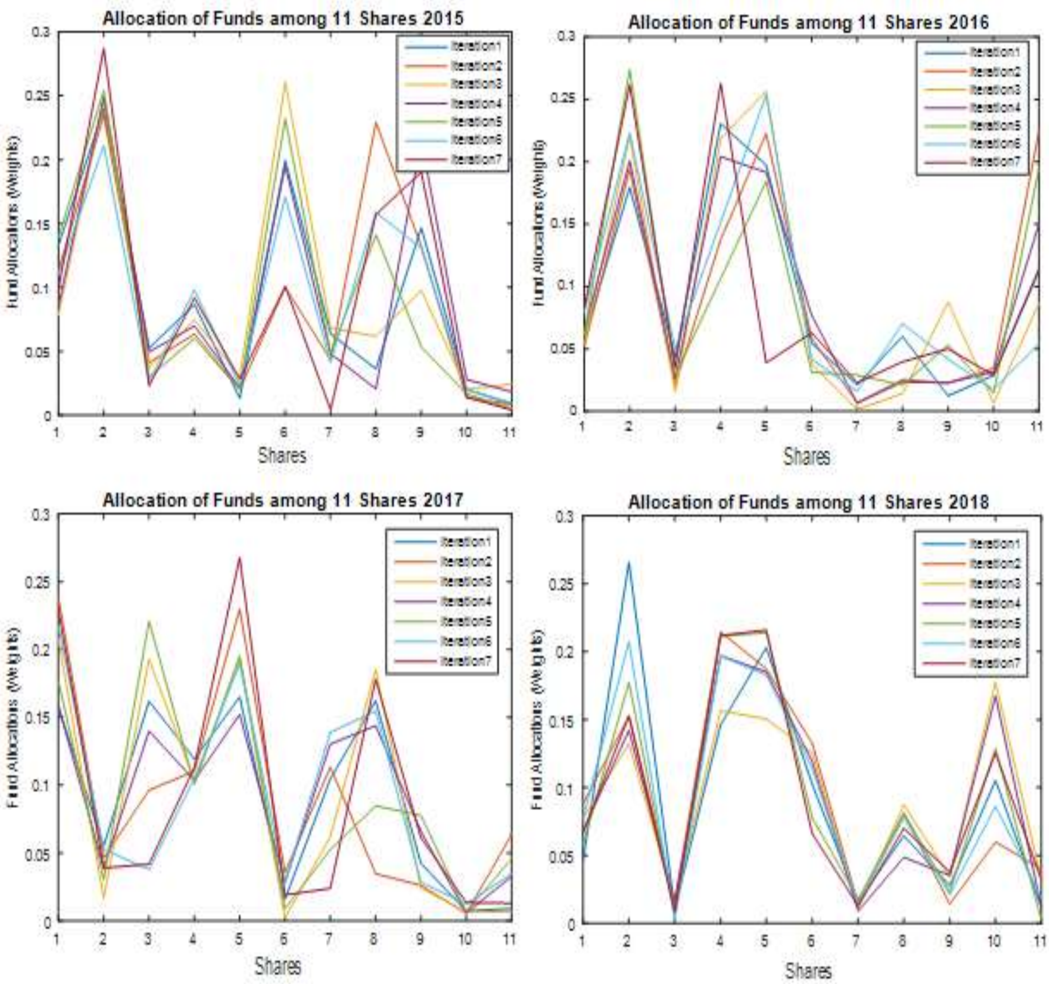


Figure 4.17 Funds Allocation After Achieving Benchmark TR

Table 4.20 presents the weights of all seven iterations generated in each year when the required Treynor ratio was attained. The results revealed that EABL receives more weights for 2015, 2016, and 2017 for all iterations except in the fourth iteration in 2015 and the first iteration in 2016 where TPCC appeared to be the most weighted share. Different shares appear to have maximum weight in different iteration during 2018. In the first and last iteration, only EABL granted the highest weight equivalent to 16 and 20 percent while in the second and third iteration the highest weight was allocated to TPCC which was equal to 17 and 16 percent respectively. BERG found most weighted with 18 percent in the fourth iteration while UNGA in fifth and sixth iteration received 21 and 14 percent respectively.

Table 4.20: Optimal Allocation of Funds for CAPM Portfolios from 2015 to 2017

Year	Iteration	TPCC	UNGA	TOTL	BERG	TCC	TBL	TCCL	BAT	FTGH	TOL	EABL
2015	1	0.22	0.12	0.15	0.00	0.01	0.09	0.02	0.00	0.00	0.07	0.31
	2	0.25	0.09	0.15	0.03	0.04	0.00	0.01	0.03	0.00	0.07	0.32
	3	0.27	0.19	0.01	0.05	0.05	0.05	0.02	0.01	0.02	0.03	0.31
	4	0.35	0.17	0.00	0.06	0.03	0.02	0.03	0.05	0.02	0.03	0.25
	5	0.30	0.06	0.03	0.11	0.03	0.14	0.02	0.00	0.01	0.01	0.28
	6	0.17	0.23	0.09	0.01	0.03	0.00	0.00	0.07	0.04	0.02	0.33
	7	0.28	0.04	0.06	0.13	0.03	0.04	0.00	0.03	0.02	0.07	0.30
2016	1	0.08	0.25	0.03	0.07	0.00	0.07	0.02	0.03	0.00	0.01	0.43
	2	0.14	0.25	0.27	0.07	0.01	0.01	0.00	0.00	0.01	0.01	0.22
	3	0.24	0.28	0.06	0.01	0.01	0.03	0.03	0.03	0.00	0.01	0.29
	4	0.19	0.30	0.11	0.03	0.00	0.02	0.05	0.01	0.00	0.00	0.28
	5	0.23	0.25	0.02	0.01	0.02	0.05	0.01	0.00	0.02	0.00	0.38
	6	0.16	0.29	0.14	0.02	0.00	0.03	0.00	0.02	0.00	0.03	0.30
	7	0.26	0.13	0.11	0.05	0.06	0.00	0.00	0.00	0.01	0.02	0.34
2017	1	0.17	0.03	0.09	0.02	0.07	0.10	0.04	0.14	0.04	0.19	0.11
	2	0.12	0.10	0.18	0.08	0.01	0.01	0.01	0.16	0.07	0.09	0.18
	3	0.00	0.05	0.22	0.09	0.10	0.00	0.15	0.01	0.07	0.00	0.30
	4	0.04	0.21	0.03	0.10	0.07	0.00	0.17	0.05	0.03	0.09	0.20
	5	0.08	0.01	0.07	0.01	0.19	0.13	0.05	0.11	0.00	0.12	0.22
	6	0.04	0.11	0.05	0.17	0.02	0.13	0.05	0.04	0.08	0.11	0.18
	7	0.05	0.14	0.13	0.09	0.12	0.06	0.04	0.03	0.07	0.14	0.13
2018	1	0.10	0.09	0.12	0.04	0.06	0.13	0.08	0.09	0.01	0.13	0.16
	2	0.17	0.12	0.14	0.08	0.02	0.10	0.01	0.11	0.01	0.12	0.12
	3	0.16	0.09	0.11	0.05	0.01	0.01	0.04	0.16	0.09	0.15	0.12
	4	0.01	0.14	0.02	0.18	0.08	0.12	0.04	0.07	0.03	0.17	0.12
	5	0.00	0.21	0.01	0.13	0.05	0.06	0.05	0.02	0.17	0.16	0.15
	6	0.03	0.14	0.12	0.13	0.07	0.11	0.06	0.02	0.04	0.14	0.13
	7	0.07	0.01	0.01	0.09	0.04	0.15	0.06	0.18	0.04	0.15	0.20

Some shares such as TCC, TCCL, and BAT were

excluded in the portfolios at least three times during 2016. For instance, TCC appeared with zero weight in the first, fourth, and sixth iteration in 2016, BAT appeared on the second, fifth, and seven iterations in 2016 while TCCL appeared on second, sixth, and seventh. Moreover, shares like TBL and FTGH were not considered in the portfolio for three years consecutively from 2015, 2016, and 2017 in different iterations. Surprisingly, TPCC which was among the most weighted share during 2015 and 2016 was excluded in the portfolio in 2017 and 2018 during the third and fifth iteration. Generally, all shares except UNGA and EABL at least once have been excluded in the portfolio in any period and iteration.

The efficient portfolios were constructed from the weight shown in Table 4.20 and summarised in Table 4.21. The program run in thousands epoch to compute the optimum CAPM portfolio mean returns and beta to meet the minimum required Treynor's ratio. Different epoch produced different portfolio mean returns and beta. Immediate observation found on maximum optimum portfolio means returns oscillated between 0.04 throughout from 2016 to 2018 although there was an abrupt change of portfolio beta with iterations across different years. Moreover, there were several portfolios which produced almost zero returns during 2015 including those portfolio formed using weights generated in first, fifth, sixth, and seven iterations. The results also revealed the portfolio beta was high during 2015 to a maximum of 26.90 percent in the sixth iteration and start to decrease to zero in 2018. Although the objective function defined was to maximize portfolio mean returns and beta subject to the minimum required Treynor ratio was attained, yet the sensitivity portfolio mean return outnumbered by portfolio beta in all years and all iterations which signified that MOO is less effective in CAPM although it was attained at a minimum level.

Table 4.21: CAPM Optimal Portfolio Returns and Risks in Different Iteration

Year	Required SR	Iteration	Epoch	Returns	Beta	TR
2015	0.01	1	42619	0.00	25.91	0.01
		2	694637	0.01	25.02	0.02
		3	58859	0.01	21.68	0.05
		4	163042	0.01	23.15	0.03
		5	300420	0.00	24.60	0.02
		6	37616	0.00	26.90	0.01
		7	30554	0.00	25.90	0.01
2016	0.70	1	6367690	0.04	5.33	0.75
		2	8480753	0.04	5.37	0.74
		3	11872396	0.04	5.32	0.75
		4	3071979	0.04	4.57	0.88
		5	1978276	0.04	4.16	0.98
		6	3799222	0.04	5.42	0.73
		7	7444993	0.04	5.29	0.75
2017	5.50	1	7168	0.04	0.01	7.69
		2	3012	0.04	0.00	18.99
		3	11248	0.05	0.01	6.14
		4	4757	0.04	0.00	32.94
		5	2928	0.04	0.00	22.59
		6	6235	0.04	0.01	6.80
		7	9183	0.04	0.01	6.05
2018	3.98	1	1919	0.04	0.01	5.76
		2	1321	0.04	0.00	9.35
		3	1768	0.04	0.01	4.84
		4	3497	0.04	0.00	8.20
		5	3022	0.04	0.00	17.26
		6	5578	0.04	0.01	4.93
		7	13631	0.04	0.00	18.34

Note: All values of portfolio returns and beta presented in the Table are converted into percentage. This is because the values were very small in such a way that cannot be seen when were rounded in two decimal point.

Although the algorithm runs several epochs, the higher epoch does not always correspond to higher portfolio mean returns. For example, a maximum epoch in 2015 was 693637 and corresponding returns were 0.01. Likewise, other epochs such as 58859 and 163042 both produced the same returns of 0.01 during 2015, similar trends can be observed in 2016, 2017, and 2018. The behaviour and trends of optimum portfolio returns, beta, and Treynor ratio can be observed in Figure 4.18, 4.19 and 4.20

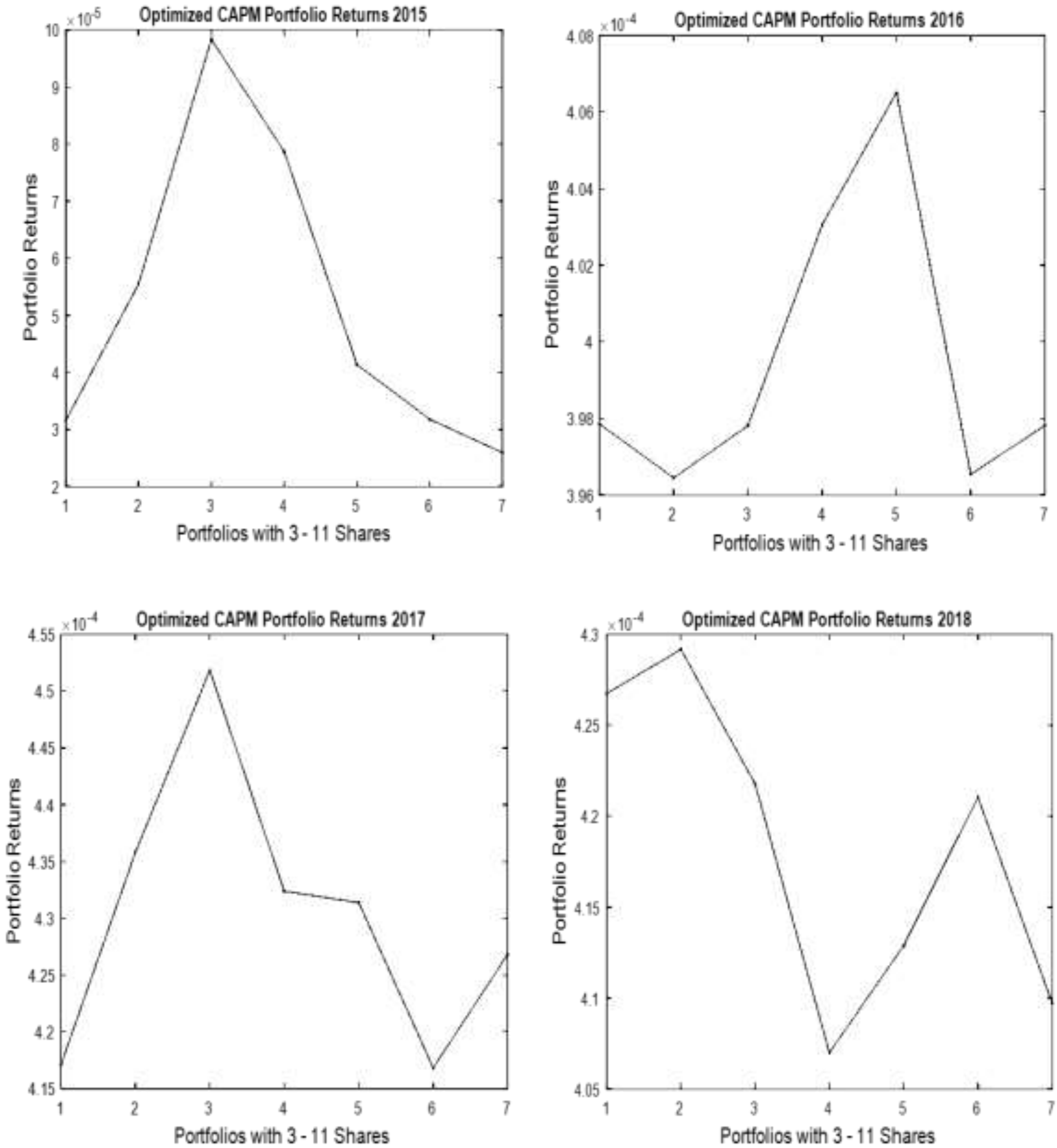


Figure 4.18 The Trend of Optimized CAPM Portfolio Returns in 7 Iterations.

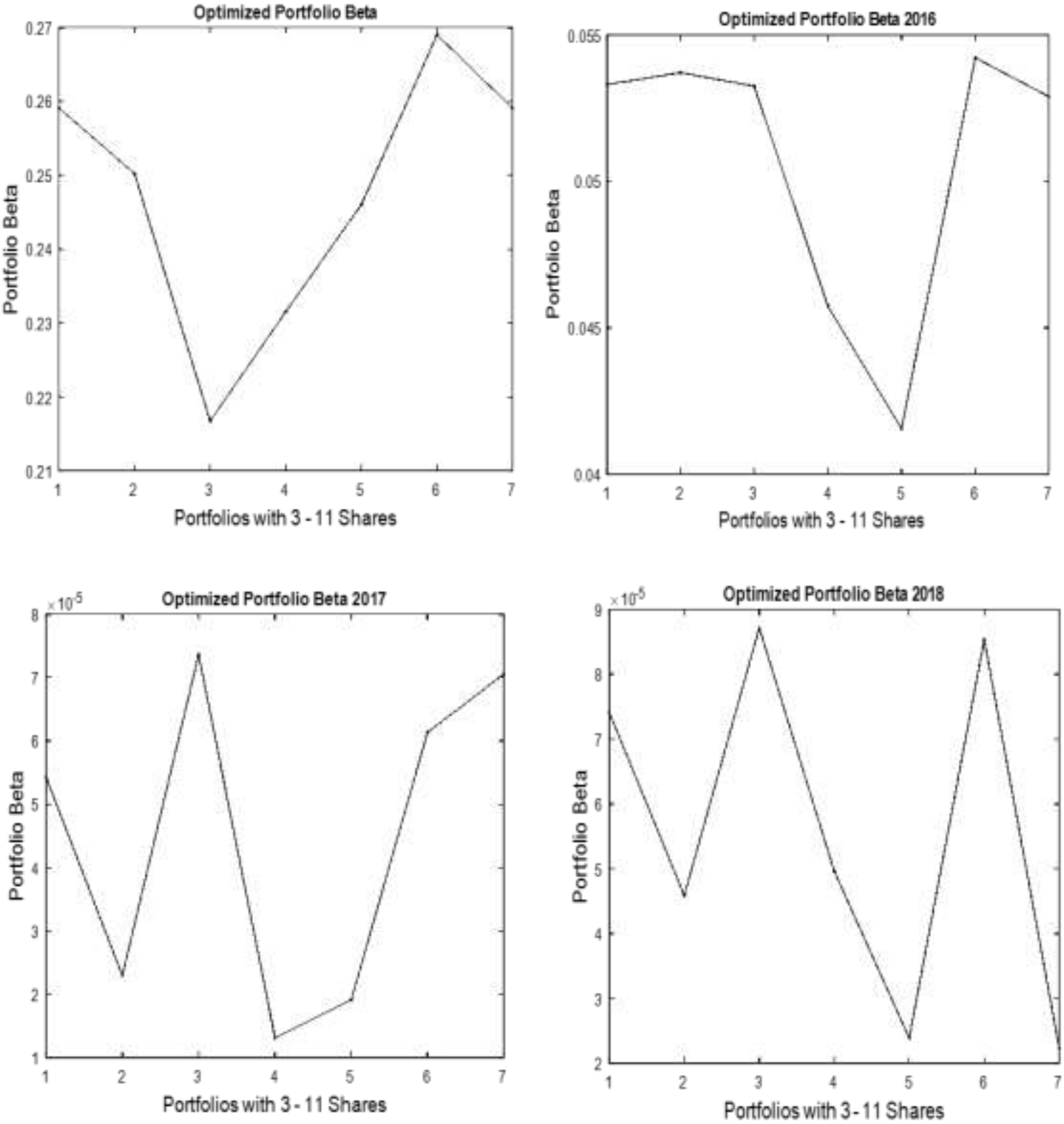


Figure 4.19 The Trend of Optimized CAPM Portfolio Risks in 7 Iterations.

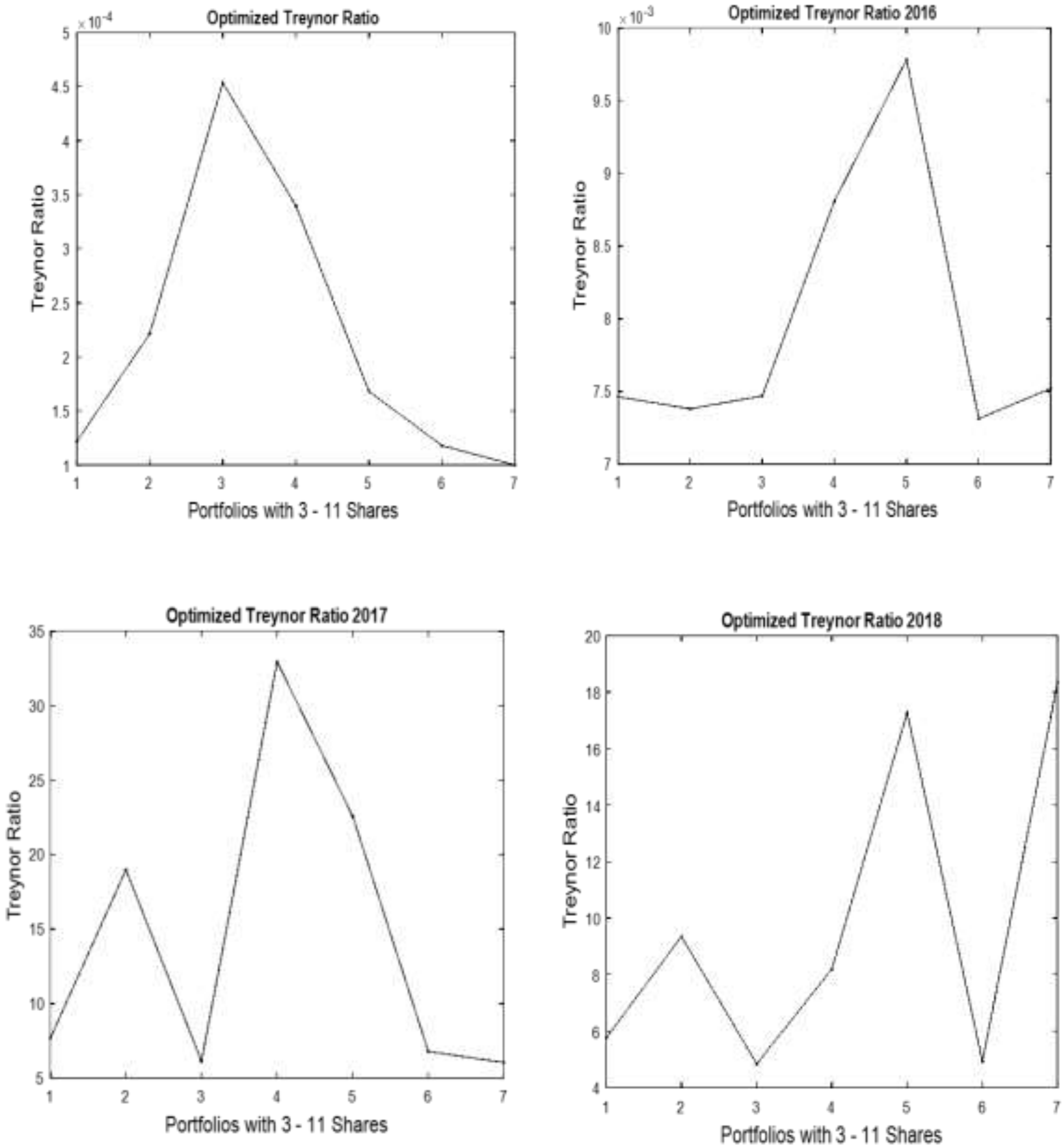


Figure 4.20 The Trend of Optimized CAPM Portfolio Traynor ratio in 7 Iterations.

4.6 Portfolio Stress Tests

This section presented the analysis related to fifth research question which corresponds to fifth, sixth, seventh and eighth research hypothesis of this study as stated below.

Research question 5: What are the patterns, behaviours and directions of the various portfolios constructed will have during good times and extreme conditions?

Hypothesis 5: There is no significant mean difference between sensitivity portfolio mean returns computed by MVCM-DEA in different states of the economy.

Hypothesis 6: There is no significant mean difference between sensitivity risks computed using MVC-DEA in a different state of the economy.

Hypothesis 7: There is no significant mean difference between the sensitivity of portfolio mean returns computed by CAPM-DEA in different states of the economy.

Hypothesis 8: There is no significant mean difference between the sensitivity of risks computed using CAPM-DEA in a different state of the economy.

The four hypotheses stated above which are hypothesis 5 to hypothesis 8 are all extracted from research question 5 which is.

Portfolio stress was conducted by observing the change of portfolio mean returns computed using MVCM and CAPM, standard deviations and beta when the funds allocated in different shares in a portfolio are changed with respect of defined state of economy such as good, bad, and worst.

4.12.1 Stress test of MVCM Portfolio Returns

Table 4.22 presents the MVCM portfolio mean returns in different uncertainty levels defined as a current, poor, and worst state of the economy. The results demonstrated that the portfolio mean returns responds differently in different states and portfolio size. During 2015 and 2016 all the portfolios constructed in any state of economy generate losses of a minimum of 0.07 to 0.42 percent except P5 in 2016 which record a profit of 0.06 percent. At least in the year 2017 and 2018, there are countable portfolios which produce positive returns. Some of them are all portfolios in the current state of the economy as well as the first four portfolios in the poor and worst state of the economy for 2017, also first three portfolios in the worst state of the economy, P5, P7, and P9 for 2018.

Generally, portfolio mean returns are more sensitive in the worst state compared to another state of the economy. This can be observed clearly in the current state of the economy, for example in 2015 where the P4 to P8 are all report the same returns equivalent to -0.16 percent or from P5 to P8 in 2016 all to show the returns of -0.10 percent or from P5 to P9 in 2018 all generate returns of -0.05 percent. The existence of constant returns on different portfolios constructed signified the weak sensitivity of portfolio means returns on the current state of the economy. Although, there are a few portfolios in the worst state where the successive portfolios produce equal returns such as P6 and P7 in 2015 both generated mean returns of 0.15 percent, P3 and P4 in 2016 both generated mean returns of 0.22 percent well as P7 and P8 both generated returns of 0.09 percent.

Table 4.22: MVCM Portfolio Returns in Different States of Economy

Year	Number of Shares	Portfolio Size	States of Economy		
			Current	Poor	Worst
2015	A3	P1	-0.16	-0.15	-0.19
	A4	P2	-0.17	-0.20	-0.17
	A5	P3	-0.17	-0.16	-0.15
	A6	P4	-0.16	-0.13	-0.04
	A7	P5	-0.16	-0.17	-0.42
	A8	P6	-0.16	-0.16	-0.15
	A9	P7	-0.16	-0.16	-0.15
	A10	P8	-0.16	-0.12	-0.05
	A11	P9	-0.15	-0.12	-0.24
2016	A3	P1	-0.07	-0.06	-0.10
	A4	P2	-0.08	-0.10	-0.24
	A5	P3	-0.09	-0.11	-0.22
	A6	P4	-0.09	-0.11	-0.22
	A7	P5	-0.10	-0.13	0.06
	A8	P6	-0.10	-0.09	-0.27
	A9	P7	-0.10	-0.10	-0.16
	A10	P8	-0.10	-0.08	0.12
	A11	P9	-0.09	-0.07	-0.21
2017	A3	P1	0.12	0.09	0.02
	A4	P2	0.10	0.06	0.20
	A5	P3	0.09	0.04	0.36
	A6	P4	0.08	0.02	0.05
	A7	P5	0.06	-0.05	-0.12
	A8	P6	0.04	-0.06	0.18
	A9	P7	0.03	-0.08	-0.09
	A10	P8	0.02	-0.08	-0.09
	A11	P9	0.01	-0.09	-0.01
2018	A3	P1	-0.06	-0.08	0.01
	A4	P2	-0.07	-0.12	109.72
	A5	P3	-0.07	-0.06	0.01
	A6	P4	-0.06	-0.01	-1.00
	A7	P5	-0.05	-0.01	0.25
	A8	P6	-0.05	-0.01	-0.05
	A9	P7	-0.05	-0.06	0.74
	A10	P8	-0.05	-0.07	-0.12
	A11	P9	-0.05	-0.03	0.23

Note: All values of portfolio return in all states of economy presented in the Table 4.16 are converted into percentage. This is because the values were very small in such a way that cannot be seen when were rounded in two decimal point.

Yet, the worst state of the economy is the only state which produced the highest positive returns as well as the highest negative returns throughout from 2015 to 2018. The highest positive portfolio returns was 109.72 while the highest negative returns generated was 1.0 percent both observed in 2018 in the worst state of the economy. The trends of portfolio mean return in different states of economy can be observed in the Figure 4.21.

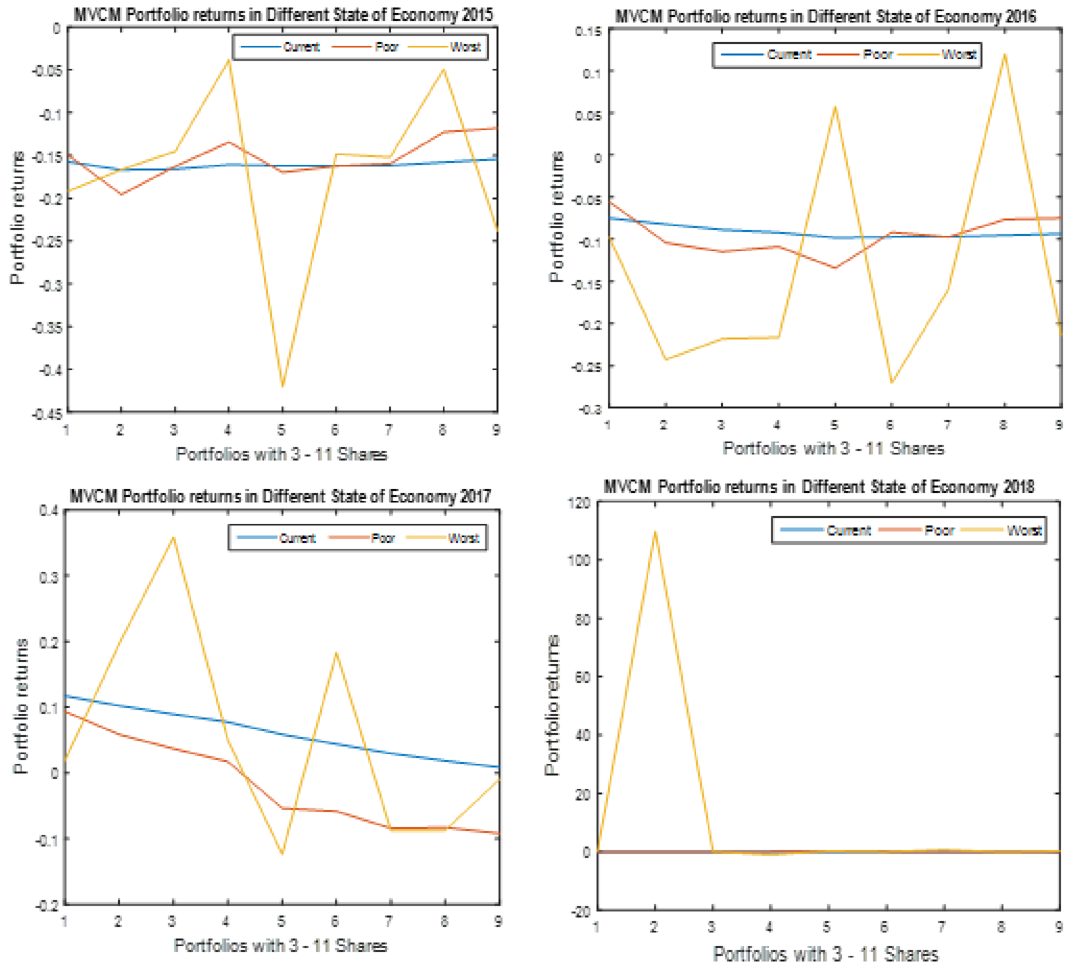


Figure 4.21: Comparison of Portfolio Mean Returns in different states of Economy

The trends of portfolio mean returns in worst state is uneven throughout except in 2018 and from P3 onward. However, both current and poor state show similar trend of portfolio mean returns. Although, the trend of poor state appeared to be less linear than current state except in 2018. ANOVA test was conducted to find whether the mean difference of portfolio mean returns between the states of economy is significant. For all four years, the results revealed that there is no significant mean difference of portfolio mean returns between different states of economy since the $p \geq 0.05$ as shown in the Table 4.23. This means that the change of economic condition within the region does not have significant effect on portfolio mean returns though the average return found to vary in different economic states. The insignificant effect was due to the portfolio diversification problem which is associated to number shares in the portfolio, shares from various industries and various allocation strategy used. Since the analysis of this study considered only 11 shares from industry sector and only used weighted based portfolio allocation strategy therefore led to the failure of capturing diversification opportunities. This finding is in line with the recent study of Theron and Vuren (2018) who evaluated four different portfolio allocation strategy such as equal weighted, minimum variance, tangent portfolio as well as maximum diversification according to the expected returns in different economic conditions. They addressed that failure to have large enough stocks will lead unexpected outcome. Similarly different sectors such as bank, biotech, gold, and REITs show different results with the same and different strategy used. However, the findings of this study contradict with that of Franco, Nicolle, and Pham (2018) who reported that that the mean returns of the portfolios change with uncertainty level. However, they overlook to test the level of significancy to understand whether the change across different levels is significant. Moreover, the model used in the study of Franco, Nicolle, and Phan (2018) was Bayesian strategy while this study used MVCM. Generally, they concluded that Bayesian strategy is fit for higher uncertainty level compared to MVCM as they further reached to the scale of 10 when classifying the uncertainty level while in this study reached to the scale of 3.

Table 4.23: Summery of ANOVA Results for Portfolio Mean Returns

Year	Groups	Sum	Average	Variance	P-Value	Decision
2015	Current Poor Worst	-1.45 -1.37 -1.55	-0.16 -0.15 -0.17	0.00 0.00 0.01	0.83	Not Significant
2016	Current Poor Worst	-0.82 -0.86 -1.24	-0.09 -0.10 -0.14	0.00 0.00 0.02	0.41	Not Significant
2017	Current Poor Worst	0.55 -0.16 0.50	0.06 -0.02 0.06	0.00 0.00 0.03	0.22	Not Significant
2018	Current Poor Worst	-0.52 -0.46 109.79	-0.06 -0.05 12.20	0.00 0.00 1337.70	0.38	Not Significant

4.12.2 Stress test of MVCM Portfolio Standard Deviation

The results presented in the Table 4.24 show the sensitivity of portfolio standard deviations of various state of economy and portfolio size from 2015 to 2018. Overall, the sensitivity of portfolio risks is high in all states of economy. However, the results revealed that risk is high in worst state of economy compared to current and poor state in any portfolio size within time frame. Since the investors are randomly allocated the funds during the worst economic state, it could be among the reason which caused such variation. The highest risk recorded in P2 during 2018 which was equivalent to 4148.85. Such huge risk observed was associated to huge returns realized on the same year within the same portfolio. Interesting observation was found on P5 where the portfolio risks recorded highest among all portfolios from 2015 to 2017. The combination of assets which form P5 involve 4 assets of frequently traded and 3 assets which are less traded. That mix of assets found to be much affected with random allocation of funds. Likewise, the variability of risk against portfolio size is also high compared to other state of economy and the higher change can be observed in the last two portfolio which are P8 and P9 in every year. For example, during 2015 it changes from 5.68 to 13.72, also during 2016 it changes from 14.85 to 21.56, in 2017 it changes from 16.94 to 4.39 while in 2018 it changes from 6.12 to 14.30. When the current and poor state is compared, the variability of risk with portfolio size appeared to be higher in a poor state.

Table 4.24: MVCM Portfolio Standard Deviation in Different States of Economy

Year	Number of Shares	Portfolio Size	States of Economy		
			Current	Poor	Worst
2015	A3	P1	2.49	2.72	2.91
	A4	P2	2.78	3.95	6.18
	A5	P3	3.00	3.16	4.36
	A6	P4	3.13	2.73	4.88
	A7	P5	3.20	2.75	13.59
	A8	P6	3.24	2.93	3.76
	A9	P7	3.27	3.26	8.27
	A10	P8	3.29	3.01	5.68
	A11	P9	3.30	2.74	13.72
2016	A3	P1	2.27	2.26	3.50
	A4	P2	2.51	2.97	8.06
	A5	P3	2.65	2.81	6.85
	A6	P4	2.74	2.32	7.88
	A7	P5	2.79	2.50	69.72
	A8	P6	2.81	2.33	8.80
	A9	P7	2.83	2.87	8.76
	A10	P8	2.84	2.56	14.85
	A11	P9	2.85	2.37	21.56
2017	A3	P1	1.89	2.36	6.29
	A4	P2	2.15	2.44	6.48
	A5	P3	2.29	2.23	11.01
	A6	P4	2.37	2.05	3.50
	A7	P5	2.41	1.87	32.54
	A8	P6	2.43	2.03	5.96
	A9	P7	2.44	2.54	4.82
	A10	P8	2.45	2.21	16.94
	A11	P9	2.46	2.05	4.39
2018	A3	P1	1.97	2.66	5.84
	A4	P2	2.27	2.65	4148.85
	A5	P3	2.42	2.20	5.93
	A6	P4	2.49	1.89	40.39
	A7	P5	2.64	5.73	14.18

	A8	P6	2.84	5.01	5.02
	A9	P7	3.04	4.86	42.27
	A10	P8	3.20	4.25	6.12
	A11	P9	3.33	3.80	14.30

Generally, the risks in the Current state are found to be less volatile when portfolio size increases. The change of risk across different portfolios is less than subunit in any year. Figure 4.22 illustrated the behavior of the portfolio standard deviation of current, poor, and worst state in various portfolio size from 2015 to 2018.

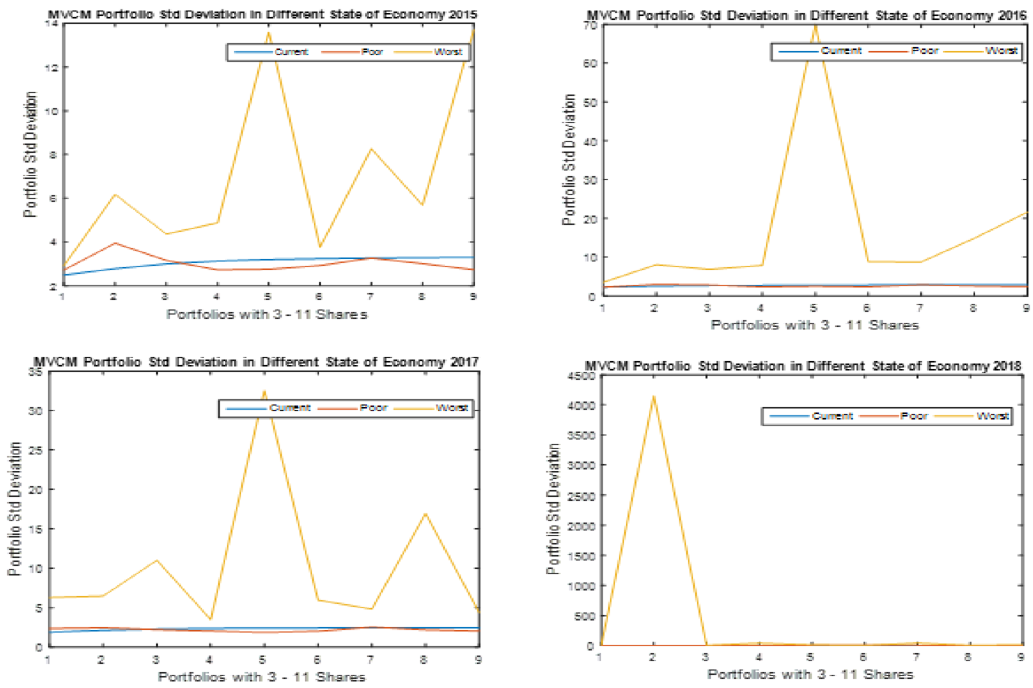


Figure 4.22: Comparison of Portfolio Standard Deviation in different states of Economy

All three states behave differently with the increase of portfolio size. Although the pattern of the current and poor state is nearly moving together. A huge difference can be observed in the trend standard deviation in the worst state of the economy. The trend is unpredictable and more volatile with the increase of portfolio size except in the few portfolios during 2018. Generally, there are mean differences between the sensitivity of standard deviations and different states of economy. The ANOVA test results presented in the Table 4.25 revealed that there are significant mean differences of portfolio risks in different states of economy during 2015, 2016 and 2017 with $p = 0.00 (p \leq 0.00)$, $p = 0.03 (p \leq 0.05)$ and $p = 0.01 (p \leq 0.05)$ respectively. Only during 2018 where the mean difference of risks of portfolio returns in all states of economy found not significant as $p = 0.36 (p \geq 0.05)$ which is the minimum tolerable P-value.

Table 4.25: Summery of ANOVA Results for Portfolio Standard Deviation

Year	Groups	Sum	Average	Variance	P-Value	Decision
2015	Current	27.686	3.076	0.076	0.00***	Significant
	Poor	27.238	3.026	0.159		
	Worst	63.348	7.039	16.396		
2016	Current	24.30	2.70	0.04	0.03**	Significant
	Poor	22.99	2.55	0.07		
	Worst	149.99	16.67	423.44		
2017	Current	20.882	2.320	0.036	0.01***	Significant
	Poor	19.793	2.199	0.049		
	Worst	91.936	10.215	87.461		
2018	Current	24.21	2.69	0.20	0.36	Not Significant
	Poor	33.05	3.67	1.91		
	Worst	4282.92	475.88	1897344.29		

*** Significant at 0.01 level (2-tailed)
** Significant at 0.05 level (2-tailed)

In average, more years show significant differences of portfolio risks across different states are exist. This give the confidence to accept the null hypothesis which state that there is significant mean difference of standard deviations in different states of economy.

4.12.3 Stress test of CAPM Portfolio Returns

Table 4.27 shows portfolio returns of 9 portfolios constructed using 11 shares from 2015 to 2018 in a different state of the economy. The results revealed the returns produced in any state of the economy is below subunit. Likewise, the variability of the portfolio means returns in the different portfolio is very low particularly in the current state. Sometimes the portfolio mean returns remain constant with the increase of portfolio size.

Table 4.26: CAPM Portfolio Mean Returns in Different States of Economy

Year	Number of Shares	Portfolio Size	States of Economy		
			Current	Poor	Worst
2015	A3	P1	0.01	-0.02	-0.07
	A4	P2	0.00	-0.03	-0.06
	A5	P3	-0.01	-0.04	-0.03
	A6	P4	-0.01	-0.05	-0.06
	A7	P5	-0.02	-0.05	0.03
	A8	P6	-0.03	-0.06	-0.07
	A9	P7	-0.03	-0.07	-0.17
	A10	P8	-0.03	-0.07	-0.01
	A11	P9	-0.04	-0.05	-0.15
2016	A3	P1	0.04	0.04	0.05
	A4	P2	0.04	0.04	0.04
	A5	P3	0.04	0.03	0.07
	A6	P4	0.04	0.03	0.05
	A7	P5	0.04	0.03	0.03
	A8	P6	0.04	0.03	0.04
	A9	P7	0.03	0.03	0.02
	A10	P8	0.03	0.02	0.01
	A11	P9	0.03	0.03	0.01
2017	A3	P1	0.05	0.05	0.05
	A4	P2	0.05	0.05	0.05
	A5	P3	0.05	0.05	0.05
	A6	P4	0.05	0.05	0.33
	A7	P5	0.05	0.05	0.05
	A8	P6	0.05	0.05	0.04
	A9	P7	0.05	0.05	0.05
	A10	P8	0.05	0.06	0.06
	A11	P9	0.05	0.06	0.05
2018	A3	P1	0.04	0.04	0.07
	A4	P2	0.04	0.03	0.03
	A5	P3	0.04	0.03	0.77
	A6	P4	0.03	0.02	-0.11
	A7	P5	0.03	0.01	0.00

	A8	P6	0.03	0.01	0.00
	A9	P7	0.03	0.01	0.02
	A10	P8	0.02	0.02	0.06
	A11	P9	0.03	0.03	-0.04

Example of successive portfolios which produce equal returns are P6 to P8 of 2015 with portfolio returns of -0.03 percent, P1 to P6 of 2016 with portfolio returns of 0.04 percent, all portfolios in 2017 with portfolio returns of 0.05 percent, P1 to P3 and P4 to P7 in 2018 with portfolio returns of 0.04 and 0.03 percent respectively. It was also noted that all the portfolios constructed in any state during 2015 produced negative returns except P1 and P2 in the current state as well as P5 in the worst state. Also, there are negative returns generated by P4 and P9 in the worst state during 2018. Otherwise, the portfolios constructed in the preceding years in all states of the economy generates positive returns. Generally, the worst state of the economy produced higher portfolio mean returns compare to other states. Figure 4.23 illustrated the movement of CAPM portfolio mean returns produced various portfolios in different states of economy from 2015 to 2018.

In the first two years, the portfolio returns of all three states found to decrease with the increase of portfolio size. While the movement of current and poor state are almost linear, the worst state behave different. There was up and down of portfolio returns in worst state of economy during 2015 and 2016. Correspondingly, the portfolio returns of current and poor state during 2016 and 2017 observed to move together in all portfolio size. Likewise, the trend of portfolio mean returns in worst state in 2017 is the reflection of that of 2016. Although, the highest returns 2017 is double of that of the highest portfolio returns of 2016.

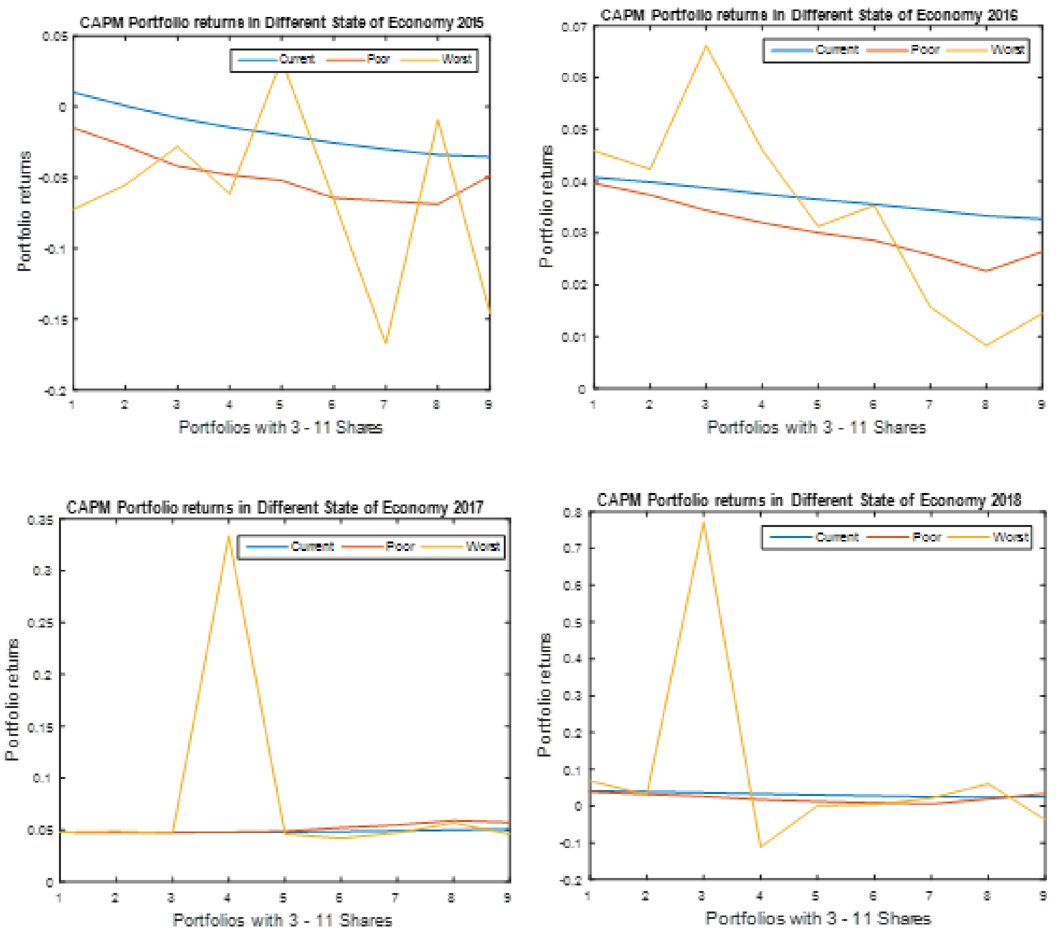


Figure 4.23: Comparison of CAPM Portfolio Returns in different states of Economy

The ANOVA test between the sensitivity of portfolio mean returns and different states of economy was conducted to measure whether there are significant mean differences. The results in Table 4.28 revealed that there is a significant mean difference between portfolio mean returns calculated in different states of economy only during 2015 with $(p = 0.05\ , p \leq 0.05)$.

While the rest of the years, no significant mean differences were found as all the p-values were above the minimum threshold. This lead to conflicting conclusion of the hypothesis drawn which state that there are significant mean difference on CAPM portfolio mean returns in different states of economy. Since in many years, the results shows there were no significant mean difference which indirectly neutralize the strength of the argument which lead to reject the state hypothesis.

Table 4.27: Summery of ANOVA Results For CAPM Portfolio Mean Returns

Year	Groups	Sum	Average	Variance	P-Value	Decision
2015	Current Poor Worst	-0.16 -0.43 -0.57	-0.02 -0.05 -0.06	0.00 0.00 0.00	0.05**	Significant
2016	Current Poor Worst	0.33 0.28 0.31	0.04 0.03 0.03	0.00 0.00 0.00	0.56	Not Significant
2017	Current Poor Worst	0.44 0.46 0.72	0.05 0.05 0.08	0.00 0.00 0.01	0.43	Not Significant
2018	Current Poor Worst	0.28 0.19 0.81	0.03 0.02 0.09	0.00 0.00 0.07	0.59	Not Significant

** Significant at 0.05 level (2-tailed)

4.12.4 Stress test of Portfolio Beta

Table 4.29 shows the portfolio beta of 9 portfolios constructed from 2015 to 2018 in different states of the economy. It can be observed that the portfolio betas of all state of economy and time frame are high. The highest beta was 3404.24 percent which was recorded on P4 in the worst state of the economy during 2017. Also, the results confirmed the existence of negative beta in some portfolios constructed specifically in the worst state of the economy. The highest negative beta was recorded by P3 in 2018 which was equivalent to -594.99 percent. Other portfolios that produced negative beta are P1, P3, and P4 in 2016, P2 in 2017, and P1 in 2018. Furthermore, the data show the existence of a direct relationship between the proportional change of portfolio beta and portfolio size mostly during the current state of the economy.

The increase of portfolio beta was higher in small size portfolio than big portfolios. This can be observed during 2015 where beta produced by P1, P2, and P3 are 22.93, 28.60, and 34.13 percent while beta produced by P7, P8, and P9 are 47.57, 49.86, and 50.57.

Table 4.28: Portfolio Beta in Different States of Economy

Year	Number of Shares	Portfolio Size	States of Economy		
			Current	Poor	Worst
2015	A3	P1	22.93	39.94	78.75
	A4	P2	28.60	45.63	61.15
	A5	P3	34.13	56.22	48.72
	A6	P4	38.19	58.49	60.52
	A7	P5	41.29	59.91	5.29
	A8	P6	44.80	69.33	72.39
	A9	P7	47.57	69.78	117.32
	A10	P8	49.86	70.40	28.44
	A11	P9	50.57	57.76	118.56
2016	A3	P1	3.71	5.41	-2.77
	A4	P2	4.86	8.33	1.89
	A5	P3	6.44	12.76	-30.38
	A6	P4	8.11	16.18	-3.78
	A7	P5	9.65	18.86	16.97
	A8	P6	11.05	20.91	11.80
	A9	P7	12.57	24.56	39.08
	A10	P8	14.18	28.62	47.70
	A11	P9	15.04	23.60	39.02
2017	A3	P1	1.54	2.29	1.57
	A4	P2	2.24	4.32	-2.36
	A5	P3	3.33	7.68	4.24
	A6	P4	4.48	10.27	3404.28
	A7	P5	5.61	12.34	4.59
	A8	P6	7.15	17.98	0.35
	A9	P7	8.81	22.07	7.22
	A10	P8	10.75	28.21	27.49
	A11	P9	11.88	23.21	5.09
2018	A3	P1	5.23	7.26	-15.69
	A4	P2	6.08	8.65	9.69
	A5	P3	7.73	14.34	-594.99
	A6	P4	9.62	19.07	78.43
	A7	P5	11.42	22.18	29.32

	A8	P6	13.04	24.37	25.55
	A9	P7	14.53	26.48	15.85
	A10	P8	14.57	14.96	-4.95
	A11	P9	13.71	5.06	62.40

The Trends of Portfolio beta with portfolio size in different states of economy in all four years can be visualized in the Figure 4.24.

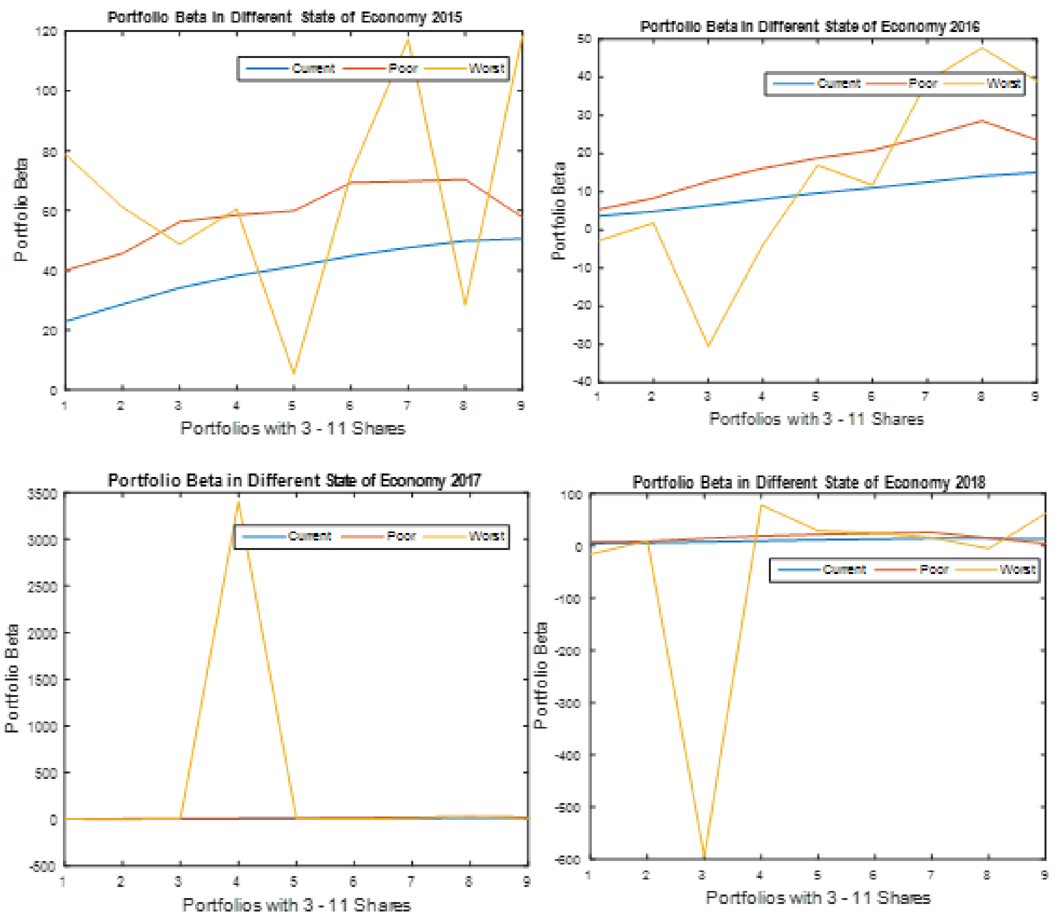


Figure 4.24: Comparison of Portfolio Beta in different states of Economy

A zigzag movement of portfolio beta against portfolio size was observed only is worst state of economy during 2015 and 2016. The trend was little appeared between P3 and P5 also P2 and P4 during 2017 and 2018 respectively. The portfolio beta of the remaining portfolio of worst state during 2017 and 2017 show similar behaviour with that of current and worst state. They almost remain unchanged when portfolio size increased. The ANOVA test was conducted in order to examine whether there are significant mean difference on value of beta of different states of economy. The results presented in Table 4.30 show that no significant mean differences are exist since the p-values in four years are above the minimum required level of significance. There was $(p = 0.07, p \geq 0.05)$, $(p = 0.54, p \geq 0.05)$, $(p = 0.39, p \geq 0.05)$ and $(p = 0.54, p \geq 0.05)$ for 2015, 2016, 2017 and 2018 respectively. Therefore, the evidence gathered was not enough to accept the hypothesis which was stated that there is significant mean difference of portfolio in different states of economy, therefore the hypothesis was rejected.

Table 4.29: Summery of ANOVA Results For Portfolio Beta

Year	Groups	Sum	Average	Variance	P-Value	Decision
2015	Current Poor Worst	357.94 527.47 591.14	39.77 58.61 65.68	93.69 112.98 1380.88	0.07	Not Significant
2016	Current Poor Worst	85.62 159.23 119.53	9.51 17.69 13.28	16.34 59.80 639.24	0.54	Not Significant
2017	Current Poor Worst	55.79 128.37 3452.48	6.20 14.26 383.61	13.71 81.83 1283203.90	0.39	Not Significant
2018	Current Poor Worst	95.93 142.37 -394.40	10.66 15.82 -43.82	13.24 60.17 43612.43	0.52	Not Significant

General, Table 4.31 summarised the results of all ten hypotheses tested with respective decision either supported or not supported.

Table 4.30: Summary of the All Hypotheses Tested

Sn	Hypothesis	Decision
1	There is no significant difference on performance of the companies before and after combining with the performance of other components which are country economy, stock markets and economic sectors.	Not supported
2	There is no significant mean difference between mean returns calculated by MVCM-DEA and that calculated using CAPM-DEA.	Not supported
3	There is no significant mean difference between risk calculated by MVCM-DEA and that calculated by CAPM-DEA.	Not supported
4	There is no significant mean difference between Sharpe ratio and Treynor ratio.	Not supported
5	There is no significant mean difference between sensitivity portfolio mean returns computed by MVCM-DEA in different states of economy.	Supported
6	There is no significant mean difference between sensitivity risks computed using MVC-DEA in different state of economy.	Not supported
7	There is no significant mean difference between sensitivity of portfolio mean returns computed by CAPM-DEA in different states of economy.	Supported
8	There is no significant mean difference between sensitivity of risks computed using CAPM-DEA in different state of economy.	Not supported

4.13 Summary

This chapter presents the findings of this study which the main objective is to examine the applicability of equity portfolios in various EACMs and compare them to assist institutional investors and young people within the region in making an investment decision, broaden the knowledge of quantitative techniques and narrow the heuristic common sense approach. The developed model substantiates the adequacy of share selection and portfolio construction. A total of ten hypotheses were formulated to test the existence of mean differences. One hypothesis test the mean difference before and after combining the performance of the country's economy, stock markets, economic sectors with the company’s financial performances. Two hypotheses addressed the mean difference between expected returns and risks of various portfolios computed using mean-variance and capital asset pricing model incorporated with data envelopment analysis. One hypothesis compared the mean difference between the Sharpe ratio and the Treynor ratio. Four hypotheses were developed based on returns measured by MVCM and CAPM, risks measured in standard deviation and beta as well as performance measured by Sharpe ratio and Treynor ratio in different uncertainty levels which are good, bad, and worst. Out of eight hypotheses, only two hypotheses were supported while six hypotheses were not supported. In the next chapter, the summary of the findings will be reported, followed by research implications, limitations of the study, and suggestions for future studies

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CHAPTER 5

SUMMARY, RECOMMENDATIONS AND CONCLUSION

5.1 Introduction

This chapter presents a summary of the findings, their implications, and inference to both institutions and individual investors within EACMs. More importantly, this chapter detail the contributions both theoretically and the practically in-stock selection and portfolio construction. Likewise, this chapter indorses the management of capital markets, regulatory bodies, and other stakeholders of EACMs. Furthermore, this chapter highlights some areas which were overlooked in this study due to various constraints and suggested areas for further studies.

5.2 Summary of the Research Findings

The findings related to stock selection, portfolio construction, performance, optimization, and stress test were summarised.

5.2.1 Stock selection

This study able to demonstrates the technique of quantifying the operational and managerial performance of fundamental components using DEA models. It reveals a different level of performance among country economy, economic sectors, stock markets as well as shares listed in East African Stock Exchanges. The development degree of the country's economy shows that Kenya and Tanzania are fully performed in overall, operational, and managerial in all years from 2015 to 2018. This indicated that the government of Kenya and Tanzania have sufficient competence in managing and identifying ideal expenditures and investments to maintain the required rate of inflation and balance of the public debt. This builds confidence in existing and prospective investors both within and outside these countries while making an investment decision. Contrary to the performance of Uganda and Rwanda which were observed to fluctuate throughout 2015-2018.

While stock markets performance recorded that only DSE meet full performance in all measures throughout from 2015 to 2018. NSE show full performance for the last three years from 2016 to 2018 in all measures and in the year 2015 only management records full performance, other measures like overall and operational both performed only for 51 percent. USE performance of all measures was inconsistent throughout while in RSE at least management was fully performed from 2015 to 2018 and remaining measures fluctuated over time. Only during 2018 where all four stock exchanges record 100 percent managerial performance. Except for DSE, the overall performance of EACMs is disappointed, although management of individual stock exchanges shows exemplary performance yet the operationally not convincing investors to make an immediate decision. Performance of economic sector growth indicates that only the industry sector in Tanzania reached 100 percent performance in overall, managerial and operational throughout from 2015 to 2018.

Uganda and Rwanda both account for 100 percent managerial performance in the service sector for the last three years from 2016 to 2018. Unexpectedly, no sector in Kenya is fully performed in any measure, only the industry sector reports a significant score of 43 percent on overall performance during 2015, while managerial and operational performance was 66 and 67 percent during 2015 and 2016 respectively. The industry is the most prominent sector in the region followed by the service sector in recent years. The listed companies performance were inconsistence in either overall, managerial, or operational measure. Only five companies including BAT, FTGH, KQ, SCOM, and BOBU records 100 percent overall, managerial, and operational performance in all four years consecutively. MSC maintains full performance for three years consecutively from 2015 to 2017 in all performance measures while TPCC maintains for two years which are 2017 and 2018 and of 13 companies which were full performed in the year 2015 alone.

A group of companies was performed in all year from 2015 to 2018, also their performance scores were not predictable. It was further exposed that when the performance scores of the country economy, stock market, economic sectors, and company fundamental were integrated, the combined score concerning the listed companies was random in all three measures. The independent t-test confirmed that there are significant mean differences in performance of the various companies before and after combination with other components. Therefore, the selected companies were based on a benchmark defined which was 70 percent and for overall performance, 88 percent and above for managerial performance as well as 79 percent and above for operational performance throughout from 2015 to 2018. Those companies are BAT, BERG, FTGH, TOTL, UNGA, EABL, TBL, TCC, TCCL, TOL, and TPCC. Generally, all listed companies from USE, RSE, and all companies from the service and manufacturing sectors in the region were not attained the minimum performance stated, therefore were excluded for further analysis. Only some companies that fall under the industry sector in Kenya and Tanzania were shortlisted as they are the equal or above benchmark. Out of 11 companies, 6 are from Kenya which is equivalent to 16 percent of the total companies, and 5 from Tanzania which is equivalent to 56 percent of the total companies evaluated from Kenya and Tanzania respectively.

5.2.2 Portfolio Construction

Eleven shares selected were used to construct nine portfolios using both MVCM and CAPM. The first portfolio starts with three shares and for each successive portfolio, one more share is added in decreasing order of returns until all shares are included. Among the findings which were observed are the relationship between expected returns and risks of each portfolio constructed and the impact of portfolio change of portfolio size on expected returns and risk in each model from 2015 to 2018. When the MVCM model has used the significant positive correlation between portfolio returns and risks was only observed during 2018 with $r = 0.734, p \leq 0.05$. A strong negative correlation during 2016 and 2017 with $r = -0.863, p \leq 0.01$ and $r = -0.925, p \leq 0.01$ respectively.

While during 2015, there was no correlation observed between returns and risk of different portfolio constructed. When the CAPM model was used, it was revealed the existence of strong negative correlation between CAPM returns and Beta during 2015, 2016, 2017 and 2018 with r=-1,p≤0.00),r=-1.00,p≤0.00and r=-0.99,p≤0.00) respectively. Only during 2017 where the expected returns and beta become positive correlated with ,r=0.92,p≤0.00. Likewise, the effect of portfolio size in any model used revealed that when more shares are added in the portfolios the returns decreases and risk increases which gives doubt on observing diversification benefit for the selected shares listed within EACMs.

When the trends analysis of portfolio returns computed using MVCM and that computed using CAPM for 2015, 2016, 2017, and 2018 were conducted, it was observed that portfolio returns generated using MVCM differ from that generated by CAPM in any time frame. CAPM portfolio returns appear to the top during 2015, 2016, 2018 in any portfolio size constructed and in 2017 when portfolio size is above 8 shares. While MVCM portfolios reported the highest returns only during 2017 when portfolio size is below 8 shares. An Independent t-test conducted to examine whether the mean difference of the portfolio returns computed using MVCM and CAPM revealed that there are significant mean difference in the returns of the portfolio constructed from 2015 to 2018 with $p=0.00$ ($p \leq 0.00$).

The trends analysis of standard deviation and a beta of 9 portfolios constructed in each year from 2015 to 2018 demonstrated that the portfolio betas are always higher in any portfolio size for the years 2015, 2016, and 2018, also during 2017 when the portfolio size is above 4 shares. When a single share is added to the portfolio beta increases by more than one point. While, the trend of the portfolio standard deviations is almost remain stationary even when portfolio size increases to the maximum. This means that portfolio betas are more sensitive to portfolio size. Comparatively, the trends betas and standard deviation are different throughout. The results of the independent t-test justified that there are significant mean differences between standard deviation and beta in all four years with $p=0.00$($p \leq 0.00$).

5.2.3 Portfolio Performance

The Sharpe ratios and Treynor's ratios were computed concerning portfolio mean returns generated by MVCM and CAPM respectively and explain the portfolio performances. It was revealed that the higher Sharpe ratio corresponds to higher portfolio mean returns and the lower Sharpe ratio produces lower portfolio mean returns for the portfolios that generated positive returns. Likewise, the portfolios which generated negative returns produce a negative Sharpe ratio. The negativity of the Sharpe ratio becomes higher when the portfolio losses increase. The sensitivity of the Sharpe ratio against portfolio size demonstrated that the Sharpe ratios are more sensitive with portfolio size. Sensitivity becomes higher when portfolios are poorly performed,

contrary to the outperformed portfolio where Sharpe ratios are less linear with portfolio size. There is a linear relationship between portfolio returns and Treynor's ratio across various portfolios constructed. Treynor ratios were found to be more sensitive with portfolio returns and portfolio size throughout from 2015 to 2018. In all four years, the Treynor ratios were observed to decrease sharply with the increase of portfolio size.

When the portfolio Sharpe ratio and Portfolio Treynor ratio computed from 2015 to 2018 were compared, the results show that the two performance measures differ in all four years. Treynor ratios appeared to be higher than Sharpe ratios for three years are 2015, 2016, and 2018 while the Sharpe ratio was on top of the Treynor ratio only during 2017. The trends of the Treynor ratio and Sharpe ratio are opposing. The Treynor ratio was found to decrease with the increase of portfolio size while the Sharpe ratio increase with the increase of portfolio size except during 2017. Treynor ratio is less sensitive with portfolio size as most of its curves have shallow slopes while that of Treynor ratio is steeper in all years except 2016. The independent t-test was conducted to examine the existence of a significant mean difference between the two performance measures. The results indicated that for 2015, 2016, and 2018 the mean difference between Sharpe ratio and Treynor is significant with $p=0.00$ ($p\leq0.00$). While in 2017 the mean difference was significant with $p=0.02$($p\leq0.05$).

5.2.4 Portfolio Optimization

A self-developed MATLAB algorithm was used to generate unbiased random weights used to construct optimal portfolios using both MVCM and CAPM from 2015 to 2018. The weight generated based on Sharpe and Treynor ratios required to be attained in each year. The benchmark Sharpe ratio was 6.72, in 2016, 14.90, in 2017 and 2018 both was 11.15. while for Treynor ratio were was 0.01 for 2015, 0.70 for 2016, 5.50 for 2017, and 3.98 for 2018. When the MVCM and Sharpe ratio benchmarks were used it was observed that in 2015 the maximum optimal portfolio mean returns generated in the first iteration which is equivalent to 2.12 and the minimum was 1.65 produced in the seventh iteration. In 2016, the maximum optimal portfolio mean returns were 1.48 generated in the sixth iteration and the minimum was 0.93 produced in the third iteration. Similarly, in 2017 the maximum optimal portfolio mean returns which were equal to 1.19 was generated in the sixth iteration and the minimum was 0.66 produced in the third iteration. While for 2018 the maximum optimal portfolio mean return was 1.24 generated in the second iteration and the minimum was 0.91 produced in the first iteration. In each year the variability of risks in different iterations is very small, this signified that the algorithm able to reduce the influence of risk to attain an optimal solution.

Contrary to CAPM where immediate observation found on maximum optimum portfolio mean returns oscillated between 0.04 throughout from 2016 to 2018 although there was an abrupt change of portfolio beta with iterations across different years. Moreover, there were several portfolios which produced almost zero optimum portfolios mean returns during 2015 including that portfolio were formed using weights generated in first, fifth, sixth, and seven iterations. The results also revealed the portfolio beta was high during 2015 to a maximum of 26.90 percent in the sixth iteration and start to decrease to zero in 2018. Although the objective function defined was to maximize portfolio mean returns and beta subject to the minimum required Treynor ratio was attained, yet optimal portfolio mean returns are less sensitive compare to portfolio beta in all years and all iterations which signified that MOO is less effective in CAPM although it was attained at a minimum level.

5.2.5 Portfolio Stress Test

Portfolio stress was conducted to detect the sensitivity of mean returns, standard deviations and beta for the portfolio constructed based on the funds allocated in different shares concerning the defined state of the economy such as good, bad and worst using both MVCM and CAPM. When the MVCM was used the portfolio mean returns produced were different in all states and portfolio sizes. In the years 2015 and 2016, all the portfolios constructed in any state of the economy generate losses of a minimum of 0.07 to 0.42 percent except P5 in 2016 which record a profit of 0.06 percent. During 2017 and 2018 some portfolios produced positive returns such as all portfolios in the current state of the economy, the first four portfolios in both poor and worst state of the economy for 2017, all portfolios in the worst state of the economy for the year 2018 except P4 and P8.

Overall, portfolio mean returns produced in the worst state are more sensitive compares to the current and poor state of the economy. The weak sensitivity was observed due to the existence of constant returns on different portfolios constructed on the current state of the economy. However, there are a few portfolios in the worst state where at least two consecutive portfolios in 2015 and 2016 produce equal returns. Some of them are P6 and P7 in 2015 both generated mean returns of 0.15

percent, P3 and P4 in 2016 both generated mean returns of 0.22 percent as well as P7 and P8 both generated returns of 0.09 percent. Yet, the worst state of the economy is the only state which produced the highest positive returns as well as the highest negative returns throughout from 2015 to 2018. When the ANOVA test was conducted on portfolio mean returns produced in all states of economy, the results revealed that there is no significant mean difference of portfolio mean returns computed using MVCM between different states of the economy since the $p \geq 0.05$.

Likewise, the risk measured by standard deviation was high in the worst state of the economy compared to the current and poor state in any portfolio size within the time frame. However, when current and poor states are compared, the variability of risk with portfolio size appeared to be higher in a poor state. Generally, the risks in the Current state are found to be less volatile when portfolio size increases. Also, the change in risk across different portfolios is less than subunit in any year. Regarding the behavior of risks concerning portfolio size in all three states, the pattern of the current and poor state is nearly moving together. The only great diversion was observed in the trend standard deviation in the worst state of the economy. The ANOVA test revealed that there are significant mean differences in portfolio risks in different states of the economy during 2015, 2016, and 2017 with $p=0.00 (p \leq 0.00)$, $p=0.03 (p \leq 0.05)$ and $p=0.01 (p \leq 0.05)$ respectively. Except in the year 2018, the mean difference of portfolio risks in all states of economy found not significant with $p=0.36 (p \geq 0.05)$.

When CAPM was used, the portfolio mean return produced were below subunit in any state of the economy. Moreover, the variability of the portfolio means returns in the different portfolio is very low particularly in the current state. Sometimes the portfolio means returns remain constant with the increase of portfolio size. For example, portfolios which produce approximately equal returns are P6 to P8 of 2015 with portfolio returns of -0.03 percent, P1 to P6 of 2016 with portfolio returns of 0.04 percent, all portfolios in 2017 with portfolio returns of 0.05 percent, P1 to P3 and P4 to P7 in 2018 with portfolio returns of 0.04 and 0.03 percent respectively. It was also noted that all the portfolios constructed in any state during 2015 produced negative returns except P1 and P2 in the current state as well as P5 in the worst state. Also, there are negative returns generated by P4 and P9 in the worst state during 2018. While the portfolios constructed in other years and all states of the economy generates positive returns. comparatively, the worst state of the economy produced higher portfolio mean returns compare to current and poor states of the economy. However, the ANOVA test revealed that there is a significant mean difference between portfolio mean returns calculated in different states of the economy only during 2015 with ($p=0.05, p\leq0.05$) other years shows not significant. The sensitivity of risk measured by beta is observed to be high in all states of economy and time frame. The highest beta was 3404.24 percent which was recorded on P4 in the worst state of the economy during 2017.

Also, the results disclose that the negative beta was generated in some portfolios constructed in the worst state of the economy and the highest one was recorded by P3 in 2018 which was equivalent to -594.99 percent. Additionally, there was a direct relationship on proportional change of portfolio beta and portfolio size mostly during the current state of the economy except in worst state during 2015 and 2016 where the trend of portfolio beta against portfolio size was unpredictable. However, the ANOVA test confirmed that the mean difference of portfolio beta in all states of the economy was not significant as ($p=0.07$, $p\geq0.05$), ($p=0.54$, $p\geq0.05$), ($p=0.39$, $p\geq0.05$) and ($p=0.54$, $p\geq0.05$) for 2015, 2016, 2017 and 2018 respectively.

5.3 Research Implications

The findings reported in this study lead to two major critical implications. Firstly, is based on theoretical perspective and secondly is for practical perspective. Both implications were directly extracted on the research findings and discussions presented in the previous sections as detailed below.

5.3.1 Theoretical Implication

Among the theoretical gaps addressed in this study is the use of a bottom-up approach to combine operational performance as well as the managerial performance of the country's economy, stock market, economic sector, and company fundamentals computed by DEA which was further considered as a base of stock selection. The study found that combining the performance of various components has a major impact on screening the stocks to be used for portfolio construction.

The developed hybrid model combined various scholarly works that found the existence of a positive contribution of each component on stock selection. Started from the study of Rose (1976) who addressed the influence of country economy proxies, Calderon-Rossell (1991) who suggested the importance of stock market development, Lewis (1954); Kuznet (1966); Chenery (1975) and Kuznet (1979) who hypothesized on economic sector growth, also Graham and Dodd (1934) who focused on company fundamentals. Such studies are the extension of value investing theory which is among the theories used in this study. Similarly, this model offers a base to MVCM and CAPM governed by modern portfolio theory and capital market theory before computing stock returns, standard deviation, and beta. Moreover, the model extends its applicability to cross countries, markets, and sectoral diversification. It provides multiple options to investors on funds allocation.

Another numerous contribution is laying on efficient allocation of funds using MOO specifically on CAPM. The objective function was to maximize CAPM portfolio returns and beta subject to the required Treynor ratio. That is beyond to CAPM hypothesis which reported that the efficient allocation is formed by stocks that are lied on the security market line. Commonly, the scholars used MOO in MVCM and pay limited attention to CAPM. These study findings were able to show the alternative method of identifying efficient portfolios constructed using CAPM. Also, the use of uncertainty based under the hypothetical scenario approach while conducting a stress test on portfolio returns and risks in a different state of economy computed using CAPM and MVCM is considered among the contribution of this study. Although some criticism has been raised by Franco, Nicolle, and Pham (2018) on using MVCM and further suggested to use Bayesian strategy, yet the use of CAPM remained uncontested.

5.3.2 Practical Implications

The practical implications of the findings of this study can be observed by stakeholders in EACMs such as capital markets authorities, individual investors, institutional investors, etc. When the combined effect of the development of country economy, stock markets, economic sectors, and company fundamental on stock selection is understood would give a signal to the authorities of capital markets, investors, policymakers, and other regulatory bodies to take immediate measures on designing policies and practices. Also, fund managers can achieve the dual benefits claimed by investors which are maximization of portfolio returns and minimizing portfolio risk computed using MVCM or maximization of CAPM portfolio mean returns as well as market beta when the MOO approach is used. This study further offers empirical evidence to demonstrate that conducting a stress test can easily tackle the impact of an unusually severe event that may affect the stock market particularly those with extreme volatility.

5.4 Recommendations of the Study

This section provides several recommendations with the reference to the findings of this study. Specifically, these recommendations are directed to capital market authorities, investors, fund's managers, boards of directors, and management of listed companies and other regulatory bodies within the East Africa region. However, they may work in any other country with infant stock markets. The following are some of the recommendations that may serve the purpose: -

- The capital market authorities within the region have to ensure the growth of managerial and operational performance of stock exchanges. This can be achieved by increasing the number of listed shares, market capitalization, market turnover as well as a market index of the respective stock exchange.
- Regulatory bodies, policymakers, and higher-level administration of each country within the region have to take responsibility to uplift the country's economy as well as economic sectors growth. To attain this, they can reduce the inflation rate, public debt, government spending, and increase country investment. Also, they can increase labor force, value-added as well as the growth rate of various economic sectors such as the service sector, industry, and agriculture.

- The Board of directors and management of listed companies should formulate strategies and plan to improve both managerial and operational performance. This concern goes hand in hand with the growth of the company's equity, total assets, revenue, company profit as well as proper management of cash flow including operating, financing, and investment cash flows.
- Funds managers and investors should ensure the attainment of efficient allocation of funds by considering dual benefits simultaneously which is the maximization of Markowitz portfolio mean returns and minimizing risk measured by the standard deviation or maximizing CAPM portfolio mean returns and market risk. Furthermore, they should ensure that the stress test is conducted to understand the patterns, behaviors, and directions of the various portfolios constructed will have during good times and extreme conditions.

5.5 Limitation of the Study

Though this study has significant contributions from both theoretical and practical perspectives, yet it has also suffered from some limitations. The following are the basic limitations that have been noted when conducting this study.

The data used in this study were collected in a short time frame which is from 2015 to 2018 and only for four countries. Although the data are aging but also was due to the nature of the stock markets as they are still very young, some of them were opened from 2011 with a limited number of listed shares. the limiting number of stock markets or countries used was due to other countries in the region like Burundi and South Sudan do not have stock exchanges

This study employs a bottom-up approach to combine various components such as country economy, stock markets development, economic sectors, and company fundamentals instead of using both bottom-up and top-down approaches. Although the methodology is still new in the field of stock selection, also limited literature demonstrated quantitatively performance evaluation of each component, yet is recommended by the scholars when the combined components involve more than one country.

The methodology used to differentiate efficiency and effectiveness was based on model orientations and the product of the two was referred to as performance. The IO which is more on minimizing the input used was considered as efficiency and OO which is more on maximizing the output required which is also can be understood as goal-oriented was referred to as effectiveness.

The study selects the MOO approach while identifying optimal portfolios and forgone other optimization approaches such as stochastic dominance, ambiguity evasion, robust optimization, and socially responsible investment which are commonly debatable in current literature. The stability of MOO and its capability to serve as a benchmark approach among various approaches that are currently emerged are among the reasons the influence its use in this study.

The study only considers the uncertainty level under the scenario approach when conducting a stress test. Other bases such as leverage, portfolio review frequency, and portfolio rebalancing frequency were ignored. Other approaches such standard and historical scenario was also excluded which it was due to the scope of the study.

5.6 Areas for Further Studies

Given the above-mentioned limitations, this study would suggest possible future studies to be conducted.

This study was pioneering in examine the applicability of equity portfolios in various EACMs and compare them to assist institutional investors and young people within the region in making an investment decision, broaden the knowledge of quantitative techniques and narrow the heuristic common sense approach. Thus additional studies need to be conducted with a long time frame and a wide range of countries, stock markets, economic sectors, and company fundamentals to confirm these study findings.

This study also suggests to employ both bottom-up and top-down approaches when combining the performance scores of operational as well as managerial of various components and compare the results. It might be likely that a different number and type of stocks can be generated. Also, combining both and observe the list of stocks that qualify for further analysis.

With the respect to the methodology used to compute effectiveness, this study suggests reconsidering the computation of effectiveness ratio based on the objective of the study. Although other studies that use DEA models usually swapping between efficiency, effectiveness, and performance, this study's findings observe a huge difference between these three terms.

The researcher also interested to see other study conducted examining portfolio stress test on the base of leverage, portfolio review frequency and portfolio rebalancing frequency under standard and historical scenario.

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APPENDICES

APPENDICES

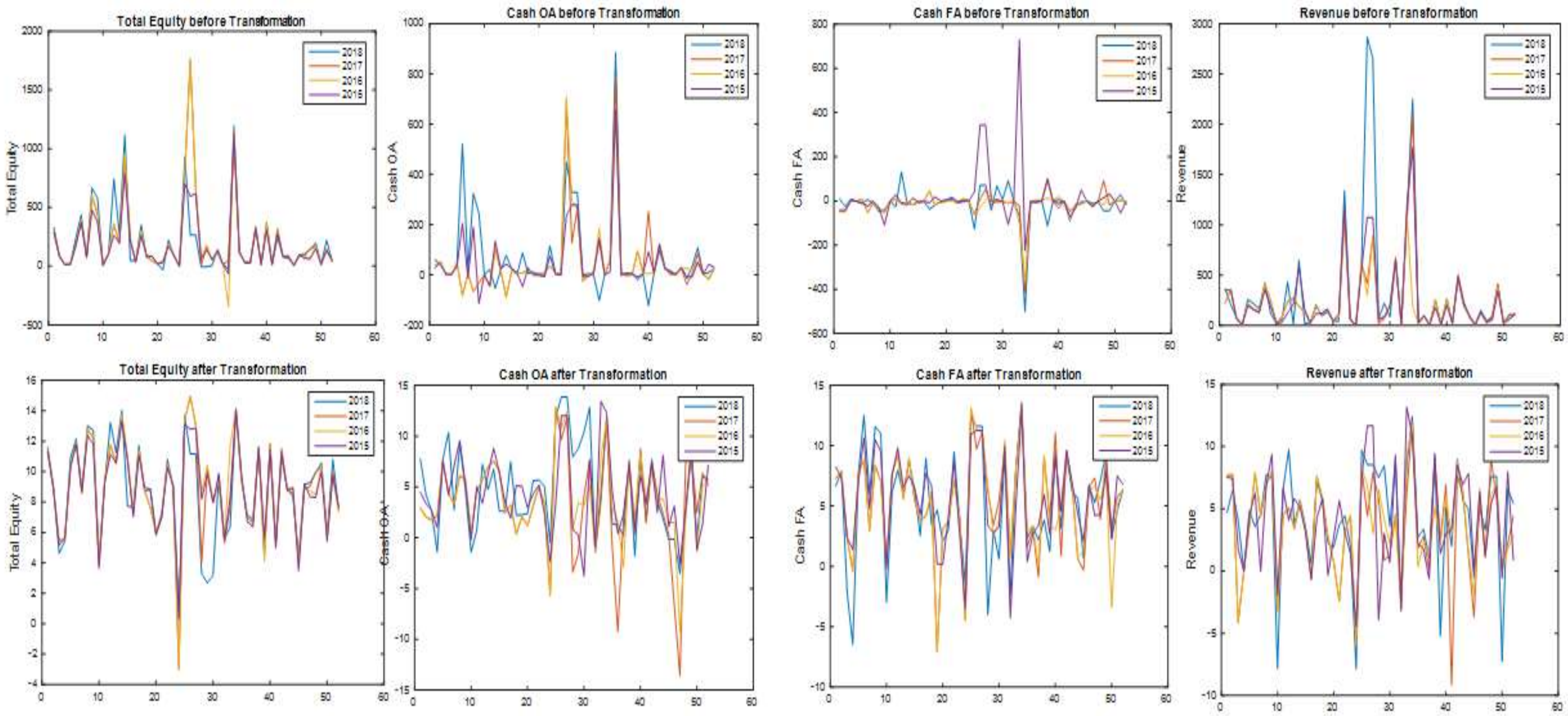
Appendix 1: List of Companies Extracted

Sn	Code	Company	CM	Country	Business	Sector
1	BAMB	Bamburi Cement	NSE	Kenya	Cement	Industry
2	BAT	BAT Kenya	NSE	Kenya	Cigarette	Industry
3	BERG	Berge Paint	NSE	Kenya	Paints	Industry
4	BOC	BOC Gases	NSE	Kenya	Gas	Industry
5	BRIT	Britam Holdings Plc	NSE	Kenya	Asset Mgt	Service
6	CFC	Cfc Stanbink Holdings	NSE	Kenya	Banking	Service
7	CIC	CIC Insurance	NSE	Kenya	Insurance	Service
8	COOP	Cooperative bank of Kenya	NSE	Kenya	Banking	Service
9	DTK	Diamond Trust Bank	NSE	Kenya	Banking	Service
10	FTGH	Flame Tree Group Limited	NSE	Kenya	Plastic	Industry
11	HFCK	HF Group	NSE	Kenya	Banking	Service
12	I&M	I&M Holdings	NSE	Kenya	Banking	Service
13	JUB	Jubilee Holding	NSE	Kenya	Insurance	Service
14	KCB	Kenya Commercial Bank	NSE	Kenya	Banking	Service
15	KNRE	Kenya Re-insurance Corp.	NSE	Kenya	Insurance	Service
16	KUKZ	Kakuzi Plc	NSE	Kenya	Agricultur	Agriculture
17	NIC	NIC Holdings	NSE	Kenya	Banking	Service
18	NMG	National Media Group	NSE	Kenya	Media	Service
19	SCAN	WPP Scangroup	NSE	Kenya	Marketing	Service
20	SGL	Standard Group	NSE	Kenya	Media	Service
21	TCL	TransCentury	NSE	Kenya	Cable	Industry
22	TOTL	Total Kenya	NSE	Kenya	Oil	Industry
23	TPSE	TPS Eastern Africa	NSE	Kenya	Hotel	Service
24	XPRS	Express Kenya Limited	NSE	Kenya	Logistic	Service
25	EQTY	Equity Group Holding	NSE	Kenya	Banking	Service

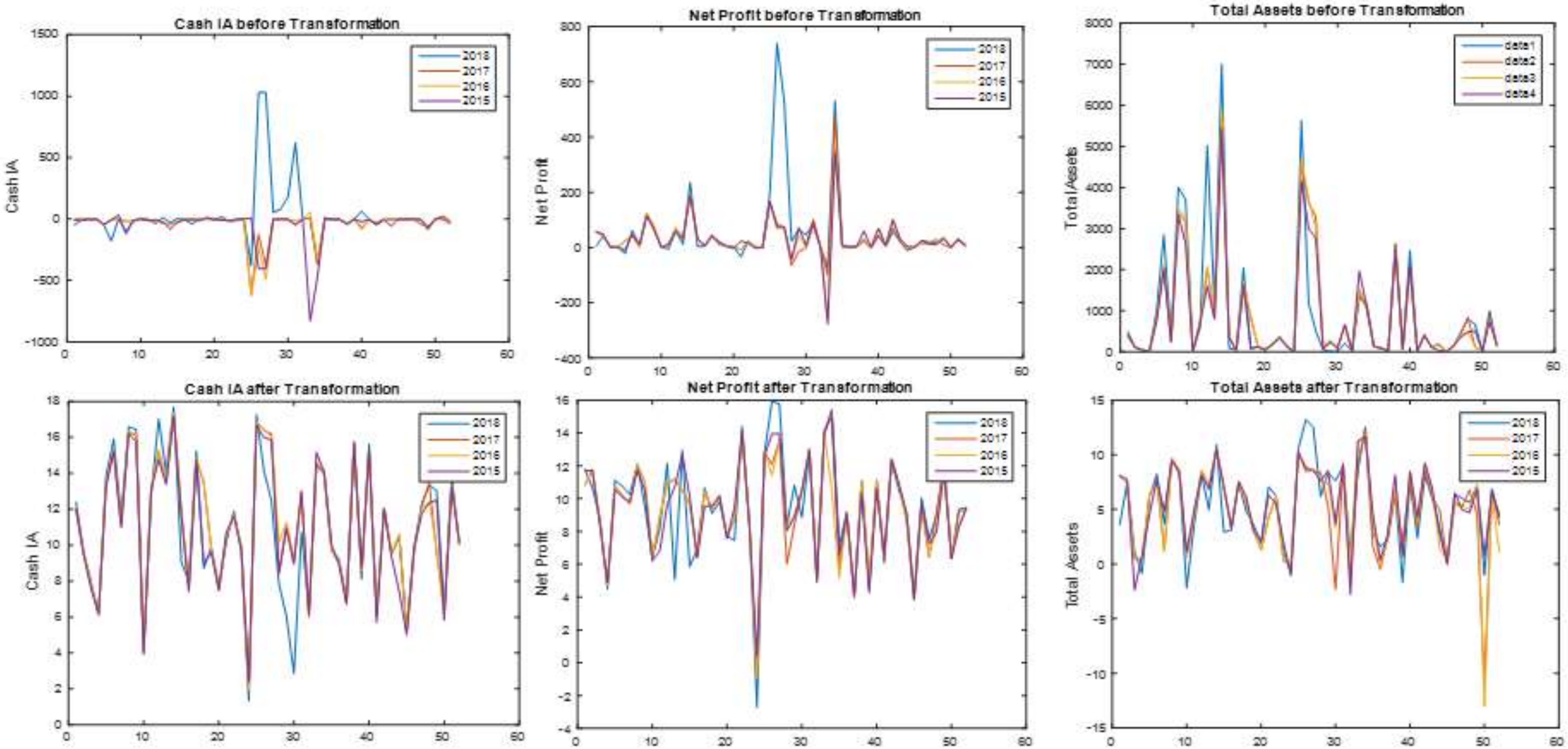
Appendix 1 Continued…

Sn	Code	Company	CM	Country	Business	Sector
26	KEGN	KenGen Company	NSE	Kenya	Electricity	Service
27	KPLC	Kenya Power and Lighting	NSE	Kenya	Electricity	Service
28	MSC	Mumias Suga Co.	NSE	Kenya	Agriculture	Agriculture
29	PORT	East African Portland Cement	NSE	Kenya	Cement	Industry
30	UNGA	Unga Group	NSE	Kenya	Food	Industry
31	EABL	East African Breweries	NSE	Kenya	Beer	Industry
32	KAPC	Kapchorua Tea Kenya	NSE	Kenya	Agriculture	Agriculture
33	KQ	Kenya Airways	NSE	Kenya	Airline	Service
34	SCOM	Safaricom	NSE	Kenya	Telecom	Service
35	SASN	Sasini	NSE	Kenya	Agriculture	Agriculture
36	C&G	Car and General Kenya	KSE	Kenya	Car	Service
37	CARB	Carbacid Investment	KSE	Kenya	Gas	Industry
38	CRDB	CRDB Bank	DSE	Tanzania	Banking	Service
39	DCB	DCB Bank	DSE	Tanzania	Banking	Service
40	NMB	National Microfinance Bank	NSE	Tanzania	Banking	Service
41	SWIS	Swiss Tanzania	DSE	Tanzania	Logistic	Service
42	TBL	Tanzania Breweries Plc	DSE	Tanzania	Beer	Industry
43	TCC	Tanzania Cigarette Comp.	DSE	Tanzania	Cigarette	Industry
44	TCCL	Tanga Cement Company	DSE	Tanzania	Cement	Industry
45	TOL	TOL Gas Limited	DSE	Tanzania	Gas	Industry
46	TPCC	Tanzania Portland Company	DSE	Tanzania	Cement	Industry
47	BOBU	Bank of Baroda Uganda	USE	Uganda	Banking	Service
48	DFCU	Dfc Uganda	USE	Uganda	Banking	Service
49	UMME	Umeme	USE	Uganda	Electricity	Service
50	NVL	Vision Group	USE	Uganda	Media	Service
51	BOK	Bank of Kigali	RSE	Rwanda	Banking	Service
52	BRL	Braliwa	RSE	Rwanda	Beer	Industry

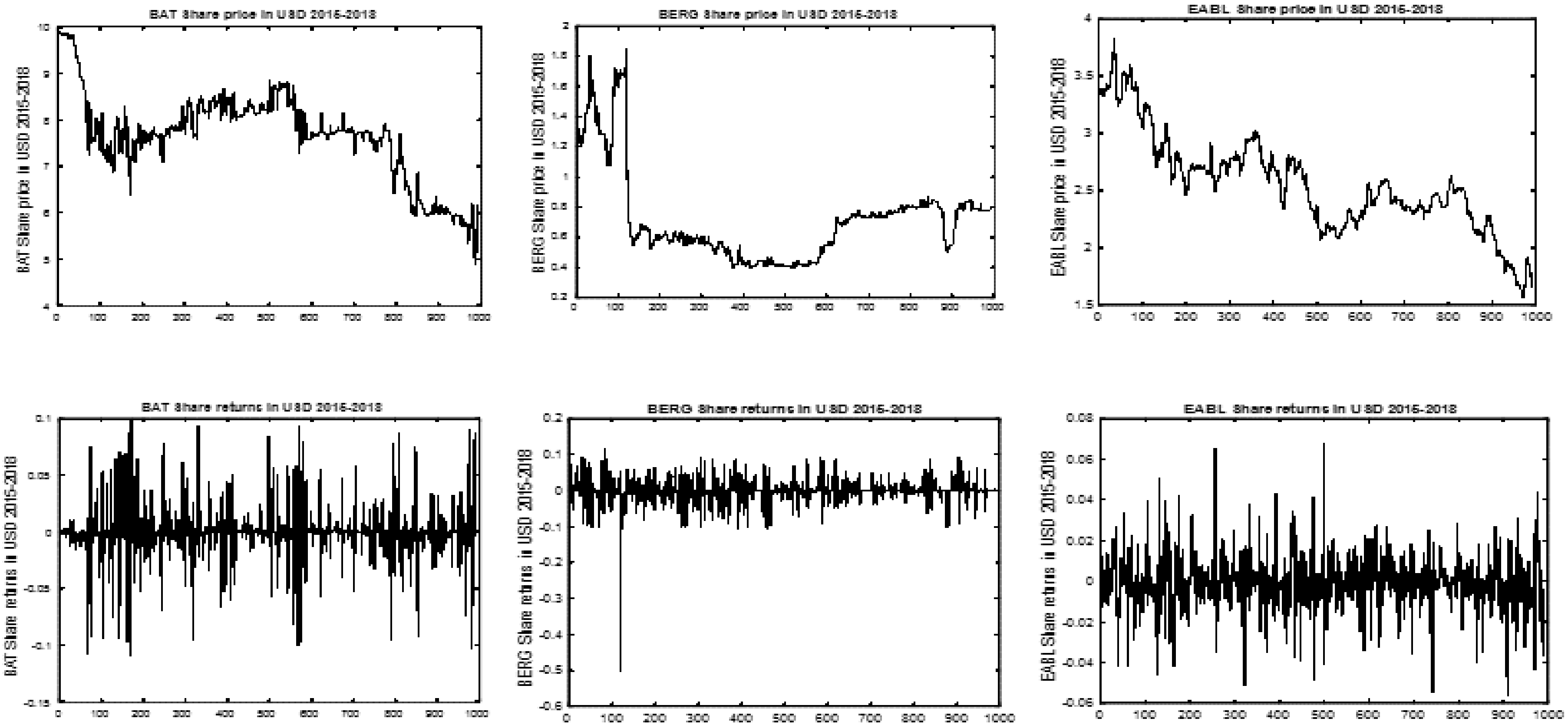
Appendix 2: Transformation of the Selected Company's Fundamentals

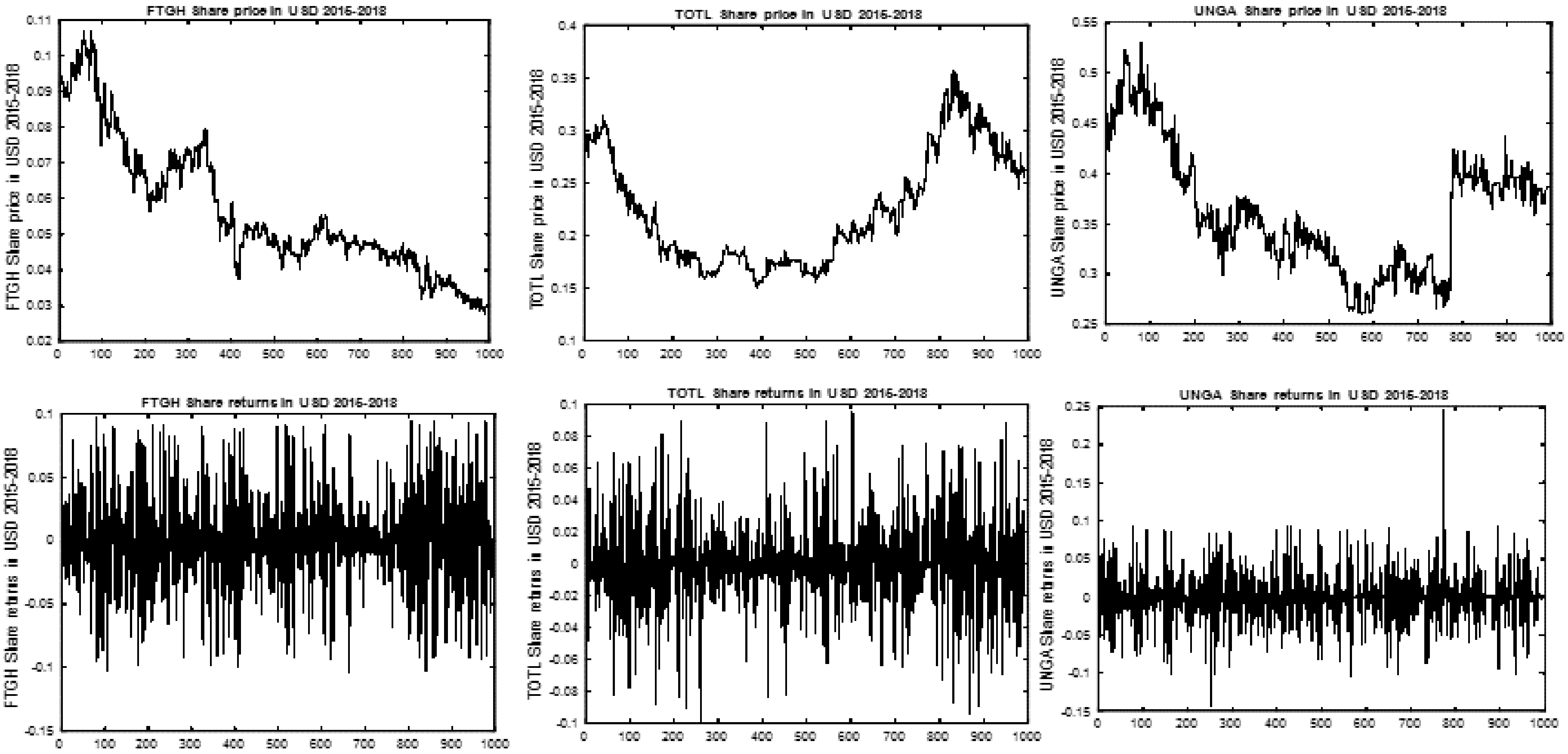


Appendix 2 Continued…

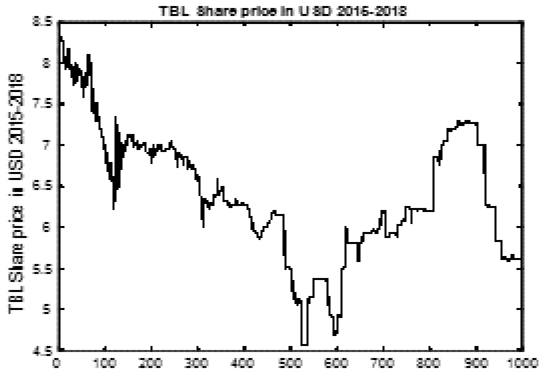


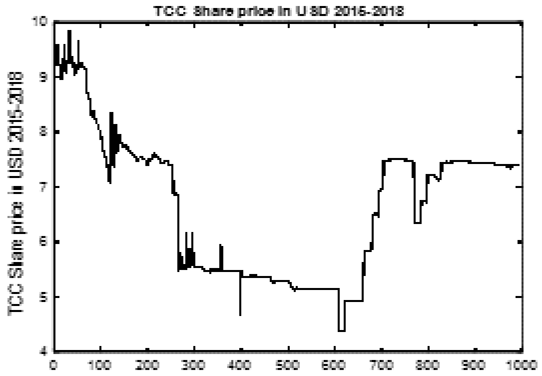
Appendix 3: Share prices and Share Returns of the Selected companies

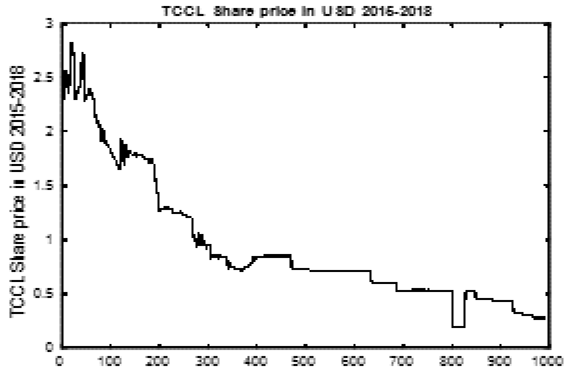


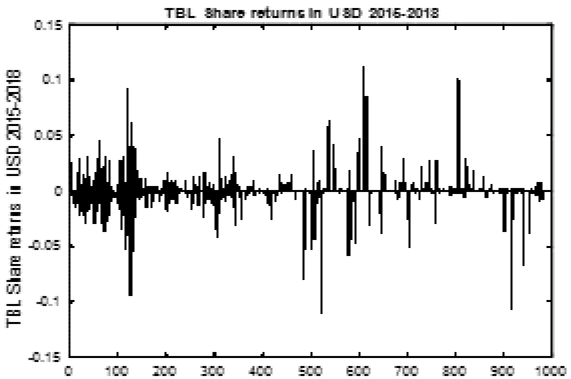

FTGH Share price in USD 2015-2018
FTGH Share price in USD 2015-2018
TOTL Share price in USD 2015-2018
TOTL Share price in USD 2015-2018
UNGA Share price in USD 2015-2018
UNGA Share price in USD 2015-2018
FTGH Share returns in USD 2015-2018
FTGH Share returns in USD 2015-2018
TOTL Share returns in USD 2015-2018
TOTL Share returns in USD 2015-2018
UNGA Share returns in USD 2015-2018
UNGA Share returns in USD 2015-2018

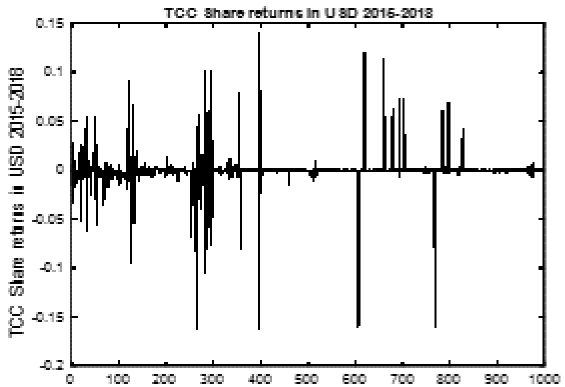
Appendix 3 Continued…

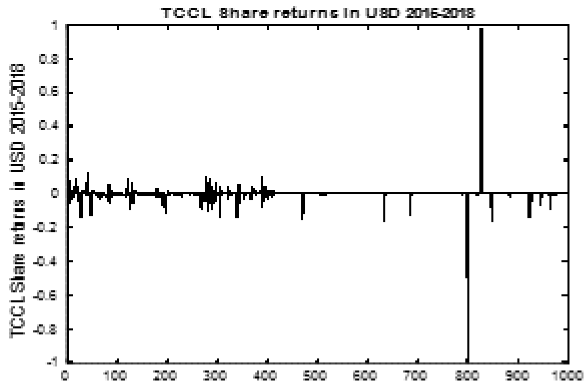












Appendix 3 Continued