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TESTING STOCHASTIC DOMINANCE OF MANUFACTURING STOCKS AT THE NSE MARKET

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Isaac Otieno Obwocha June 2020

Submitted to the School of Mathematics in partial fulfillment for a degree in Master of Science in Actuarial Science

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Master Thesis

Submitted to the School of Mathematics in partial fulfillment for a degree in Master of Science in Actuarial Science

Submitted to: The Graduate School, University of Nairobi, Kenya

Declaration and Approval

This project research is my original work and has not been presented for a degree in any other university or institution of learning for examination.

Isaac Otieno Obwocha

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Approval

This project research has been has been under our supervision and has our approval for submission.

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Acknowledgment

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List of Abbreviations and Acronyms

SD Stochastic Dominance

EMH Efficient Market Hypothesis

NSE Nairobi Stock Exchange

NSE-20 Nairobi Stock Exchange 20 Share Index

CAPM Capital Asset Pricing Model

FSD First-Order stochastic dominance

SSD Second Order Stochastic Dominance

TSD Third-order Stochastic Dominance

MV Mean Variance

DARA Decreasing Absolute Risk Aversion

NYSE NewYork Stock Exchange Market

SML Security Market Line

CML Capital Market Line

DARA Decreasing absolute risk aversion

SMM Studentized Maximum Modulus

Abstract

Stochastic dominance relationships between two or more variables is crucial in the field of actuarial science, econometrics and in studying reliability. This project applies the Stochastic Dominance (SD) portfolio optimization methods to test the stocks that would do better during Kenyan electioneering periods. More and more scholars have shifted their attention to studying stochastic dominance relationships in decision theory. Some evidences presented by scholars in the area for many years have revealed that the methodology dominates many other solutions. Many methodologies assume contemporaneous as well as serial independence (assumption of no independence between samples and within a sample) which cannot be met by most observations in application since financial data features time series properties and positive correlation among observations from various samples. SD uses a distribution-free assumption framework which makes it suitable in checking dominance relationships between agricultural and manufacturing stocks. Besides, the SD relationships are based on empirical distribution differences. The methodology requires non-parametric statistical estimation as well as inference methods. SD is quite appealing to asset classes as well as investment strategies that exhibit asymmetric risk profiles. For example, small-cap stocks and momentum strategies where variance would not adequately measure investment risk since it makes no distinction between bad risk and good risk. The assumptions of no arbitrage and tendency of investors to dislike risk are largely supported by capital market equilibrium models. The project focuses on first degree SD, second degree SD and third-degree SD tests to check for the stocks that would dominate the other in the two sectors of the economy during hard economic times brought about by electioneering periods.

Chapter 1

Introduction

1.1 Background of the Study

A securities market studies such as Nairobi Securities Exchange market is an essential concept in financial modeling, especially in terms of a comprehensive of the working of the capital markets as well as in their performance together with development of any country's economy progress for the investors see[Chen et al., 2020]. In past couple of years, the an analysis of the has been a huge topic for many researchers in financial due to the significant implications when determining on whether an investor will buy securities of a given company or not at the same time enabling the investors to understand the trends within the market prior to making their investment decisions as this will enable them make investment decisions especially when looking for the best returns for the amount of money invested.

Prices that falls or rise in the stock market will always show a particular trend that the investors need to know about when making investment opportunities. For instance, the fall in securities prices started this year mainly reflecting concern and uncertainty over the global spread of Covid-19 thus having a huge effect on the market economy see [Odhiambo et al., 2020b]. This has led to the experienced securities prices falling by over 25 percent across many stocks worldwide. Any investor always believes that the securities prices in the market will have a reflection of a real economic activities in the specific country.

When an investor have information about the fundamentals of a securities exchange market in terms of its market efficiency, they will be capable of making an informed investment decision on whether it is viable to buy a certain type of security or not depending on the value of a specific index that trades in the securities market[Mogambi, 2017] for the investors.

1.1.1 Stock Market

Stock market can be described as any form of organized market used for buying or/and selling financial instruments such as bonds, shares, swaps, options and commodities. A stock market exchange is a specific location where buyers and sellers meet to make a tradoff of securities of different characteristics. A company listed by stock exchange market must satisfy the laid down trading requirements see[Kairu, 1976]. Stock markets facilities free transfer of shares between companies and investors thus mobilize people's savings and directing them to growth of the economy. The efficiency of any form of emerging market has been so vital to investors as regulatory reforms are made and barriers are removed for internationally equity investments.

In Kenya, the dealing or trading in shares and stock started in 1920's whenever the market was in a rudimentary stage for the colonist investors who inviting foreigners to make tradings on the floor of trade. However, there was none of a formal market with rules and regulations that would govern the activities of securities brokerage. Trading that took place was based on gentleman's agreements that lacked standard commissions which were charged on clients who were obligated to honor the terms and conditions of contractual commitments when making good delivery at the same time settling relevant incurred costs during the period.

In 1980s when the Kenyan Government realized the significance of designing and implementing policy reforms that would foster sustainable economic development both with efficient and effective way after development of the infrastructure for trading thus allowing for many investors who would wish to trade within the securities market at the same time increasing its liquidity.

1.1.2 Kenya Stock Market

Kenya became independent from British colonial powers in 1963, however it became a republic in 1964 that allows it to open market for those international traders who were looking forward to invest in the country. It took the country many more years to introduce a democratic system that came in the year 1991 that was having an impact on the kind of trade activities taking place in the Nairobi Securities Exchange due to worst political environment for investors. The above phenomena was attained after many years of turbulence and pressure foreign countries. Currently Kenya is among the best performing economies in Eastern Africa with the highest GDP when compared to all other neighboring countries. In the year 1964, NSE-20 share index was introduced and it was the main index in the country's security market. However it is only after 1993 that NSE-20 share index started performing so well as a result of relaxed taxation, less control on foreign investments and exchange controls. Unfortunately, political instability has been a key causative of high market volatility mostly during the general elections.

In many cases, for instance, the Nairobi Stock Exchange (NSE) uses indices to determine the trends in the market such as Nairobi All Share Index and NSE-20 share Index among many others that are being used as a market index to determine whether the economy of the country is doing well or not. Its measure is an overall indicator of the market performance see[Mumo et al., 2017]. The index always incorporates all the tradings in the number of shares of the day from those companies that are perceived to perform well thus making them lucrative for the investors for investment purposes. It has attention that is therefore important on the determining the trends on the overall market capitalization and the price movements of the selected securities that are being traded on the market.

1.2 Justification of the Study

While in Kenya, thee stock market is measured using three stock indices namely NSE-20 Index, the NSE All Share Index and MCSE Share Index. NSE-20 Index is the most commonly used since it incorporates 20 companies cutting across all sectors in the economy. This index has always been a great importance in the world markets NSE being one of these growing markets see[Guo et al., 2013]. The index has helped the world market in the analysis and portfolio management. Therefore, the index value is used when measuring the performance of a stock market and the institutions as well as the individuals can get to know how the market is performing and their investments in general see [Gichuru, 2018].

The companies that formed the NSE-20 share index are as follows Saini Ltd, Nation Media Group, WPP Scangroup Ltd, Kenya Commercial Bank, The Cooperative Bank, Diamond Trust Bank Ltd, Barclays Bank Ltd, Equity Bank Ltd, CFC Stanbic Holdings Ltd, East African Breweries Ltd, British American Tobacco Kenya Ltd, Athi River Mining, Bamburi Cement Ltd, Kenol Kobil Ltd, Kenya Power & LightingLtd, Kengen Ltd, British American Investments Company Ltd, CIC Insurance Group, Centum Investments Ltd and Safaricom Ltd. The 20 share index is dominated by the financial sector, all other sectors of the economy are represented.

All the companies in NSE are categorized into different forms. The forms includes Banking, agricultural,Construction and Allied, telecommunication among others. Table 1.1 shows all categories of Manufacturing and Agricultural Securities traded at the NSE:

No.	Manufacturing Securities	Agricultural Securities
1.	British Tobacco (BAT)	Sasini Ltd (SASN)
2.	East Africa Breweries Limited (EABL)	Kakuzi (KUKZ)
3.	Unga Group Ltd (UNGA)	Williamson Tea Kenya Ltd (WTK).
4.	Mumias Sugar Co. Ltd (MSC)	Kapchorua Tea (KAPZ)

Table 1.1: Manufacturing and Agricultural Securities at NSE

1.3 Stochastic Dominance

This thesis uses stochastic dominance (SD) tests to check for dominance relationships between the manufacturing and agricultural stocks at the Nairobi Securities Exchange (NSE). Stochastic dominance relationships is classified among the basic concepts of decision theory. Investors aim to maximize their expected utility from a particular investment which forms a major issue in decision theory under a risk. Each investor perceives risk proneness and utility maximization differently which renders it hard to come up with a specific decision rule that could be rational for a large group of investors. The concept of stochastic dominance relies on the assumption that if one alternative stochastically dominates its counterpart, it would be essentially preferred by a group of investors who follow a similar utility function. The first order stochastic dominance (FSD), second order stochastic dominance (SSD) and the third order stochastic dominance (TSD) decision rules are the most important in decision making. Under FSD, an investor would prefer an investment offering a payoff of F to G if every other individual who prefers more to less also prefers F. In the SSD, an investment offering a payoff of F is preferred to that offering a payoff of G by investors who are non-satiated and risk averse. FSD implies SSD. In the TSD, investors prefer investments offering positive skewness to those with negative skewness.

Kenya is one of the most important markets in Africa and one of the fastest growing economies as well as the biggest economy in East Africa. This attracts investors from developed countries who would want to invest in Kenya. However, when it comes to the election periods, most foreign investors fear investing in the NSE and fly back to their countries due to fears of a political risk that they perceive may affect the stock market.

Local investors also slow down their investment activities due to similar reasons. Most research studies of international markets in Africa will include the Kenyan market due to its large contribution to the economy of the East African region. In essence, the Kenyan market is one of the most important financial hubs in Africa that has attracted funding from the Middle East and world economies such as China, the European Union, and America.

1.4 Statement of the Problem

Long time ago investors could buy shares or sell them the same day. The above could pose a bigger threat as investors could assess the trend of the securities prices before predicting future prices thus getting chances of making arbitrage profits. The above was countered by the new policy where once shares were bought then they could only be sold after a fortnight. The main aim of the study is to test the weak form of market efficiency in NSE by assessing whether a person can use the prices of the securities to predict future prices.

The project uses the Agricultural and manufacturing stocks for the study because the two sectors make a major contribution to the country's economy and determine its economic growth. Also, the sectors are some of the major victims of adverse political climate during electioneering periods. Thirdly, many investors and practitioners doubt the rationality and efficiency of Kenya's stock market because Kenya is one of the developing economies. There are worries that insider trading and manipulation is not uncommon even if it is illegal. As a result, arbitrage opportunities are expected to exist in the Kenyan stock market.

1.5 Hypothesis of the Study

During the research, it is important to make the first hypothesis that the null hypothesis is that the stock prices in the Nairobi Stock market do follow a Gaussian distribution and an alternative hypothesis that the stock prices in the Nairobi Stock market do not follow a Gaussian distribution. The second null hypothesis is that the stock prices are random during the study period against the alternative hypothesis of the stock prices are not random in this study period. This is important since modeling of the indices will be used when making forecasting of the future trends for investors.

Another key principle of the weak form of the EMH is in the randomness of securities prices thus making it impossible when finding price patterns as a way of taking advantage of movement of the individual prices. To be more specific, daily securities price fluctuations can sometimes be over entirely independent from each other; thus, making an assumption that price momentum in the market does not exist, which may be difficult during trading. Moreover, past earnings in terms of growth does not always forecast current or even the growth in future especially in terms of stock earnings.

1.6 Objectives of the study

1.6.1 General Objective

The general objective is this study is to test Stochastic Dominance of Manufacturing Stocks Over Agricultural Stocks at The NSE Market During Electioneering period in Kenya.

1.6.2 Specific Objectives

The Specific objectives of this study are:

1. To Test Stochastic Dominance of Manufacturing Stocks Over Agricultural Stocks.
2. To Predict the future prices of securities of Manufacturing Stocks for a longer period.
3. To Determine the Correlation between Manufacturing Stocks and Agricultural Stocks

1.7 Significance of the Study

The project offers a study which compares the performance of Agricultural Stocks against their manufacturing counterparts using a robust statistical technique, the stochastic dominance (SD) approach based on the stocks' weekly returns and compares the results with those of CAPM. The SD approach reveals information from the first two moments as well as the higher moments of the distributions. It is interesting to study the behaviors of the two major contributors to the country's economy during the electioneering period when most people worry about the impact of politics or the possibility of political instability that could plunge the stock market into difficulties.

This study adopts the SD approach to assess the entire distribution of the weekly returns of the manufacturing and agricultural stocks. Stochastic Dominance approaches are applied in branches various branches such as studying economics of uncertainty by conducting portfolio diversification, and defining risk. SD has also been used in studying social welfare theory, finance and agricultural economics. SD reveals information from the first two moments as well as the higher moments of the distributions.

The analysis involves use of the R program and excel spreadsheets -Microsoft Excel and The Model Risk Excel adding to determine the dominance that exists between the Agricultural stocks and the manufacturing stocks. Important to note is that the Stochastic Dominance approach proves to be better than using the Capital Asset Pricing Model (CAPM)and the Mean Variance (MV) approaches because the methodology offers a good framework to help examine a portfolio of stocks without having to employ pricing benchmarks. Besides, the well known CAPM and MV approaches make a heavy reliance on the assumption that returns are normally distributed and use quadratic utility functions.

The SD approach does not depend on such assumptions. To test the type of stochastic dominance between the manufacturing and their Agricultural peers, the project makes use of weekly returns from stocks of 4 Agricultural companies and 4 manufacturing companies trading in the NSE during the three election periods 2007, 2013, and 2017. Dividing the study into investigating the three periods offers important results on the effects of election period on the stock market in Kenya. The project will make a good contribution to the effect of election period on stock markets to come up with findings that could be interesting to individuals who track stocks at the NSE, lawmakers, domestic institutions that trade at the NSE and any international investors who may take an interest in investing at the NSE.

Over the periods of 2007/2008, 2013/2014, and 2017/2018, the findings from the project indicate that most Agricultural stocks dominate the manufacturing stocks at the second order. This result shows that Agricultural stocks outperform their manufacturing counterparts during election periods. The findings from the project indicate that investors who trade agricultural stocks at the NSE during the election periods in Kenya are likely to outperform those who invest in the manufacturing stocks during the same period.

Chapter 2

Literature Review

One of the greatest contributions to solve this problem was put forward by [Markowitz, 1952] but the methodology has some drawbacks. For instance, [Markowitz, 1952] also only considers the parameters mean and variance but does not the full distribution. The mean-variance approach is a great contribution but it neglects important information which leads to promoting unreasonable decisions such as that pointed out by [Kotler and Levy, 1969]. Therefore, the stochastic dominance methodology is a universal decision rule and forms a benchmark for other rules in decision making.

[Hanoch and Levy, 1969] investigated weak form of market hypothesis by use of daily stock prices of Kengen for the time period 17th may 2006 to even December 2009 and also with Kenya power and Lighting from 2nd January 2002 to 31st December 2009. [Hanoch and Levy, 1969] did use a serial correlation test, Run tests and Durbin Watson tests where the results showed that the NSE is not efficient in the weak form. However the researchers did not tell us the reason for the choice of the Kengen and Kenya Power and Lightning companies.

Two researchers in the paper of[Rothschild and Stiglitz, 1970] had tested the inefficiency with long memory, persistence and anomalies of the NSE 20 share using date from 2001 to 2009. The above researchers used the concept of fractional integration, they concluded that there is evidence of long memory. [Whitmore, 1970] also carried a research using unit root, auto-correlation, variance ratio and runs test on the daily indices of Kenya and other many African countries having vibrant securities exchange markets in between time periods 2007 to the year 2017 during the election periods in Kenya when the investors are looking for the avenues that they can use when looking for returns from the market.

[Davidson and Duclos, 2000b] did a research on the Statistical inference for the stochastic dominance at the same time for the measurement of poverty as well as inequality that is important for the investors looking for the options of making investment in the market thus making decision based on the statistical inference based on the stochastic dominance of two competing investment options. [Khazali, 2001b] did a paper on the trade between Risk, Return, and Equilibrium especially in the Emerging Capital Market is important for a trader with more than two competing risks. This means that proper analysis has to be done to make the best choice of the two options for the investors who would wish to get the best returns from the given options of investment opportunities.

[Müller and Stoyan, 2002] explained in his book on the on the comparison methods for stochastic models as well as risks that most investors face whenever they are making investments in the market. This means that all investors must understand the importance of risk analysis in the market before settling for the options that they need with a view of making the best returns in the market. [Warren, 2019] explained on the ways of making a choice as well as options when selecting the available Utility Functions to be used in Forming Portfolios in the market of securities trade. A proper balance between risk and reward trade-off is important for those looking for the best returns not only in the short run but also in the long run.

The philosophy of efficient market is mainly concerned with assessment of whether prices of securities at any particular time do reflect the information that is available for the public investors[Chen et al., 2020]. There has always been a natural mechanism through which the price competition among financial markets make the prices to converge to an efficient state. The convergence to efficient state is also caused by exploitation of arbitrage opportunities by the operators. Thus, with the market operators taking advantage of price differential, the above forces will always push the prices of the securities to their expected values. Thus, profit opportunities are also eliminated as the markets tend towards equilibrium price, which means that the market is therefore efficient.

Two common approaches have been applied in evaluating portfolio performance. The first approach is using the traditional Mean-Variance (MV) approach which requires one to make assumptions on the stock return normality as well as use quadratic utility functions hypotheses (e.g., [Markowitz, 1952]; [Treynor, 1965]; [Jensen, 1972] where all investors in a market must understand all the potential risks before deciding on how they can invest to get the best returns at the same time reducing the risks from the securities exchange market.

The Mean Variance approach would not be as appropriate if the returns are not normally distributed and if the utility functions the investor is relying on are not quadratic (Lean et al., 2010). One of the alternatives to MV approach is applying the Stochastic Dominance (SD) criterion which was first developed by[Hadar and Russell, 1969], [Hanoch and Levy, 1969], [Rothschild and Stiglitz, 1970] and [Whitmore, 1970]. The Stochastic Dominance approach does not require many assumptions such as normality of returns. Besides, the SD approach requires less restrictive assumptions as compared to the Mean Variance approach.

The SD approach includes all information on the entire distribution of stock returns including the skewness as well as kurtosis and not the two first moments only (i.e., the mean and variance) as it is in the Mean-Variance case [Markowitz and Todd, 2000]. The level of stochastic dominance tested puts conditions on the stochastic dominance requirements on investors' utility functions. There are three forms of Stochastic Dominance. First, utility functions must exhibit non-satiation, which means the investors would prefer more to less under the first-order stochastic dominance (FSD). In the second order stochastic dominance (SSD), investors are assumed to be non-satiated and also risk averse.

Finally, under the third-order stochastic dominance (TSD), the conditions required are that the investor is non-sated, risk averse, and they exhibit a decreasing absolute risk aversion (DARA). The theory of rational decisions under risk is essentially based on the findings of [Fishburn, 1989a] axioms of utility. Let the symbol represent a preference relation that one investment is weakly preferred to another. Consider a set of M real valued random variables consisting of i, j, k uncertain but real valued outcomes. According to [Gasbarro et al., 2007], the following assumptions hold for the preferences of a particular investor.

The SD looks more attractive than the Mean Variance criterion and Capital Asset Pricing Model since it is non-parametric in nature where no explicit parameter specification of the utility function of an agent or restrictions are needed especially on the functional form of the statistical probability distribution . Many researchers have used SD approach in numerous empirical studies when doing performance evaluation. One should point out that SD using this concept in previous researches before making a comparison of efficient frontiers commonly generated by MV models from efficient frontiers are generated using these SD models. [Levy and Sarnat, 1970] did ascertain that the efficient set as per the MV criteria can be reasonably similar when compared to a set of concave utility function. From their suggestions, however, one can use SD when reducing the number of alternatives through ensuring that first data to be used is screened.

[Markowitz and Todd, 2000] did make a comparison of the MV frontier using the frontier that has been developed through SD procedures. The two did reports with suggestions on two efficient frontiers, which are similar or having a minor discrepancy in the results. [Kjetsaa and Kieff, 2003] did show ways of using SD to reduce iteratively a large number of equity mutual funds when operating over the period year 1985 to the year 2000 to one single-digit collection of non-dominated funds. The two made suggestions on SD as it may be used when identifying funds capable of outperforming market indexes during the trading times.

Post (2003) made use of the value-weighted mean of all AMEX, Nasdaq and NYSE stocks as shown by [Fama and French, 1996], which is type of analysis that uses SD. From his findings, which indicated that the markets under which tradings occur are inefficient as in SSD thus confirming results that are indicating that the inefficiency are both statistically at the same time economically significant. However, his suggestions that return distributions often vary over time at the same time indicating that his findings can be influenced through the particular sampling period or return horizon whenever making the given kinds of investments especially when the country like Kenya is experiencing hard economic recession after the pandemic like Covid-19 see [Odhiambo et al., 2020a]reflected in the securities market for those looking for investment opportunities.

[Levy et al., 2000] acknowledges the effectiveness of using stochastic dominance rules and the mean-variance criterion in constructing efficient sets and monitor the performance of stocks. However, the author explores FSD and finds it to be ineffective for making investment decisions because it results in a large efficient set for an investor to choose from. This means that investment advise from experts tracking the stock markets have a large set of efficient investments to choose from. This unpleasant result leads to the need to introduce the SSD and TSD rules and narrow down the size of efficient sets. [Levy et al., 2000] found out that SSD rules and the Mean Variance criterion are effective in determining efficient sets of investment. In essence, SSD yields a similar size of efficient set as the Mean Variance approach, even though the sets may not be similar in content. Applying the TSD narrows down the efficient set even further but only slightly than that of SSD.

[Levy et al., 2000] acknowledges the disadvantage of SD whereby analysts are yet to come up with an efficient algorithm to carry out SD analysis as opposed to Mean Variance criterion. The implication is that a researcher can only conduct a SD analysis to determine some efficient diversification strategies and not all the efficient strategies. However, in a case where there are finite combinations of investments, stochastic dominance application proves to be the best when compared to any other methodology. Some of such sectors include the agricultural sector where a farmer has a finite number of irrigation methods he could consider for his farm, the advertising industry to find the best advertising strategy and in medical industry to choose the best medical equipment.

Stochastic Dominance is distribution free and involves minimal assumption on preferences. SD is used in problem solving in economics and evaluate alternative methods. Furthermore, SD has been employed to explore various calendar anomalies in the equity markets as well as the bond market. A research conducted by [Khazali, 2001a] reveals that the January effect in high yield bond markets is robust and previous findings are not an artifact deriving from violations of distributional assumptions. A study by [Al-Khazali et al., 2008] also shows a strong day effect and weak week and January effects in the Greek stock market. In the Asian markets, [Lean, 2007] support the existence of weekly and monthly seasonality effects while [Kjetsaa and Kieff, 2003] find a strong Monday effect in the US market. Virtually all prior studies have relied on parametric t and F-tests to examine portfolio performance or to investigate ethical versus unethical investing.

Researchers recognize that the parametric tests used are not strictly appropriate for assets which exhibit non-normal distributions in returns. The researchers assume that the robustness of the parametric methods compensates any deviation from normality. This study extends the current literature by using SD analysis to examine whether investing in the agricultural sectors offers superior investment performance compared to investing in the manufacturing portfolios.

Chapter 3

Methodology

3.1 Introduction

Market efficiency hypothesis is made that the prices of securities are random at the same time that distribution is Gaussian distributed. This means that it is important in testing on whether the market exhibit the characteristics of being efficient. The main advantages of this Gaussian distribution is that it has only two measures, which is mean and variance that will describe all the distribution. In addition, the distribution makes basic assumptions when modeled as underlying CAPM (capital asset pricing model). The histogram of all prices is computed with the curve for normal distributions fitted with an aim of ascertaining whether the distribution of all price values do fit the Gaussian distribution.

A Gaussian distribution, which is not symmetric has in many cases, or more often has had a tail that ends in the distribution known as skewed. In addition, when the tail is running towards larger values, then it is safe to say that it skewed positively to the right and when the tail is towards the smaller values, the distribution is negatively skewed to the left. Kurtosis is a statistical measure that indicate the extent to which, for the standard deviation, observations cluster do around a given central points. If in any case in a distribution cluster more than those in the Gaussian distribution, the distribution is termed as leptokurtic. If cases cluster far less than in the Gaussian distribution, the distribution is known as platokurtic. The values for kurtosis as well as skewness are zero if all observed distributions then it is called a Gaussian distribution.

The theory of rational decisions under risk is essentially based on the findings of [Fishburn, 1989b] axioms of utility. Let the $\wp$ symbol represent a preference relation that one investment is weakly preferred to another. Consider a set of M real valued random variables consisting of i, j, k uncertain but real valued outcomes and the values of the stocks to be traded in a stock exchange market.

According to [Fishburn, 1989b], the following assumptions hold for the preferences of a particular investor. For $I, J, K \in M$, the following relationships holds; first, the feature of completeness: $I \geq J$ or $J \geq I$. and secondly the feature of the transitivity relationship where $I \geq J$ or $J \geq I$ will result in a more of the transitive approach when looking at different types of financial securities traded in a stock exchange market for any time period of investment.

The monotonicity axiom feature of $I \geq J$ which almost surely gives the best value of the stocks when being traded in market. The continuity axiom of $I > J > K$ is surely an almost surely hold, there is a $\alpha, \beta \in (0,1)$ that satisfies the relationship J and JK whereas the substitution axiom of $I \geq J$ results in K for all values of $\alpha \in [0,1]$.

3.2 Capital Asset Pricing Model (CAPM)

From the expected utility point of view, The Mean-Variance approach and SD represent two different methodologies of making investment choices. The two methodologies have their advantages and disadvantages. Some advantages of the MV criterion is that it can be employed in portfolio diversification among risky assets and this is a useful result in the application of CAPM. However the disadvantage of the MV approach is its reliance on normality of returns which is not necessary in the application of stochastic dominance.

The requirement of the assumption of normal distribution of returns is not appropriate for securities in stock markets since asset prices cannot be negative. Prices going below zero implies a rate of return of -100 percent, which is not appropriate because the normal distribution should remain unbounded. Nevertheless, the equilibrium risk-return relationships derived from CAPM has important results which has led to development and testing of CAPM in frameworks that do not rely on the assumption that returns from assets are necessarily normally distributed [LEVY, 1977]. This includes using discrete time models involving the log-normal distribution. The problem associated with employing discrete time models is that if two assets say i and j have their prices following a log-normal distribution, their constituent portfolio k, will not have exhibit a log-normal distribution where.

$$k = \alpha i + (1 - \alpha) j \tag{3.2.1}$$

Using continuous time portfolio revision [Merton, 1973] conducts a research to show that if the terminal wealth can be log-normally distributed, the CAPM holds in each step period. [Merton, 1973] gets rid of the characteristic additive problem involving log-normal distributions for discrete models by using continuous portfolio revision. One disadvantage of assuming a continuous time model is that the results from CAPM are broken down even with incorporation of very small transaction costs.

Risk-return trade off remains a key concept in finance and investment. In this project, consider a scenario where an investor is offered two investments, one consisting of purely agricultural stocks and the other manufacturing stocks in the Kenyan electioneering periods. Investors are risk averse and would would choose a portfolio that offers a higher expected return with relatively low levels of risk. Besides, if the two portfolios offered the same expected return with different levels of risk, then an investor would choose the portfolio with less risk.

The investor has to make a decision between a strategy of how to distribute their investment among the 4 companies listed in the agricultural stocks sector and the 4 companies listed in the manufacturing stocks. They need to determine which stock to invest in depending on the sector they consider does well during economic downturns in Kenya. The investor may seek services of an investment adviser. An investor tracking the two types of stocks would want to distribute their cash in a way that creates a promising portfolio.

[Markowitz, 1952] tries to answer this question in the research "Portfolio Selection" which has been advanced by various researchers into the infamous Capital Asset Pricing Model (CAPM). CAPM is used to theoretically estimate the appropriate required rate of return for each asset. The project then uses the Sharpe Ratio to determine how well the calculated return for each asset compensates an investor for the risk they undertake. A higher Sharpe Ratio implies a better investment option for an investor. An investor determines an optimal portfolio asset allocations for the set of stocks so that he or she obtains the highest Sharpe Ratio. The CAPM model can be applied to price each stock or portfolio. CAPM is modeled using the formula;

$$E(R_i) = R_f + \beta_i * (E(R_m) - R_f). \tag{3.2.2}$$

Whereby:

$E(R_i)$ is the expected return on asset i.

R_f is the risk-free rate of return, the project uses the interest rate of the 91-day government T-bill rates. $E(R_m)$ defines the expected rate of return in the market , here the project makes use of the Nairobi Securities Exchange (NSE) 20 share index as the Kenyan stock market index.

β_i is the sensitivity of the expected excess return on the market. β of security i can be obtained by a regression on the historical data of excess returns of the asset and the market.

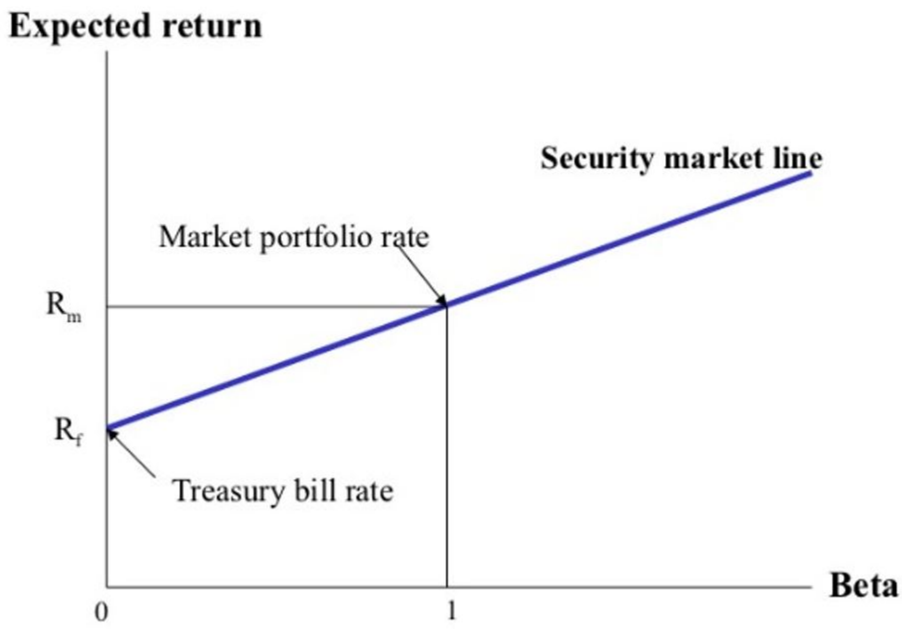

Figure 3.2.1: Security Market Line (SML)

Remark 1. The SML from the Figure 3.2.1 depicts the levels of risk that an investor should know when making investments decisions. In addition, it shows the Security Market Line (SML) that provides a general indication of the various levels of market risk with respect to different market assets plotted against the expected return.

3.3 Stochastic Dominance

Stochastic dominance is defined as a partial order in between the random variables when making a prediction on what will happen after a given event. This means that it is more of a stochastic ordering form that is helpful when modeling a given event see. In addition, the concept can arise in the decision theory as well as decision analysis in situations when a person who needs to make an investment relies on a probability distribution to make predictions over possible expected prices of outcomes called prospects during the period see[Gasbarro et al., 2007]. This means that the ranking can be done as superior to other common gamble for a wide range of classes when making decisions of which investments to make especially for the daily traders.

In many cases, the concept of Stochastic dominance is based on the decision-making, which is more on the information that has been acquired from a statistical inference. It is more based on the shared preferences, which regards sets of probable outcomes as well as their associated probabilities used when doing the calculations see [Kim and

Ryu, 2020]. Only on the limited knowledge of preferences can be used when making a determination of dominance. The Risk aversion is another factor only in second order of stochastic dominance that is important when making a determination of risk appetite of the individual investors looking for ways of making investment at the NSE-20 Share Index as well as other stated companies traded in the NSE.

Stochastic dominance does not always give the statistical total order, but rather only a partial order for the traders at the stock exchange market: for a group of investors who would rather make investments that stochastically dominates others when looking at the different available options for investment decisions.

3.3.1 First-order Stochastic dominance

First-order stochastic dominance (FSD) is defined as the special case of the statewise dominance that makes it important for investors in a given stock exchange market. Let a random variable A to have a first-order stochastic dominance over another random variable B whenever a outcome x, makes an investment in a market. Since the random variable A gives possess a higher probability of receiving at least x as does B, and for a given value of x, which means that the problem of stochastic dominance exists in the notation.

In terms of the notation form to be applied, the value of $P[A \geq x] \geq P[B \geq x]$ when it is for all values of x, as well as for some x, $P[A \geq x] > P[B \geq x]$ see [Pomatto et al., 2020]. As an investor looking for viable investment decisions, you can make a choice between investment A and B depending on the expected value of A when compared to B thus making a conclusion on the level of dominance between the two options.

3.3.2 Second-order Stochastic dominance

The second-order stochastic dominance is another common commonly used stochastic dominance type that makes it vital when assessing the relevance of making the investments decision in a stock exchange market. For instance when two traders in a stock market say, A and B make their investment decisions, the trader A is said to have a second-order stochastic dominance over another trader B if the trader can be more predictable meaning that the trader will always take less risk for a higher expected value of the return in terms of the expected level of mean.

All risk-averse traders in any market are expected-utility that maximizes as the curve will always be in an increasing as well as concave utility functions thus making a preferred second-order stochastically that is a dominant gamble to even a dominated one see[Donald and Hsu, 2016]. In addition, the second-order dominance always makes a description of the shared preferences of such those smaller decision-makers class thus making decisions.

For the sufficient conditions for the second-order stochastic dominance, it is important to note that the first-order stochastic dominance of investor A over investor B must possess a sufficient condition for the second-order dominance of investor A over investor B at the same time If investor B is a mean-preserving spread of investor A, then investor A second-order stochastically dominates investor B during the period of investment. The equation is provided as follows;

$$\int_{-\infty}^{y}\int_{-\infty}^{x}\int_{-\infty}^{z}[F_B(t)-F_A(t)]\,dt\,dy \geq 0 \text{ for all values of } x$$

Investment A dominates Investment B if and only if;

- $E_A(x) \geq E_B(x)$ is an essential condition for investor A to second-order stochastically dominate investor B during the period of investment period in a stock exchange market.
- $\min_A(x) \geq \min_B(x)$ is an essential condition for investment security A to second-order dominate investment security B. The condition implies that the left tail of F_B must be of a thicker when compared to the left tail of F_A during the period of investment in the stock exchange market.

It is important to note that these conditions are important for an investor making investments since it helps in ensuring that one gets the best returns when trading in the securities market such as NSE or $NYSE$.

3.3.3 Third-order Stochastic dominance

Let G_A and G_B be the $CDFs$ of the two distinctive investors say investor A and investor B. Investment A dominates Investment B if and only if;

- $E_A(x) \geq E_B(x)$ is an essential condition for investor A to second-order stochastically dominate investor B during the period of investment period in a stock exchange market. Investor A will always get higher returns in the stock market since A is greater than B in the stock market such as Agricultural stock over the manufacturing stock.
- $\int_{-\infty}^{x}\int_{-\infty}^{y}\int_{-\infty}^{x}\int_{-\infty}^{z}[F_B(t)-F_A(t)]\,dt\,dy \geq 0$ for all values of x

and there is at least one value of strict inequality. In equal measure, A dominates B in the $3rd$ order iff the $E_A(x) \geq E_B(x)$ for all non-decreasing, concave utility functions U, which are positively skewed (making a positive value of the third derivative when looking at the equation all together the process of making investment [Ng et al., 2017] while getting the best returns from the investments in NSE.

3.4 Stochastic Dominance Tests

Mean variance rules and SD rules employ partial information on the preferences of individual investors to order investments as those that are perceived to be best and those that would be unfavorable. For example, it is generally known that utility functions for individual investors are non decreasing,$U' \geq 0$ because they would prefer more returns to less see [Linton et al., 2020]. There is only some information on the function U, but one cannot tell its shape. The partial information on U can be used to develop an investment rule that would generally apply to all investors who exhibit a non decreasing utility function, $U' \geq 0$, having a strict inequality at some point.

Consider a set of all possible non decreasing utility functions, U_i and given that $U \in U_i$, the partial information on the function U, whereby $U' \geq 0$, can be used to define stochastic dominance. With a set of the possible investments that an investor would want to consider,a chosen investment A in U_i would be said to stochastically dominate the other, say B in U_i if for all the set of utility functions $E_A U_{(i)} \geq E_B U_{(i)}$ and there is at least one utility function $U_0 \in U_i$,for which a strict inequality holds. However, if two investments fall in the efficient set, then none of them dominates the other since the efficient set consists of investments that are undominated. This can be expressed in terms of a utility function $U_0 \in U_i$, so that $E_A U_{(i)}(x) \geq E_B U_{(i)}(x)$ with an additional utility function $U_0 \in U_i$, so that $E_A U_{(i)}(x) \geq E_B U_{(i)}(x)$. Clearly, neither investment of A or investment B has dominance over the other. However, the two investments may not be the best for all investors since some would prefer A to B or B to A even with no dominance among the two kinds of investments. Investments A and B must fall in the efficient set of investments to be preferred since no investor would select an investment in an inefficient set because all the investments in these set are already dominated by their counterparts in the efficient set.

The SD and DD test suggested by [Davidson and Duclos, 2000a] can be used to perform an initial screening of a group of investments to help advice on the most appropriate investments that an invest should partake in. Using the SD tests and with the help of some partial information say, $U \geq 0$, favorable investments would fall in the efficient set while those deemed unfavourable would be put in the inefficient set. If two or more investments fall in the set termed as efficient, it is impossible for us to tell the investor which one would be best for them since we have only done a partial ordering. The investor will only chose an investment at this stage depending on their preferences. If an investment consultant is presented with full information on an investors preferences such as $U_{(i)} > log(i)$, they can find the $E[U(i)]$ for all the investments under consideration and select the one that yields the highest expected utility after performing a complete ordering of all the investments. If two or more investments offer the same expected utility in this case, then an invest can chose any arbitrarily.

Stochastic dominance rules have a heavy reliance on distribution functions. Hence, to describe stochastic dominance tests, the first stage is to define the corresponding probability density functions (f and g) and the distribution function (cd f) of (F and G) for the returns of given indexes, Y and Z. An event x with a probability of occurrence p has a probability function $p(x)$. If the event is a continuous random variable, the probability function becomes a density function which can be denoted as $f(x)$. The corresponding probability for a discrete distribution would be represented as follows:

$$F(X) = P(X \leq x) = \sum_{\forall x} p(x) \tag{3.4.1}$$

The CDF for a continuous distribution would be represent as follows;

$$F(X) = \int_{\forall x} f(x)dx \tag{3.4.2}$$

The distribution functions F and G defined above can be seen to have common support of $[a,b]$ where $a < b$. Assume that x is from above and below as per the given support points. We can draw from this statement that for $x \leq a, F(x) = G(x) = o$. On the other hand, when the value of x is such that $x > b, F(x) = G(x) = 1$. Similar results are arrived at for the range $-\infty < x < \infty$. As illustrated by Wong et al. (2008), define the following;

$$H_0 = h \text{ and } H_j(x) = \int_a^x H_{j-1}(t)dt \text{ where } h = g, H = F \text{ and } j = 1,2,3$$

If an investor is presented with two stock choices A and B and wishes to rank the investments in the two choices, they can use the FSD rule to tell which investment has dominance over the other. If the two investments have cummulative distributions one represented by F and the other by G, and an investment consultant has the information that $U \in U_i$, with U0 > 0,. Also, to avoid a scenario where U0 would coincide with the horizontal axis, denote that U0 > 0 for some range since investors prefer more to less. Also assume that the utility function U is a continuous and non-decreasing. This would imply that the function is differentiable except for the points where a measure is zero. The dominance decision can be made as follows: For the cumulative distribution F and G, investment Y would dominate the investment Z at first-order SD (FSD) if:

$$F(x) \leq G(x) \tag{3.4.3}$$

We assume only one piece of information on the provided utility function U (non-decreasing) for $U \in U_i$,. If for all values of x in $F(x) \leq G(x)$;, there is at least one value xi for which the strict inequality holds. This relationship can also be applied for the scenario defined earlier where U ∈Ui, and be stated as follows:

$$E_B U_{(i)}(x) > E_A U_{(i)}(x) \tag{3.4.4}$$

This applies for the utility function U in the set of several other utility functions say U_A. The strong inequality for the utility function must hold for at least one scenario. [Guo et al., 2013] defines that for the first order stochastic dominance where, $B(x) - A(x) = I1(x)$ the condition for investment A to dominate the other investment B is that $I1(x) > 0$ for all the possible values of x with $I1(x_0) > 0$for at least some value of x_0. FSD captures the central tendencies.

Similarly, an investment Y would dominate over its counterpart Z in the second order if F (x) 6 G(x); For all the values of x, with the strong inequality for the utility function holding for at least one value of x. In essence, SSD overs a summary of the locally defined dispersions. In FSD, its assumed that the utility function $U \in U_i$, to be a non decreasing function with $U_0 > 0$. Ideally every investor dislikes risk and would avert it. Hence, it would be appropriate to develop a decision rule which would also take these risk averters into consideration. We will be continuing with the non decreasing utility function as stated above and assume that investors are risk averse.

Risk aversion is said to have been achieved if the following definitions are met such as when an investor who is risk averse will not prefer to play a fare game where the price of the ticket for the game has the same value as the expected price. For example, if a risk averse investor is presented with an opportunity to toss a coin and win, with the price corresponding to the head of the coin after a toss and that the ticket price to play this game is Ksh.1000, they would not play it if it is a fair game whereby; E (2)An investor has a utility function with a positive first derivative $(U_0' > 0)$ and a negative second derivative (U00 6 0) with the strict inequality$(U_0' > 0)$ holding at some point for the first derivative and $(U_0'' < 0)$ for the second derivative. (3)

For all the points on the curve of a utility function, if any two of them are joined by a straight line, it would either be located on the utility function curve or below it and none above it. Besides, there would be at least one cord that would be strictly pass below the utility function curve as shown in the graphic below: As shown in Figure 2, the points g and h are joined by a straight line which lies on the curve of the utility function while *h* and *i* are joined by a straight line which lies below the utility function curve. This is characteristic for investors who assume a risk averse function.

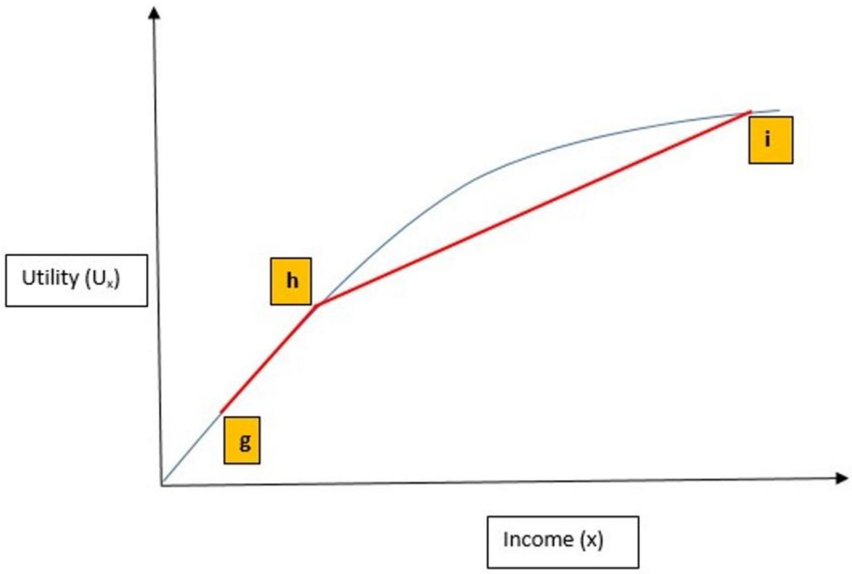

Figure 3.4.1: Points on the curve of a utility function for risk averse investor

Remark 2. It is important to note that a risk averse investor always prefer more to less thus the principle of non-satiation. This means that investors who invest in the stocks traded in NSE always prefer more return on the securities while taking the least possible risk thus making them risk averse.

(4) Risk averse investors are willing to pay a small amount of money in exchange for an insurance cover. Such an investor would prefer to pay a risk premium to transfer the risk of loss of their wealth to an insurance company. For example, the investor may purchase an insurance cover for their car against theft. If the wealth of this investor is say w and the value of their car insured against theft is x.

If this investor did not take up the insurance cover, the value of their car would be a random variable (x) and their expected utility would be given by the equation $E[U(w+x)]$. From Jensen's inequality $E[U(w+x)] \leq U(w+E(x))$. The utility function is concave since $U''(x) < 0$. The maximum amount of money this investor would be willing to pay to the insurer to transfer the risk can be given by p, whereby:

$$E[U(w+x)] = U(w+E(x)-p) \tag{3.4.5}$$

The value of p that solves the above inequality is referred to as the risk premium. This value is non-negative, i.e $p \geq 0$ In case of a car theft, the insurer is ready to lose from his wealth an amount p to transfer the risk and get compensation. However if the insured event does not take place, the investor will still pay this premium to the insurer and it will form part of the gross profits to the insurance firm. in essence, the investor's expected utility without an insurance cover is compared to the utility they would obtain with insurance for a maximum amount p that they would be willing to pay.

(5) Risk aversion can also be seen in a scenario where the expected utility that would be derived is less than or is of the same value as the expected return from an investment. Using Jensen's inequality, for a concave function $U(c)$, the following holds:

$$E[U(c)] \geq E[U(c)] \tag{3.4.6}$$

If there are two investments A and B with A offering an expected return of c_1 with probability i and its counterpart B offering an expected return of c_1 with a probability of $1-i$, then:

$$E[U(c)] = U(i(c_1) + (1-i)c_2 \geq i(U(c_1) + (1-i)Uc_2 = E[U(c)]. \tag{3.4.7}$$

In the third order stochastic dominance (TSD), investors are motivated by positive skewness as opposed to a negative one. In the first order stochastic dominance, the basis for derivation is that the utility function U is a member of a set of utility functions denoted by Ui i.e

$$U \in U_i$$

We depend on the the partial information on the function U that;

$$U' > 0$$

In the second order stochastic dominance, the assumption used is that $U \in U_i$ with that the first derivative $U' > 0$ and the second derivative $U'' > 0$. Similar to FSD and SSD, the TSD rule is derived with the constraints $U \in U_i$, with $U' > 0$, $U'' > 0$, and $U''' < 0$. The inequality $U' > 0$, implies that the investor would want more more as opposed to less. The constraint $U'' > 0$, implies that investor following this rule is risk averse and with all other conditions held constant, they would dislike risk. The additional constraint $U'' > 0$, is in relation to skewness of the distribution of the returns from an investment which is from the third central moment and can be obtained by:

$$\sum_{\forall x} p_i(x_i - \bar{x})_3 \tag{3.4.8}$$

where x is for a discrete distribution.

And for a continuous distribution, it can be obtained as follows;

$$\int_{\forall x} (x)((x_i - \bar{x})_3 dx \tag{3.4.9}$$

The diagram in Figure 3.4.2 below illustrates the three types of skewness, i.e negative skewness, positive skewness and normal skewness.

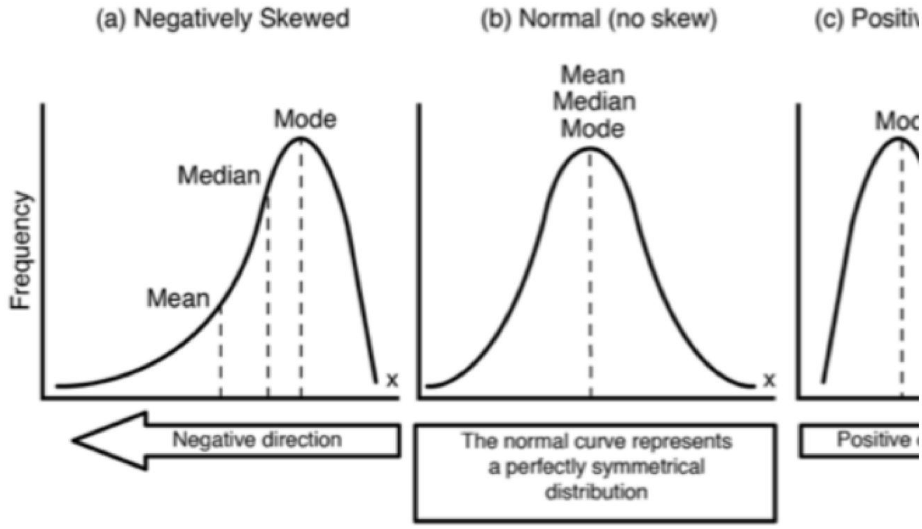

Figure 3.4.2: A diagram of the three types of skewness measuring asymmetry in a distribution's tails

For an investment with a large positive skewness such as lottery games, investors would be easily attracted. In this case a large price is attached to a relatively small probability, px, of becoming a winner. However, for a case such as not taking a comprehensive car insurance, the value of this property would be negatively skewed to the owner. This is true because the owner of the car risks losing the whole car with a very small probability px of the event of loss occurring.

The relationship between skewness and the derivative $U''' > 0$ was first brought forward by Friedman and Savage (1948) who observed investor behaviors to determine their preferences. Friedman and Savage (1948) employ a positive approach to understand why most investors would take part in playing a lottery game but at the same time, they would take up an insurance cover against loss for their properties. In essence, the researchers showed that investors would insure their homes to prevent variance of the future value of the house and also to ensure the negative skewness attached to uninsured property has been reduced to zero which would increase their expected utility.

The conclusion from this observation is that investors who partake in the lottery would take up insurance to avoid variance and negative skewness. This can be interpreted to mean that the investor purchases the insurance for their home to ensure certainty of their future income. In essence, the negative skewness and variance is transferred to the insurer at a risk premium which would mean that the investor's expected value of wealth would decrease with the premium amount. The premium charged would decrease the investor's expected utility and would only be worthwhile undertaking if the insurance cover is such that their would be a utility increase. However, when an investor partakes in the lottery game, they take a variance in their future income and introduce a positive skewness. In this case, the investor who purchases a lottery ticket to take part in the game likes variance and positive skewness. Although it is unlikely that an investor would like to have a variance in their investment, the lottery introduces a positive increase in both variance and skewness.

The theory brought forward by Friedman and Savage (1948) can also be extended to a case whereby an investor decides to take up an insurance policy for their house and he buys a ticket for an unfair lottery game. These events would increase the variance of the expected future income for the investor as well as increase skewness. The positive skewness would cancel out the effects of an increase in variance. Even though this behavioral observation does not offer a conclusive prove that $U''' > 0$, (there is change in variance and expected return) it supports the conclusion that investors would prefer positive skewness and dislike negatively skewed investments and this supports the observation $U''' > 0$ A more conclusive observation in support of $U''' > 0$, is the observation of the effects of variance and skewness on stock market expected returns from the NSE.

The expected rates of returns from stocks are generally positively skewed since the stock market prices can go to zero which would indicate a -100% rate of return to the investor. The prices of stocks are unbounded from above which implies that the distribution of returns would exhibit a long right tail that introduces positive skewness illustrated in Figure 3.4.2 Unlike the illustration that was given earlier on home ownership insurance and taking part in a lottery with large positive skewness, it is possible to use multiple linear regression to overcome the problem of separating effects of changes in skewness from a change in variance. The rates of return from stock market indices can be used to show that the third derivative is indeed positive, i.e. $U''' > 0$.

Multiple linear regression allows for separation of effects of variance from the effects of skewness. Let the ith mutual fund be x_i , the nth central moment be represented by s_{in} , $\sigma_i^2 = s_{i2}$ represents the variance of returns and $E(r_i)$ is the expected rate of returns from the index i. The regression carried will follow the following equation: E xnsin Regression coefficients from the above model will help to tell how each moment of a distribution would affect the expected rate of return from the index i, $E(r_i)$. In essence if the coefficient $x_2 > 0$, this can be interpreted to mean that the particular investors who have purchased shares of this index are risk averse and do not like having a variance in the returns if all other factors are kept constant.

A Taylor series expansion can be used to show that $U'' > 0$. When the variance is very high when $x_2 > 0$, an investor would demand a higher expected rate of return for investing in the index i. This behavior from investors could be interpreted to mean that they dislike variance of returns in their investment and they would require an extra compensation for such an investment which has a considerably higher variance than the rest. In the event that $x_3 < 0$, the precise conclusion is that this investor prefers positive skewness to a negative skewness in the returns of the NSE index.

When the returns from the asset are positively skewed, expected rate of return from the index i, $E(r_i)$ becomes small and these particular investors will be happy with the feature. Particularly, an investor in such an index would be happy to receive a relatively low rate of return from the index i since $x_3 < 0$,. The above multiple linear regression helps to estimate the variance effect and the skewness effect separately. The component x_2 is a measure of variance effect while the component x_3 gives an estimate of the skewness effect on the return of a given stock. For most investors (if not all), $U''' > 0$. This empirical evidence is sufficient to support the hypothesis that $U'' < 0$ and $U''' > 0$ for a risk averse investor with an increasing utility function U. The result is consistent with that of F. Arditti who first performed such an analysis using individual stocks and was able to show that the conclusion that investors prefer positive skewness to a negative one holds.

A Taylor series expansion below may be used to show that $U'' < 0$, which helps explain the relationship between the second derivative of the utility function U with skewness. The utility function is expanded using a Taylor series expansion from the point $m + E(r)$ assuming the utility function takes the form $U(m+r)$, where m is the investor's certain wealth and r is the random component such as the random variable introduced when an investor does not take up insurance for their home.

Using the expected utility theorem and expanding using Taylor series, the expression becomes:

$$U(m+r) = U(m+E(r)) + U(m+E(r))(r-E(r)) + \frac{U''(m+E(r))(r-E(r))^2}{2!} + \ldots \tag{3.4.10}$$

The ext step is to find the expected values for the Left hand side and right hand side of the above equation.

$$U(m+r) = U(m+E(r)) + \frac{U''(m+E(r))\sigma_r^2}{2!} + U''' \frac{(m+E(r))}{3!} + \mu_3 + ... \quad (3.4.11)$$

Also, using the knowledge that $E(m+E(r) = 0$, the expression becomes: From the above expression, the inference is that when all other factors are kept constant, the expected utility of a risk averse investor tracking this stock would proportionally be lowered with a high . Besides, the expected utility of this risk averse investor increases with an increase in positive skewness with the constraint that $U''' > 0$. The conclusion from the above expansion is that if all other factors remain constant, an investor dislikes variance when $U'' < 0$. The same investor would prefer a higher positive skewness to a negative skewness when $U''' > 0$. In the earlier example involving home insurance, when a risk averse individual insures their house, the variance and skewness are reduced to zero as compared to when they do not take an insurance for their home which would mean that in that case variance to their wealth would be high and negatively skewed. When the variance (σ^2) is reduced by taking up insurance, the individual's expected utility would increase as long as $U'' < 0$. If by taking up insurance the negative skewness becomes positive or is reduced to zero, the expected utility of this investor would increase as long as $U''' > 0$.

The risk premium charged by insurers reduce an individual's expected wealth and the effect on the expected utility of the investor is a decrease. Therefore, this individual would only find it worthwhile to take up an insurance for their home when the aggregate utility is an increase. In the market of risky assets such as stocks where forces of demand and supply are in action, if there is an action from a particular company participating in the stock market such that it leads to an increase in skewness of the returns for the stock, the demand for such an investment would go up since if all factors are kept constant, investors prefer a high positive skewness in their returns as compared to a low one. The effect of a high demand would be an increase in price for the particular stock which would eventually lead to a lower average return for the stock since its price would be very high.

Using Arrow-Pratt's formulation on risk premium and the concept of decreasing absolute risk aversion, it is also possible to show that investors portray a preference to positive skewness (i.e $U''' > 0$). When an investor has a good amount of wealth, they tend to be willing pay an even smaller risk premium with respect to their wealth to transfer the risk of loss to their property to an insurer. From Arrow-Pratt's measure of absolute risk aversion, the coefficient of absolute risk aversion is given by:

$$A(m) = -\frac{U''(m)}{U'(m)} \quad (3.4.12)$$

where $U'(m)$ is the first derivative and $U''(m)$ is the second derivative with respect to an investor's wealth of amount m for the utility function $U(m)$ and $A(m)$ is the risk premium.

Using Arrow-Pratt's formulation for decreasing absolute risk aversion or increasing absolute risk aversion would be if $A(m)$ is decreasing or increasing respectively. The inequality for decreasing absolute risk aversion (DARA) is:

$$\frac{\partial A(m)}{\partial m} = -\frac{U'(m)U''(m) - [U''(m)]^2}{[U'(m)]^2} \tag{3.4.13}$$

The above inequality holds for a case where $U'''(m) > 0$. The inference from DARA as brought forward by Arrow-Pratt is that the investor's utility function has a positive skewness with $U'''(m) > 0$. The empirical evidence for positive skewness is consistent with Arrow-Pratt's formulation for decreasing absolute risk aversion which supports the hypothesis that $U'''(m) > 0$. The empirical evidences provided are sufficient to come up with an investment rule which takes a preference for positive skewness into consideration.

Let the cumulative distribution functions for Y be $Y(x)$ and that for Z be $Z(x)$ with their respective density functions $y(x)$ and $z(x)$. In essence, an investment Y would dominate its counterpart Z in the third-order stochastic dominance if and only if the following is true:

$$\int_a^x \int_a^z [Z(t) - Y(t) dt dz \geq 0; \tag{3.4.14}$$

Refer to this integral as A. Hence, the required condition is that $A \geq 0$. Also,

$$E[Y(x)] \geq E[Z(x)]$$

Let this inequality be referred to as B.

For all the values of x, with the strong inequality for the utility function holding for at least one value of x such that;

$$I_3 \geq 0$$

and $B > 0$

$$U(E[Y(x)] \geq U(E[Z(x)])$$

for a utility function U such that $U(x) \in U_3(x)$ Therefore, TSD requires that either $A > 0$ or $B > 0$ for some values of x in $U(x)$. The TSD rule has been derived with the constraints $U \in U_i$, $U' > 0$, $U' < 0$, and $U''' > 0$.

Next, the order$-j$ DD statistic,

$T_j(x), (j = 1, 2,$and 3) for a grid of pre-selected points $x_1, x_2, ...x_3$ is calculated with the formula;

$$T_j(x) = \frac{F_j(x) - G_j(x)}{\sqrt{V_j(x)}} \tag{3.4.15}$$

Where $H_i(j) = \frac{1}{N(j-1)} \sum_{t=1}^{N} (x-h)_{+}^{j-1}, H, G; h = y, z;$

And

$$\hat{V}_j(x) = \hat{V_Y}^j(x) + \hat{V_Y}^j(x) - 2,$$

$$\hat{V}_j(x) = [\frac{1}{N(j-1)!)^2} \sum_{i=1}^{N} (x-h)^{2(j-1)} - \hat{H}_j(x)^2],$$

$$\hat{V_{Y,Z}}^j(x)[\frac{1}{N(j-1)!)^2} \sum_{i=1}^{N} (x-y_i)^{2(j-1)} + (x-z_i)^{j-1} - F(x)\hat{G}_j(x)]$$

The following hypotheses are tested:

$$H_0 : F_j(x_i) = G_j(x_i), \text{for all } x_i, i = 1, 2, 3...k;$$

$$H_1 : F_j(x_i) \neq Gj(xi), \text{for some } x_i; \text{ for all}, i = 1, 2, 3...k;$$

$$F_j(x_i) < G_j(x_i), \text{for some } x_i, H_A : Fj(x_i) \neq G_j(x_i), \text{for all } xi; Fj(x_i) > G_j(x_i), \text{for some } x_i,$$

Bishop et al. (1992) propose to test the null hypothesis for a pre-designed finite numbers of values x. The null hypothesis is rejected if the DD statistic is significant at any grid point. Under the null hypothesis $T_j(x)$ is asymptotically distributed as the Studentized Maximum Modulus (SMM) distribution (Richmond, 1982) to account for joint test size. The SMM distribution with k and infinite degrees of freedom is used to control for the probability of rejecting the overall null hypothesis.

Wong et al. (2008) and others suggest of using the following decision rules based on $(1-\alpha)$ percentile of tabulated by Stoline and Ury (1979): if for $i = 1, ..., k$ accept H_0; if T_j for all i and for some i,accept HA1; if for all i and T_j for some i,accept HA2; if T_j for all i and for some i, accept HA; However, Bai et al. (2012) demonstrates that it is not appropriate for using . Thus, this project follows their recommendation to get simulated critical values for DD statistics. The existence of SD implies that the expected utility of investors is always higher when holding the dominant asset than holding the dominated asset. Consequently, the dominated asset should not be chosen. Levy (1992, 1998) argues that a hierarchical relationship exists in SD which means FSD implies SSD, which in turn implies TSD. However, the converse is not true. Thus, only the lowest dominance order of SD is reported in practice.

Chapter 4

Data Analysis and Results

4.1 Introduction

It is vital that all data of the NSE securities be checked for normality thus making them available especially when looking at the options of statistically using using R programming language. This tables in this chapter should give the summary statistics for the returns for the 8 stocks in the chosen two sectors of the economy. The first table shows the descriptive statistics for the stocks in 2007, the second table gives the descriptive statistics for the stocks in 2013 and the last table presents results for same stocks in 2017. From the overviews, there is a variation in terms of the means, standard deviation and skewness of returns for the 8 stocks monitored between 2007 and 2017.

4.2 First Order Stochastic Dominance Illustrations

For the Plot of the cumulative distributions for the return of BAT against those of MSC. On balance, MSC is more desirable than BAT.

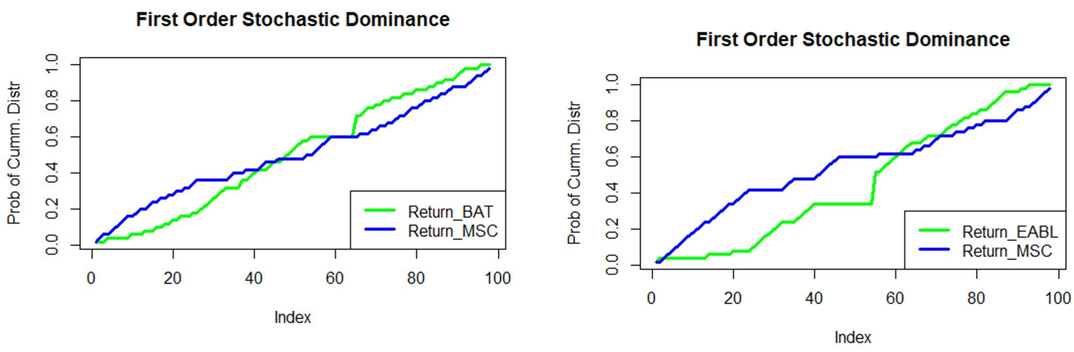

Figure 4.2.1: First Order Stochastic Dominance for EABL Vs MSC

The Plot of the cumulative distributions for the returns of EABL against those of MSC. The CDFs cross on the 60th and 70th observation but on balance, MSC is looks more desirable than EABL. The plot of the cumulative distributions for the return of KAKZ against those of MSC. The CDFs cross each other multiple times . However, MSC overpowers KAKZ and is more desirable .

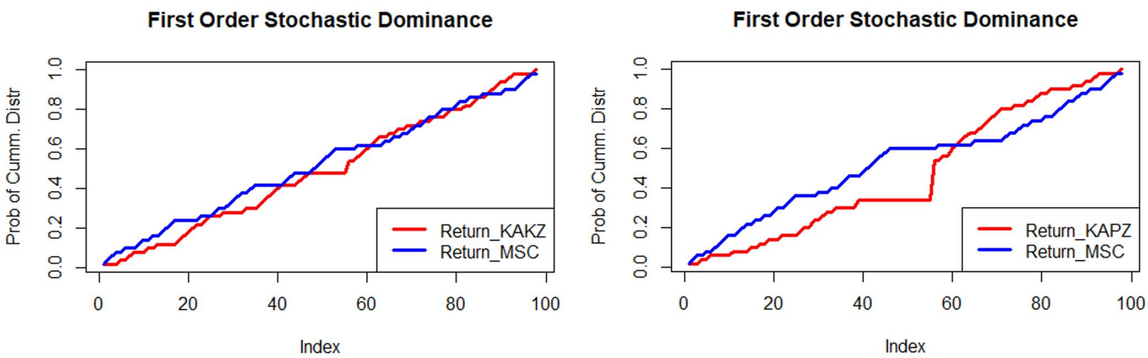

Figure 4.2.2: First Order Stochastic Dominance For KAPZ Vs MSC

The Plot of the cumulative distributions for the return of KAPZ against those of MSC. The CDFs cross each other around the 60th observation . However, on balance MSC overpowers KAPZ and is more desirable.

Returns for SASN stochastically dominate those of BAT in first order as shown below:

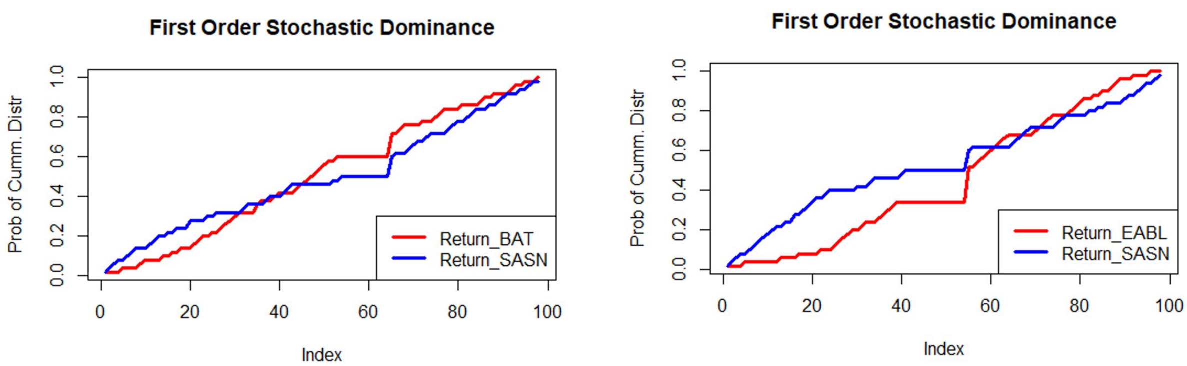

Figure 4.2.3: First Order Stochastic Dominance for EABL Vs SASN

The Returns for SASN stochastically dominate those of EABL in first order as shown above:

Returns for KAKZ stochastically dominate those of SASN in first order as shown above left

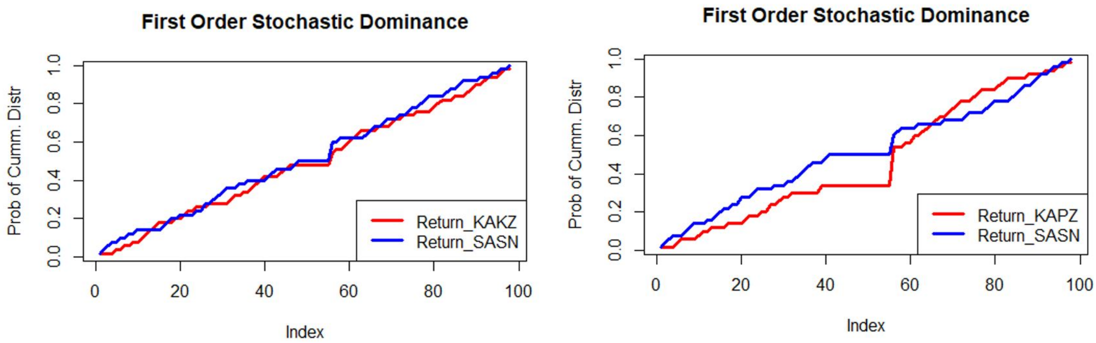

Figure 4.2.4: First Order Stochastic Dominance For SASN Vs KAPZ Return

The No clear dominance pattern between returns of SASN and KAPZ

No clear dominance pattern between returns of UNGA and BAT

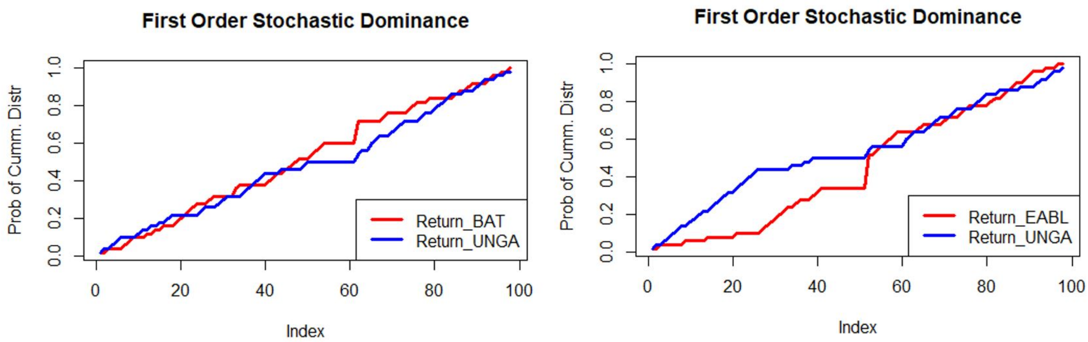

Figure 4.2.5: First Order Stochastic Dominance for EABL Vs UNGA Return

The Returns for UNGA stochastically dominate those of EABL in first order as shown below

Returns for KAKZ stochastically dominate those of UNGA in first order as shown below:

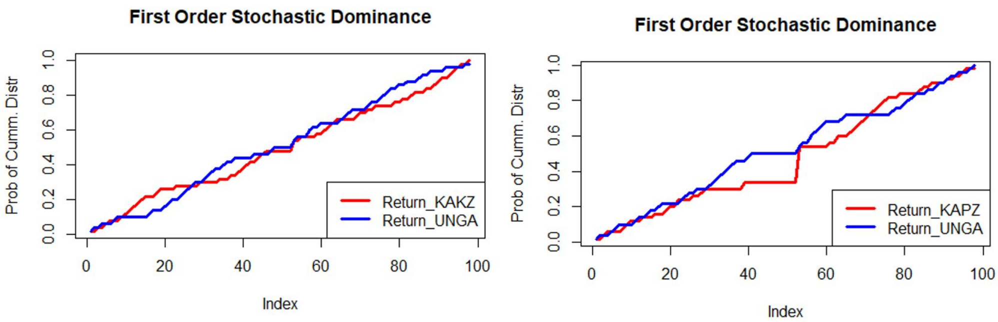

Figure 4.2.6: First Order Stochastic Dominance for UNGA Vs KAPZ Return

The No clear FSD pattern between returns of UNGA and KAPZ

Returns for WTK stochastically dominate those of BAT in first order as shown below:

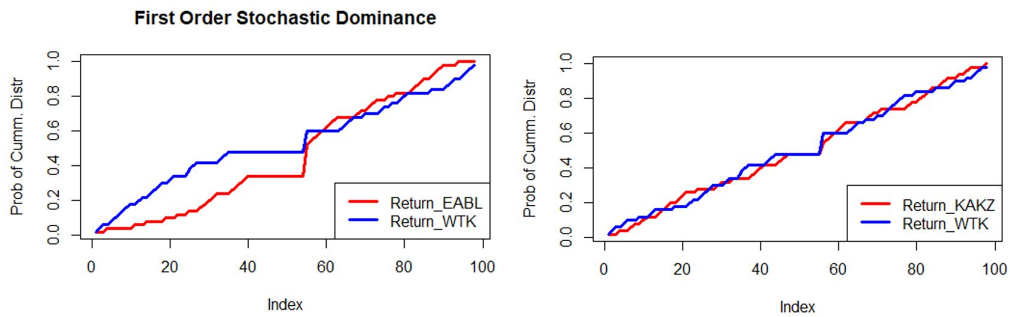

Figure 4.2.7: First Order Stochastic Dominance for EABL Vs KAKZ Return

The Returns for WTK stochastically dominate those of EABL and KAKZ in first order as shown below:

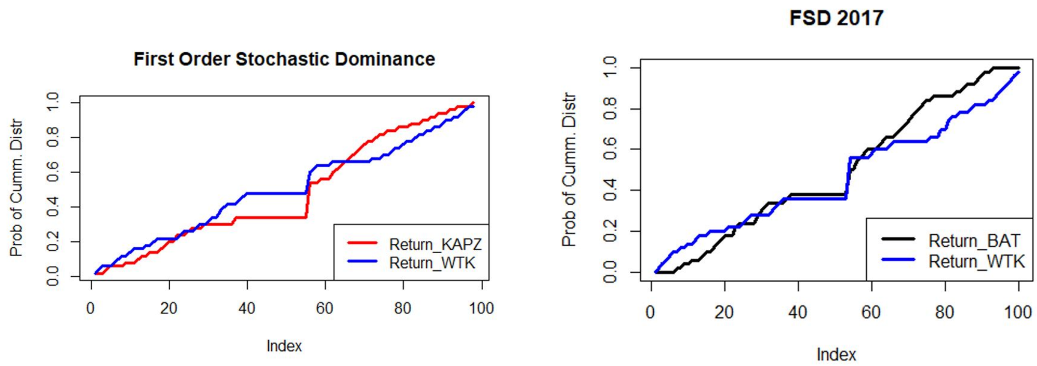

Figure 4.2.8: First Order Stochastic Dominance for BAT Vs WTK

The cumulative distributions for the returns of the agricultural stocks in 2013 (WKT and SASN) indicate a dominance over the returns of BAT a manufacturing stock. Similar results show that WTK dominates over BAT and KAPZ dominates over MSC in 2017. Therefore, in the first order, the agricultural stocks are more desirable in Figure 4.2.9 below.

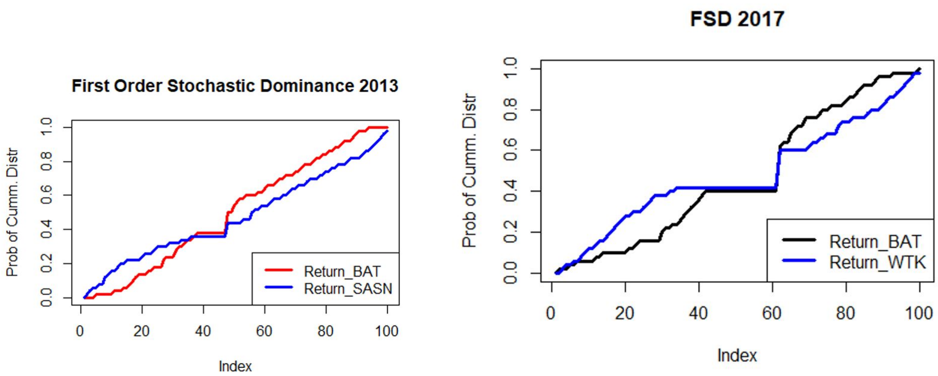

Figure 4.2.9: Third Order Stochastic Dominance

The Returns for WTK stochastically dominate those of KAPZ in first order as shown below:

Agricultural over Manufacturing	Manufacturing over Agricultural	No clear Dominance Pattern
9	3	3

Table 4.1: Overall First Order Stochastic dominance pattern for 2007

The above Table 4.1 shows the Overall First Order Stochastic dominance pattern for 2007, which is fundamental for those who investors looking for ways to make money in the NSE from trading of securities.

4.3 Data Analytics

The data analytics shows the statistical analysis of the 8 stocks trading during the election period at the NSE from the 2007,2013 and 2017 respectively.

Returns	BAT	EABL	UNGA	MSC	SASN	KAKZ	KAPZ
Nobs	50.000	50.000	50.000	50.000	50.000	50.000	50.000
NAS	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Minimum	-0.1441	-0.1618	-0.1652	-0.1504	-0.2638	-0.1241	-0.1385
Maximum	0.1437	0.0897	0.2316	0.3354	0.1905	0.2313	0.2549
1st Quartile	-0.0314	-0.0069	-0.0278	-0.0519	-0.0500	-0.0455	-0.0261
3rd Quartile	0.0072	0.0210	0.0171	0.0287	0.0229	0.0287	0.0110
Mean	-0.0069	0.0040	-0.0037	-0.0017	-0.0140	0.0005	0.0003
Median	-0.0073	0.0000	0.0000	-0.0049	0.0000	0.0000	0.0000
Sum	-0.3376	0.1948	-0.1829	-0.0839	-0.6843	0.0231	0.0131
SE Mean	0.0066	0.0050	0.0084	0.0124	0.0112	0.0091	0.0083
LCL Mean	-0.0201	-0.0060	-0.0206	-0.0267	-0.0366	-0.0179	-0.0165
UCL Mean	0.0064	0.0139	0.0131	0.0233	0.0086	0.0188	0.0170
Variance	0.0021	0.0012	0.0035	0.0076	0.0062	0.0041	0.0034
StDev	0.0461	0.0347	0.0587	0.0869	0.0787	0.0638	0.0582
Skweness	0.3457	-1.8710	0.8345	1.2674	-0.9105	0.7902	1.2673
Kurtosis	2.1315	8.9944	4.3630	3.1214	2.3941	1.7902	6.2739

Table 4.2: Summary statistics for returns in 2007

Remark 3. EABL has the highest mean (0.0040) while SASN has the lowest (-0.0140). MSC returns the highest standard deviation (0.0869) while EABL has the lowest (0.0347). The mean returns for stocks in the manufacturing and allied sector are negative except for EABL while those in the agricultural sector are all positive except for SASN. All the stocks have a positive skewness except for that of EABL which is from the manufacturing sector and that of SASN which comes from the agricultural sector.

Returns	BAT	EABL	UNGA	MSC	SASN	KAKZ	KAPZ
Nobs	50.000	50.000	50.000	50.000	50.000	50.000	50.000
NAS	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Minimum	-0.0500	-0.0945	-0.0909	-0.1765	-0.0931	-0.1011	-0.0980
Maximum	0.0399	0.3133	0.1295	0.2778	0.0846	0.1266	0.0990
1st Quartile	-0.0087	-0.0173	-0.0060	0.0000	-0.0176	-0.0116	0.0000
3rd Quartile	0.0166	0.0265	0.0199	0.0455	0.0206	0.0220	0.0140
Mean	0.0017	0.0033	0.0072	0.0027	0.0040	0.0058	0.0010
Median	0.0009	0.0047	0.0062	0.0000	0.0039	0.0000	0.0000
Sum	0.0847	0.1639	0.3581	0.3559	0.2021	0.2888	0.0830
SE Mean	0.0025	0.0087	0.0050	0.0105	0.0053	0.0057	0.0040
LCL Mean	-0.0033	-0.0141	-0.0030	-0.0185	-0.0065	-0.0057	-0.0040
UCL Mean	0.0067	0.0207	0.0173	0.0239	0.0146	0.0172	0.0100
Variance	0.0003	0.0037	0.0013	0.0056	0.0014	0.0016	0.0010
StDev	0.0176	0.0612	0.0357	0.0745	0.0372	0.0403	0.0320
Skweness	-0.2484	2.2925	0.4739	0.5156	-0.0757	0.4238	-0.3620
Kurtosis	0.0303	10.8674	2.1738	2.5764	0.4211	1.2707	2.5000

Table 4.3: Summary statistics for returns in 2013

Remark 4. The 2013 descriptive statistics presented in table 2, UNGA Group offers the highest mean returns (0.0072) while both BAT and KAPZ offer the lowest mean returns (0.0017) for the year. The mean returns for 2013 are all positive. EABL has the highest standard deviation in returns while (0.0612) while BAT has the lowest (0.0176). Some of the stocks have a negative skewness in their returns (BAT, SASN and KAPZ) while the other five (EABL

Returns	BAT	EABL	UNGA	MSC	SASN	KAKZ	KAPZ
Nobs	50.000	50.000	50.000	50.000	50.000	50.000	50.000
NAS	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Minimum	-0.1101	-0.0500	-0.1324	-0.1765	-0.0651	-0.0954	-0.1158
Maximum	0.0694	0.1064	0.1695	0.2778	0.1727	0.3333	0.1548
1st Quartile	-0.0050	-0.0206	-0.0320	-0.0326	-0.0093	0.0000	-0.0123
3rd Quartile	0.0025	0.0134	0.0221	0.0455	0.0236	0.0180	0.0000
Mean	-0.0026	-0.0006	-0.0012	-0.0007	0.0126	0.0107	-0.0042
Median	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Sum	-0.1310	-0.0280	-0.0586	-0.0373	0.6298	0.5344	-0.2076
SE Mean	0.0042	0.0038	0.0077	0.0109	o.0063	0.0087	0.0063
LCL Mean	-0.0110	-0.0083	-0.0167	-0.0226	0.0000	-0.0068	-0.0168
UCL Mean	0.0057	0.0072	0.0143	0.0211	0.0252	0.0282	0.0085
Variance	0.0009	0.0007	0.0030	0.0059	0.0020	0.0038	0.0020
StDev	0.0294	0.0271	0.0546	0.0769	0.0444	0.0616	0.0445
Skweness	-1.1886	1.0965	0.3700	0.4822	1.4819	2.8025	0.3657
Kurtosis	3.3702	3.0035	1.0520	2.2040	3.0518	12.8060	3.1389

Table 4.4: Summary statistics for returns in 2017

Remark 5. The UNGA, MSC, KAKZ and WTK) have a positive skewness. Most stocks in the manufacturing and allied sector have a positive skewness, while half of the stocks in the agricultural sector have a negative skewness. Table 3 presents the summary statistics for the selected stocks in 2017. In the year, SASN has the highest mean return of 0.0126 while KAPZ has the lowest (-0.0042). All stocks in the manufacturing sector perform poorly as indicated by a negative mean in their returns. MSC has the highest standard deviation (0.0769) in returns while EABL has the lowest (0.0271). All the stocks have a positive skewness except for BAT in the manufacturing sector and WTK which belongs to the agricultural sector. The return series from the 8 stocks show significant levels of skewness as well as

The above tables shows the summary statistics for the returns of stocks in 2017 kurtosis. From the analysis in 2007 stocks data,the series of returns is negatively skewed for EABL and SASN stocks, while it is positive for other 6 stocks. In the 2013 analysis, the skewness results are negative for BAT and KAPZ stocks with the other 6 being positive. In 2017, BAT and WTK stocks have a negative skewness with the other 6 having a positive skewness.

4.4 Jarque-Bera Test

4.4.1 Testing for the Normality of the Securities

Jarque-Bera	Normality Test
Data: BAT	Data: EABL
JB=2.3001, P-value=0.3166	JB=5.8807, P-value=0.05285
Alternative Hypothesis: Greater	Alternative Hypothesis: Greater
Data: UNGA	Data: MSC
JB=4.303, P-value=0.1163	JB=2.39938, P-value=0.2238
Alternative Hypothesis: Greater	Alternative Hypothesis: Greater

Table 4.5: Jarque-Bera test for 2007 manufacturing stocks data

The Table 4.5 above shows the skewness and kurtosis for 2007 agricultural stocks data. The errors are not normally distributed.

Agricultural Securities	Skewness	Kurtosis
SASN	2.1751372	6.374321
KUKZ	0.3967163	2.756618
KAPZ	0.3382801	1.888423
WTK	0.8644525	2.909249

Table 4.6: skewness and kurtosis for 2007 agricultural stocks data

The table 4.6 above shows the skewness and kurtosis for 2007 agricultural stocks data. The errors are not normally distributed.

Jarque-Bera	Normality Test
Data: BAT	Data: EABL
JB=3.2355, P-value=0.03343	JB=7.45688, P-value=0.06566
Alternative Hypothesis: Greater	Alternative Hypothesis: Greater
Data: UNGA	Data: MSC
JB=5.1125, P-value=0.1254	JB=2.32268, P-value=0.23468
Alternative Hypothesis: Greater	Alternative Hypothesis: Greater

Table 4.7: Jarque-Bera test for 2013 manufacturing stocks data

The Table 4.7 above shows the skewness and kurtosis for 2013 agricultural stocks data. The errors are not normally distributed.

Agricultural Securities	Skewness	Kurtosis
SASN	2.234515	6.23783
KUKZ	0.4078963	2.64556
KAPZ	0.30248	1.908453
WTK	0.845968	2.890786

Table 4.8: skewness and kurtosis for 2013 agricultural stocks data

The Table 4.8 above shows the skewness and kurtosis for 2013 agricultural stocks data. The errors are not normally distributed.

Jarque-Bera	Normality Test
Data: BAT	Data: EABL
JB=1.9845, P-value=0.12568	JB=4.9954, P-value=0.045980
Alternative Hypothesis: Greater	Alternative Hypothesis: Greater
Data: UNGA	Data: MSC
JB=4.12348, P-value=0.107818	JB=2.29808, P-value=0.30925
Alternative Hypothesis: Greater	Alternative Hypothesis: Greater

Table 4.9: Jarque-Bera test for 2017 manufacturing stocks data

The Table 4.9 above shows the skewness and kurtosis for 2017 agricultural stocks data. The errors are not normally distributed.

Agricultural Securities	Skewness	Kurtosis
SASN	2.078708	6.35899
KUKZ	0.323589	2.45602
KAPZ	0.3382801	1.76903
WTK	0.8644525	2.87855

Table 4.10: skewness and kurtosis for 2017 agricultural stocks data

The table 4.10 above shows the skewness and kurtosis for 2017 agricultural stocks data. The errors are not normally distributed.

A negative skewness in the series of returns indicates that the stock returns are skewed to the left as compared to the normal distribution while a positive skewness means the returns are skewed to the right of the normal distribution. The skewness results indicate that the returns are not normally distributed. The Kurtosis figures for the stocks tell that the stock return distributions for the 8 companies have a very sharp peak when compared to that of the normal distribution. The results on kurtosis further confirm the non-normality feature in the returns of the 8 stocks. Jarque-Bera (JB)statistics obtained help to confirm that returns from the 8 stocks are not normally distributed. Below follows the results from Jarque-Bera test conducted on the returns of both the manufacturing and agricultural stocks. The tables 4.8- 4.10 below shows Jarque-Bera test for 2007 manufacturing stocks data. The results indicate that none of the returns from the manufacturing stocks in the year are normally distributed.

The correlation results are mixed. Some of the stocks move perfectly in the same direction while others move in opposite directions. The correlation results indicate that some stocks could be doing better during the electioneering period as compared to others. However, this result is not an indication that a particular stock has a causation relationship with another stock. An investor can choose to combine two or more stocks in their portfolio that have a low correlation to each other so as to help diversify their portfolio and reduce the risk. In essence, traders, investors,

4.4.2 Correlation between the Securities

The following are the test that can be used when testing for the correlation between the securities in the NSE.

	BAT	EABL	UNGA	MSC	SASN	KAKZ	KAPZ	WTK
BAT	1.0000	-0.4765	0.7462	-0.1453	0.6984	0.7749	0.1731	0.4790
EABL	-0.4765	1.0000	-0.2333	0.3610	-0.2419	-0.2376	-0.2099	-0.4670
UNGA	0.7462	-0.2333	1.0000	0.2113	0.8277	0.6753	-0.0502	0.1100
MSC	-0.1453	0.3610	0.2113	1.0000	0.4872	0.0575	-0.7232	-0.5760
SASN	0.6984	-0.2419	0.8277	0.4872	1.0000	0.6164	-0.2781	-0.1020
KAKZ	0.7749	-0.2376	0.6753	0.0575	0.6164	1.0000	-0.0475	0.3110
KAPZ	0.1731	-0.2099	-0.0502	-0.7232	-0.2781	-0.0475	1.0000	0.2890
WTK	0.4799	-0.4679	0.1106	-0.5763	-0.1020	0.3118	0.2900	1.0000

Table 4.11: Correlation between the Securities for 2007

The above Table 4.11 shows the Correlation between the Securities for 207 that were traded at the NSE when the country was experiencing the elections that led to post election violence after the contested contest between ODM and PNU.

	BAT	EABL	UNGA	MSC	SASN	KAKZ	KAPZ	WTK
BAT	1.0000	-0.5775	0.7363	0.6017	0.3290	0.5498	-0.4885	-0.6646
EABL	-0.5775	1.0000	-0.5191	-0.7906	-0.2654	-0.3673	0.2646	1.0000
UNGA	0.7363	-0.5191	1.0000	0.4299	0.3965	0.7845	-0.4314	0.3555
MSC	0.6017	-0.7906	0.4299	1.0000	-0.0098	0.1706	-0.2817	0.2806
SASN	0.3290	-0.2654	0.3965	-0.0098	1.0000	0.5789	0.1131	0.6149
KAKZ	0.5498	-0.3673	0.7845	0.1706	0.5789	1.0000	-0.3102	0.3446
KAPZ	-0.4885	0.2646	-0.4314	-0.2817	0.1131	-0.3102	1.0000	0.5261
WTK	-0.4373	0.2469	-0.5324	-0.3401	0.1038	-0.4239	0.3540	1.0000

Table 4.12: Correlation between the Securities for 2013

The above Table 4.12 shows the Correlation between the Securities for 2013 that were traded at the NSE when the country was experiencing the elections.

	BAT	EABL	UNGA	MSC	SASN	KAKZ	KAPZ	WTK
BAT	1.0000	-0.6646	-0.0340	0.0274	-0.8617	-0.6488	-0.1561	-0.5991
EABL	-0.6646	1.0000	0.3555	0.2806	0.6149	0.3446	0.5261	0.6525
UNGA	-0.0340	0.3555	1.0000	0.6191	-0.1984	0.1759	0.3868	0.9935
MSC	0.0274	0.2806	0.6191	1.0000	-0.0816	0.1758	0.0570	0.0886
SASN	-0.8617	0.6149	-0.1984	-0.0816	1.0000	0.5855	0.0590	0.9844
KAKZ	-0.6488	0.3446	0.1759	0.1758	0.5855	1.0000	-0.1973	-0.2245
KAPZ	-0.1561	0.5261	0.3868	0.0570	0.0590	-0.1973	1.0000	0.8298
WTK	-0.2431	0.4972	-0.1535	-0.2638	0.3052	-0.1414	0.4470	1.0000

Table 4.13: Correlation between the Securities for 2017

The above Table 4.13 shows the Correlation between the Securities for 2017 that were traded at the NSE when the country was experiencing the elections.

4.5 CAPM Fitting and Testing

The CAPM model is used to check whether investing in the various assets during the electioneering periods would be profitable and to help investors determine which sector as well as stocks would be worth investing in during the volatile electioneering periods. The project applies the CAPM model by carrying out a multiple linear regression model.

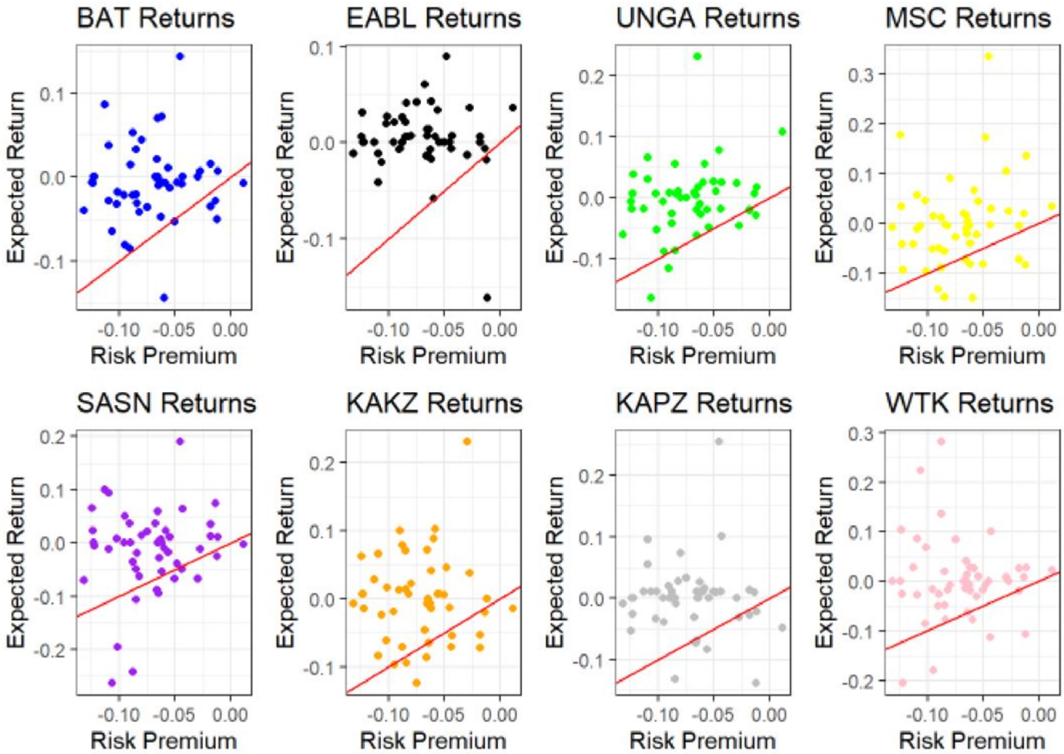

Figure 4.5.1: The higher the expected return, the higher the risk premium

The Figure 4.4.1 above shows the variation of expected return against the risk premium for 2007 stocks. The corresponding results of the expected return among the stocks during the electioneering years are as shown in Figure 8 The CAPM results of the expected returns are mixed. Therefore, an investor cannot tell precisely which stocks from the two sectors dominate over the other. However, it is evident that the returns from UNGA and MSC stocks have always been positive during the three electioneering periods. Investors in the two stocks can be assured of some positive returns during electoral periods.

The sector of the two stocks (Agriculture), gives mixed results in the rest of the two companies (BAT and EABL). In the manufacturing sector, all the four stocks show mixed results in returns. The results of CAPM statistics are mixed and do not indicate any consistent.

Security	Expected Return(2007)	Expected Return(2013)	Expected Return(2017)
BAT	0.0198	-0.0911	0.0419
EABL	-0.1132	-0.0515	0.0294
UNGA	0.3949	0.0000	0.1000
MSC	0.4896	0.0955	0.0541
SASN	0.3612	-0.0887	-0.9582
KAKZ	0.0157	-0.3482	0.0962
KAPZ	-0.1644	-0.0825	0.0362
WTK	-0.1826	-0.0003	0.0681

Table 4.14: Expected Returns of Stocks

Remark 6. The dominance of an agricultural stocks over their manufacturing counterpart or vice versa, and therefore CAPM results can be misleading. Thus we rely on the SD approach. Results from the JB test reveal that norm parametric methodologies such as the stochastic dominance approaches could result in significantly different conclusions especially when the given results are driven with assumptions that lead to a violation of the parametric features. Therefore, the next analysis includes an using the stochastic dominance approach to compare the manufacturing stocks with the agricultural stocks pairwise for the 8 stocks.

4.6 Interpretation of the Stochastic Dominance tests Results

The the stochastic dominance results of the [Davidson and Duclos, 2000b] test for Agricultural Stocks and Manufacturing stock indexes over the three election periods. FSD, SSD, and TSD denote first-, second-, and third-order stochastic dominance, respectively.

	BAT				EABL			
2007	G>F	G>F	G>F	F>G	G>F	G>F	F>G	F>G
2013	F>G	G>F	G>F	F>G	F>G	G>F	G>F	G>F
2017	G>F	F>G	G>F	F>G	G>F	F>G	G>F	F>G

UNGA				MSC			
G>F	G>F	F>G	F>G	G>F	G>F	G>F	G>F
F>G	F>G	F>G	F>G	F>G	G>F	G>F	F>G
G>F	G>F	G>F	F>G	G>F	F>G	F>G	F>G

Figure 4.6.1: First Order Stochastic Dominance results

Th figure above 4.6.1 shows the report $F > G$ means the Agricultural stock dominates the manufacturing stocks. $G > F$ indicates that the manufacturing stock index dominates the agricultural index. The term ND means no stochastic dominance between the two stocks especially on the Agricultural Stocks.

	F is greater than G	G is greater than F
2007	5	11
2013	9	7
2017	8	8
Overall	22	22

Table 4.15: Summary of First Order Stochastic Dominance results

The stochastically dominate manufacturing stocks in first order results are stated in Table 4.15 that illustrates how the statistical distributions G and F trades in terms of returns for the years when Kenya is in electioneering period.It is important to conclude the inconclusive means no dominance and *2d means second order stochastic dominance Agricultural stocks having dominance of 13 and Manufacturing Stocks Dominance of 11 Manufacturing stocks stochastically dominated over their Agricultural stock counterparts 11 times in the three periods while agricultural stocks dominated over their manufacturing counterparts 13 times. The stock combinations exhibited no second order stochastic dominance 23 times in the three periods. This, therefore, shows although stochastic dominance is not consistent throughout the election periods, the agricultural stocks dominate over their manufacturing stock counterparts.

	Grouped Third Order Stochastic Dominance Results				
Year	**Stock**	**Over BAT**	**Over EABL**	**Over UNGA**	**Over MSC**
	SASN	Yes	No	Yes	Yes
	KAKZ	Yes	Yes	Yes	Yes
	KAPZ	Yes	Yes	No	Yes
2007	**WTK**	Yes	No	Yes	no
	SASN	No	No	Yes	No clear dominance
	KAKZ	Yes	No	No	No
	KAPZ	Yes	Yes	No clear dominance	Yes
2013	**WTK**	Yes	Yes	Yes	Yes
	SASN	Yes	Yes	Yes	Yes
	KAKZ	Yes	Yes	Yes	Yes
	KAPZ	Yes	Yes	Yes	No clear dominance
2017	**WTK**	Yes	no	Yes	Yes

Figure 4.6.2: Second Order Stochastic Dominance Results

Remark 7. The agricultural stocks dominate the manufacturing stocks in 35 instances while manufacturing stocks dominate over agricultural stocks in 10 instances. There is no clear third order stochastic dominance pattern in 3 instances Clearly, agricultural stocks dominate over the manufacturing stocks in the third order.

Chapter 5

Conclusions and Recommendations

5.1 Conclusions

As a result of recent improved statistical procedures, it is possible to conduct a better assessment to determine a better return distribution. The study employs a stochastic dominance approach to determine the better stocks during Kenyan electioneering periods. Stochastic dominance can be applied in studying economics of uncertainty such as in finance to conduct portfolio diversification. The project performs a comparison between stocks of two different sectors in Kenya: agricultural and manufacturing sector. A pairwise comparison is performed to compare a manufacturing stock and its counterpart in the agricultural sector. Further, the returns from the stocks are examened for both skewness and kurtosis for the years 2007, 2013 and 2017.

The eight stocks exhibit significant levels of skewness and kurtosis which means that their returns are not normally distributed. The non-normality in distribution feature is further confirmed by the JB statistics. A stochastic dominance approach is used to compare four stocks from each of the two sectors during a period of major elections in Kenya that are often associated with political risks. When we compare the performance of agricultural and Manufacturing sector using both mean–variance and Capital Asset Pricing Model approaches, the results are seen to be conflicting.

Notably, the returns of the agricultural and manufacturing stocks are not normally distributed and it would be erroneous to depend entirely on these approaches since they depend on the stock return normality as well as make use of quadratic utility functions. Hence, the hypotheses would be misleading and that is why it is best to use an improved approach such as SD that does not necessarily rely on normality of stock returns and a hypothesis on quadratic utility functions. Using weekly data, the findings indicate that agricultural stocks stochastically dominate over the manufacturing stocks. Stochastic dominance approaches have been employed in fields such as finance, statistics, medicine, insurance and economics.

5.2 Recommendations

Stochastic dominance approach is found to be more robust in use than mean–variance and CAPM approaches as the SD does not depend on the stock return normality or quadratic utility functions hypotheses. Besides, Stochastic dominance allows computation of higher moments unlike the other approaches that are limited to the first two moments of returns. The overall stochastic dominance pattern is that stocks from the agricultural stocks in Kenya stochastically dominate those from the manufacturing sector.

The findings documented in the study could prove useful to local and international investors, policy makers, institutions and people who follow the two analyzed sectors at the Nairobi Stock Exchange. Traders in Agricultural stocks during the Kenyan electioneering period are seen to outperform those following stocks in the manufacturing sector. In addition, during electioneering period, the NSE is always volatile since most investors do not have any information on the outcomes of the elections, which are always contested in many times. This reduces the investor confidence that ultimately affects the amounts of trades made as well as the returns from all forms of securities in the market.

5.3 Room for Further Research

While the stochastic dominance approach is important for those investors looking for investment opportunities at the Nairobi Securities Exchange market, the testing of efficiency of the type of stock that an individual can buy is an option for further research. Analysis of several forms of efficient market hypothesis when testing the Stochastic dominance approach is important in ultimate investment decisions.

Under the three forms of efficient market hypothesis, it would be perfect to learn on how they affect the Stochastic dominance approach on the individual stocks being traded at the stock exchange market. The choice of the securities to be traded at the NSE will always be different when made under the considerations of the efficient market hypothesis, which makes an investor get the best returns from trading whichever position they hold of the securities at the exchange market.

Testing the three forms of efficient market hypothesis when making decision to invest in any securities within the sector of the NSE would enable the investors to make informed investment decisions that would ultimately yield higher returns. Investors are able to understand how every decision they make will have an impact on the amount of returns they are likely to receive during the period of investment at the Nairobi Securities Exchange market.

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Osamah Al Khazali. Risk, return, and equilibrium in the emerging capital market: the case for jordan. *Academy of Accounting and Financial Studies Journal*, 5(1):171, 2001b.

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Appendices

R Codes

1.#Lower Partial Moment

```
LowerPartialMoment<-function(degree,target,variable)
sum((target-(variable[variable<target]))^degree)/length(variable)
#The function finds the sum of observations that fall below target
#Sum is raised to a loss aversion degree n. #
The result is divided by the number of observations
##############
#FSD #############
FoSD<-function(a,b)
{ a_ordered<-sort(a,decreasing = FALSE)
b_ordered<-sort(b,decreasing = FALSE)
AB=c(a_ordered,b_ordered)
OrderAB=sort(AB, decreasing = FALSE)
LowerPartialMoment_a_ordered=numeric(0)
LowerPartialMoment_b_ordered=numeric(0)
output_a=vector("numeric",length(a))
output_b=vector("numeric",length(a)) for (i in 1:length(AB)) {
#Indicator function
if(LowerPartialMoment(0,OrderAB[i],b)-LowerPartialMoment(0,OrderAB[i],a)>=0)
{output_b[i]<-0} else {break}} for (j in 1:length(OrderAB))
{ LowerPartialMoment_a_ordered[j]=LowerPartialMoment(0,OrderAB[j],a) LowerPartialMoment_b_ordered[j]=LowerPartialMoment(0,OrderAB[j],b) }
# CDF plot
plot(LowerPartialMoment_a_ordered,type = "l",lwd=3, col="red",
```

```
main = "First Order Stochastic Dominance", ylab = "Prob of Cumm. Distr")
lines(LowerPartialMoment_b_ordered,type = "l",lwd=3, col="blue")
legend("bottomright",c("Return_KAPZ","Return_WTK"),lwd = 3,col=c("red","blue"))
ifelse(length((output_a)==length(AB),"a FSD b",
ifelse(length(output_b)==length(AB),"b FSD a","NO FSD")))}
setwd("C:/Users/Admin/OneDrive/MSC(Act)/PROJECT MSC")
mydata<-read.csv("C:/Users/Admin/OneDrive/MSC(Act)/PROJECT MSC/data2007.csv")
summarystat2007=mydata[12:length(mydata)]#use column 11 onwards
summarystat2007=summarystat2007[-1]#exclude the first row
attach(summarystat2007)
#FoSD(Return_BAT,Return_MSC); #FoSD(Return_EABL,Return_MSC)
#FoSD(Return_KAKZ,Return_MSC) #FoSD(Return_KAPZ,Return_MSC)
#FoSD(Return_BAT ,Return_SASN) #FoSD(Return_EABL,Return_SASN)
#FoSD(Return_KAKZ,Return_SASN) #FoSD(Return_KAPZ,Return_SASN)
#FoSD(Return_BAT ,Return_UNGA) #FoSD(Return_EABL,Return_UNGA)
#FoSD(Return_KAKZ,Return_UNGA) #FoSD(Return_KAPZ,Return_UNGA)
#FoSD(Return_BAT ,Return_WTK) #FoSD(Return_EABL ,Return_WTK)
#FoSD(Return_KAKZ ,Return_WTK) #FoSD(Return_KAPZ ,Return_WTK)
2.#Lower Partial Moment
LowerPartialMoment<-function(degree,target,variable)
sum((target-(variable[variable<target]))^degree)/length(variable)
#The function finds the sum of observations that fall below target
#Sum is raised to a loss aversion degree n.
#The result is divided by the number of observations
SoSD<-function(a,b){ a_ordered<-sort(a,decreasing = FALSE)
b_ordered<-sort(b,decreasing = FALSE)
AB=c(a_ordered,b_ordered) OrderAB=sort(AB, decreasing = FALSE)
LowerPartialMoment_a_ordered=numeric(0)
LowerPartialMoment_b_ordered=numeric(0)
output_a=vector("numeric",length(a))
output_b=vector("numeric",length(a)) for (i in 1:length(AB)) {
#Indicator function
if(LowerPartialMoment(1,OrderAB[i],b)-LowerPartialMoment(1,OrderAB[i],a)>=0)
```

```
{output_a[i]<-0} else {break}} for (i in 1:length(AB))
{ #Indicator function
if(LowerPartialMoment(1,OrderAB[i],a)-LowerPartialMoment(1,OrderAB[i],b)>=0)
{output_b[i]<-0} else {break}} for (j in 1:length(OrderAB))
{ LowerPartialMoment_a_ordered[j]=LowerPartialMoment(1,OrderAB[j],a) LowerPar-
tialMoment_b_ordered[j]=LowerPartialMoment(1,OrderAB[j],b) }
# CDF plot plot(LowerPartialMoment_a_ordered,type = "l",lwd=3, col="red",
main = "Second Order Stochastic Dominance", ylab = "Cumm. Distr Area")
lines(LowerPartialMoment_b_ordered,type = "l",lwd=3, col="blue")
legend("bottomright",c("Return_KAPZ","Return_WTK"),lwd = 3,col=c("red","blue"))
ifelse(length((output_a)==length(AB),"a SSD b",
ifelse(length(output_b)==length(AB),"b SSD a","NO SSD")))}
#set.seed(111) #X=rnorm(10)
#set.seed(112) #y=rnorm(10)
#SoSD(X,Y)
setwd("C:/Users/Admin/OneDrive/MSC(Act)/PROJECT MSC")
mydata<-read.csv("C:/Users/Admin/OneDrive/MSC(Act)/PROJECT MSC/data2007.csv")
summarystat2007=mydata[12:length(mydata)]#use column 11 onwards
summarystat2007=summarystat2007[-1]#exclude the first row
attach(summarystat2007)
#FoSD(Return_BAT,Return_MSC); #FoSD(Return_EABL,Return_MSC)
#FoSD(Return_KAKZ,Return_MSC) #FoSD(Return_KAPZ,Return_MSC)
#FoSD(Return_BAT ,Return_SASN) #FoSD(Return_EABL,Return_SASN)
#FoSD(Return_KAKZ,Return_SASN) #FoSD(Return_KAPZ,Return_SASN)
#FoSD(Return_BAT ,Return_UNGA) #FoSD(Return_EABL,Return_UNGA)
#FoSD(Return_KAKZ,Return_UNGA) #FoSD(Return_KAPZ,Return_UNGA)
#FoSD(Return_BAT ,Return_WTK) #FoSD(Return_EABL ,Return_WTK)
SoSD(Return_KAKZ ,Return_WTK)
#SoSD(Return_KAPZ ,Return_WTK)
```

3. #Lower Partial Moment

```
LowerPartialMoment<-function(degree,target,variable)
sum((target-(variable[variable<target]))^degree)/length(variable)
#The function finds the sum of observations that fall below target
```

```
#Sum is raised to a loss aversion degree n.
#The result is divided by the number of observations
ToSD<-function(a,b){ a_ordered<-sort(a,decreasing = FALSE)
b_ordered<-sort(b,decreasing = FALSE) AB=c(a_ordered,b_ordered)
OrderAB=sort(AB, decreasing = FALSE) LowerPartialMoment_a_ordered=numeric(0)
LowerPartialMoment_b_ordered=numeric(0) output_a=vector("numeric",length(a))
output_b=vector("numeric",length(a)) for (i in 1:length(AB)) {
#Indicator function
if(LowerPartialMoment(2,OrderAB[i],b)-LowerPartialMoment(2,OrderAB[i],a)>=0) {
output_a[i]<-0} else {break}} for (i in 1:length(AB))
{ #Indicator function
if(LowerPartialMoment(2,OrderAB[i],a)-LowerPartialMoment(2,OrderAB[i],b)>=0)
{output_b[i]<-0} else {break}} for (j in 1:length(OrderAB))
{ LowerPartialMoment_a_ordered[j]=LowerPartialMoment(2,OrderAB[j],a) LowerPar-
tialMoment_b_ordered[j]=LowerPartialMoment(2,OrderAB[j],b) }
# CDF plot plot
(LowerPartialMoment_a_ordered,type = "l",lwd=3, col="red",
main = "Third Order Stochastic Dominance", ylab = "Cumm. Distr Area")
lines(LowerPartialMoment_b_ordered,type = "l",lwd=3, col="blue")
legend("bottomright",c("Return_KAPZ","Return_WTK"),lwd = 3,col=c("red","blue"))
ifelse(length((output_a)==length(AB),"a TSD b",
ifelse(length(output_b)==length(AB),"b TSD a","NO TSD")))}
#set.seed(111)
#X=rnorm(100)
#set.seed(112)
#y=rnorm(1000)
#ToSD(X,Y)
setwd("C:/Users/Admin/OneDrive/MSC(Act)/PROJECT MSC")
mydata<-read.csv("C:/Users/Admin/OneDrive/MSC(Act)/PROJECT MSC/data2007.csv")
summarystat2007=mydata[12:length(mydata)]#use column 11 onwards
summarystat2007=summarystat2007[-1]#exclude the first row attach(summarystat2007)
ToSD(Return_KAKZ ,Return_WTK)
```