UNIVERSITY OF NAIROBI

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STOCK MARKET INDICES: TESTING FOR MEAN REVERTION AND BIAS OF NAIROBI STOCK EXCHANGE INDICES

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DECLARATION

This research project is my original work and has not been presented for the award of a degree in any other university.

Signed................................. Dated. 21/11/2009

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This project has been submitted for examination with my approval as university supervisor.

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DEDICATIHON

To my parents Jeremiah and Hebisibah, for their effort to have me acquire education which they never got a chance to acquire but valued most. To my wife Emily for the moral support and encouragement

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LIST OF ABBREVIATIONS

NSE .... Nairobi Stock Exchange

EMH .... Efficient Market Hypothesis

NYSE .... New York Stock Exchange

EAFE .... European, Australia and Far East Index

NASDAQ............................ Association of Securities Dealers Automated Quotation

SPSS .... Statistical Package for Social Sciences

ABSTRACT

This study uses the Pearson correlation to test whether the Nairobi Stock Market is mean reverting and the implications of such mean reversion for security valuation. To carry out this test the study first determines the bias of the Nairobi stock Indices and goes further to test the mean reversion of the market. The study was wholly based on secondary data filed with NSE secretariat

The result shows a short run bias of the NSE 20 Share Index that disappears in the long – run. The graph (I of page 26) demonstrates this result. This indicates that the Geometric mean, the method used to compute the NSE 20 Index is a better measure of performance in the long –run.

The second test result indicated that the NSE market is mean reverting, that is returns are negatively correlated. The findings were therefore in line with Cooper (1996) findings that when the market is mean reverting, the arithmetic average is not necessarily superior as a forecast of long-term future returns contrary to Kibbet (2006), Odera (2000) findings which concluded that the Geometric indices are unsuitable for long term price movement.

It would however not be overlooked that the analyses were based on a very small stock market whose comparison was made with the world's major established stock markets. The other limitation was that the study was based on the Kenyan case only and we would not conclude as to whether the mean reversion is due largely to country specific factors.

Conclusion; NSE market is mean reverting and in such a market the geometric mean is an ideal method of constructing the market Index. However the use of multiple indices may be recommended to address the shortcomings of the NSE 20 Index in the short run period.

1.0 CHAPTER ONE: INTRODUCTION

1.1 Background

An Index is a statistical measure of change in an economy or a specific section of the economy. In the case of financial markets, an index is a listing of stocks and a statistic representing a particular market or a portion of it. Each index has its own calculation methodology and is usually expressed in terms of a change from a base value. Thus, the percentage change is more important than the actual numeric value. For example, knowing that a stock exchange is at, say, 5, 000, does not tell us much. However, knowing that the index has risen 30% over the last year to 5,000 gives a much better demonstration of performance. Technically, we can't actually invest in an index. Rather, we invest in a security such as an index fund or exchange-traded fund that attempts to track an index as closely as possible. Indices can track market trends, but they're not always reliable. (Indro and Lee, 1997).

In financial management, performance evaluation of a stock market is a crucial aspect. Financial Managers often face the question "what wealth a portfolio is expected to generate over a long-term?" In order to obtain an answer suitable for managerial decisions, they must produce estimates of expected long-term returns. Expected returns are usually estimated by averaging past returns. A procedure which is logical, simple, and in many cases, appropriate. Average returns are affected by the start and terminal periods used in measurement. Among financial professionals, the most common mean returns used are the arithmetic and the geometric ones. Given measures of returns on a financial asset or index of returns on a portfolio of such asset, over a series of time periods, the arithmetic mean is the simple average of percentage returns for each time period and the geometric mean is calculated from the index of returns and reflects the compound rate of return over the investment horizon.

It is well known, however, that both these mean returns produce biased estimates when the investment horizon is greater than the unit-time (Indro and Lee, 1997). The arithmetic mean return of past returns will overestimate the expected terminal return, whereas, the geometric mean will underestimate the expected terminal return (Blume, 1974; Indro and Lee, 1997; Mayo, 2006). The magnitude of the bias grows with the length of the investment horizon. The choice between which mean to use is still a matter of academic debate among researchers. There has been a plethora of papers about the relative merits of using the arithmetic mean versus the geometric mean. The arithmetic mean receives the most support in the literature, others recommend the geometric mean, and a few support something in between such as a weighted average of the two (Fabozzi 1999 and Francis and Ibbotson 2002).

Odera (2000) tested for longterm downward bias and found out that the returns on a geometric index are independent of the base and that relative to the market portfolio; a geometric index understates price rises and overstates price falls. The study also found the market to exhibit positive serial correlation. Historical evidence suggests that stock market is mean reverting *(Poterba and Summers, (1988). Blume (1974)* and *Cooper (1996)* later, showed that the arithmetic mean of historical returns is a less biased estimator than the geometric mean. Cooper's reasoning further assumes that returns are serially independent. However, when returns are negatively serially correlated the arithmetic average is not necessarily superior as a forecast of long-term future returns

According to Cootner (1972), a geometric-mean index is, unlike an arithmetic-mean index, a downward-biased index of price changes. On the other hand, Damodaran (1999) underline that while arithmetic-mean indices are sensitive to the selection of the time interval (monthly, quarterly, semi-annual, or annual) in the model, geometric indices will produce the same calculation of returns regardless of the time interval.

1.2 Statement of the problem

The choice between Arithmetic and Geometric mean as a method for constructing a market stock index has been a controversial topic among practitioners. Keeping in mind that we are dealing with a stock market estimator, one more question arises. The construction method, should it be arithmetic or geometric? Supporters of the latter view such as Copeland et al. (2000) and Damodaran (1999) are minority. Cooper (1996) showed that the arithmetic mean of historical returns is less biased estimate than the geometric mean. Cooper's reasoning further assumes that returns are serially independent. However, when returns are negatively correlated the arithmetic average is not necessarily superior as a forecast of long-term future returns. Arithmetic mean is an unbiased estimate of, only, one-period (e.g. one year) performance estimation. Problems of bias arise when we are interested in portfolio performance for time periods greater than one. Cooper's findings recommend geometric mean as a less biased estimator for long-term period. Surprisingly, the result contradicts Kibbet (2006), Odera (2000) findings which concluded that the Geometric indices are unsuitable for long term price movement. Indeed, these results are highly questionable in the face of the methodology and choice of data. First, a weekly data was used instead of the daily data. There is a possibility, which we seek to test in this paper, that the use of the weekly prices may distort the result as the movement of prices during the week is ignored. Taking a single weekly price may not be a true representative of the whole week prices movement. Secondly, Odera (2000) results indicated that the Nairobi Stock Exchange weekly variables do exhibit a positive serial correlation. This a unique scenario since historical evidence show that the stock market is mean-reverting, That is, periods of high returns tend to be followed by periods of lower returns (Poterba and Summers, 1998). In such a case we expect the geometric mean to be a better indication of long-term future prospects. Observation of the Nairobi Stock Exchange prices over the tested period shows an upward and downward movement of prices period after period thus reflecting a totally negative result to Kibbet (2006) and Odera (2000).

A general observation of the price trend will not be satisfactory to conclude that the Nairobi stock market is mean-reverting. A different methodology will be applied to test the existence of serial correlation which is a necessary condition for the testing long term period bias of the Geometric mean as a measure of performance.

In Kibbet (2006) and Odera (2000) paper weekly data was used to test the biases of the NSE 20 Share Index. This paper reexamines the controversial results by using the daily data and a different methodology to test for the existence of short term and long-term bias of the geometric mean.

According to Spencer (1999) to calculate an average, you add the price changes in each stock together and divide by the appropriate number. What that gives you is an arithmetic average, or mean. The problem with this approach is that because of the way the result is calculated an arithmetic average tends to produce a higher return than the actual return on a typical stock portfolio. It's the same kind of overstatement that can result if you average stock returns over several years rather than finding the compound return. A straight average doesn't take into account the full impact of changing values over a number of years.

The alternative to using an arithmetic average is calculating the geometric mean, or average, which is the standard practice when looking at historical results. Because it takes compounding into account, a geometric mean tends to be more accurate about what the actual rate of return was over the period being considered. And in most cases, the result will be lower than the arithmetic average. Spencer's findings are against Kibbet (2006) and Odera (2000) that the Geometric mean tends to overestimate the result on a downward trend over long-term periods. A similar result to this using a different methodology will exhibit uniqueness of the Nairobi Stock Market which is unprecedented.

This research paper returns to the controversy of assessing long term portfolio performance. Given a historical data series from which one estimates the mean and variance of portfolio returns, should one forecast future performance using arithmetic or geometric averages? Fama and French (2002) note that if arithmetic mean portfolio's stochastic rate of return is known, an unbiased estimate of cumulative return is obtained by compounding at that rate. Despite this advice, Summer (1988), Damodaran (1999) prefer geometric averages, which are necessarily lower than arithmetic averages.

1.3 Objective of the study

1) To test whether the Nairobi stock market is mean-reverting, That is, periods of high returns tend to be followed by periods of lower returns and vice versa..

2) To test for the short-run bias of the NSE 20 Share Index, by comparing the Index with the alternative Index.

3) The study also seeks to establish the existence of long run bias of the NSE 20 Share Index by comparing it with an alternative Index.

1.4 Importance of the study

The study will provide information to the Investment managers in determining whether the NSE 20 Share Index is a true measure of their Portfolio performance and whether they should form their own reliable Index to supplement the NSE Share Index.

The investors would use the study to determine the decision made by the Investment Manager based on the NSE 20 Share Index would yield to profitability and for
the study will form the basis for academics who wish to study and come up with any alternative Index.

2.0 CHAPTER TWO: LITERATURE REVIEW

2.1 The History of indices

Charles Gide was the first economist to have dealt in more detail with changes in the value of money thus opening debate of indices. In his textbook he describes the development of the value of money from the days of Charlemagne around 850 AD through to the 1890s. From the late nineteenth century to the First World War, prices increased only moderately, and economists showed scant interest in changes in the value of money. Indeed neither the concept of "index" nor that of "inflation" were yet in widespread use.Charles Gide(1904)

For a long time the development of the value of money was largely dependent on the demand for and supply of corn. In 1375-1500AD, deflation saw the value of money rising and prices coming down; this was mainly due to the Black Death that ravaged Europe. The upsurge in prices and the declining value of money in 1500-1600 was due, at least in part, to the discovery of America and the precious metals that were brought back to Europe from the new continent. Deflation in 1600-1750 was due to constant warfare in Europe. In the mid-eighteenth century, with the invention of the Spinning Jenny and the ensuing Industrial Revolution and economic growth, the value of money started on a steady track of decline. The era of inflation had dawned. Charles Gide(1904)

2.2 The development of the cost-of-living index

The value of money plummeted in Europe in the wake of the First World War. This prompted growing interest in the theory of inflation and in monitoring inflation. Throughout Europe, almost every country began to compile and compute its own cost-of-living index.The purpose of the cost-of-living index was to measure the development of the prices of goods and services purchased by households. Work to compute the index was started soon after the war, with the base period set at a time-point before the war. In Finland, the first cost-of-living index was compiled in 1921, and the base period was set at January-June 1914. The index's consumption structure was based on the first ever household consumption survey in Finland in 1908-1909, where urban households were asked about their spending on food, clothes, housing etc. Since then, cost-of-living time series have been retrospectively built back to 1860. Like almost all other countries, Finland decided to calculate its indices using the formula developed by German economist Etienne Laspeyres. Charles Gide(1904

The Statistical Office of Finland began to compile and publish the wholesale price index in 1924. This index measures the price development of goods from the producer's point of view. The base year for the index was 1913. Time series have been calculated retrospectively for the wholesale price index to 1878 using research materials. Customs statistics on the volumes and values of exports and imports have been used to calculate unit value indices for exports and imports (export or import prices for a certain unit, kilograms or numbers) since 1921. Calculation of the index for sale prices of agricultural produce (i.e. the prices received by the farmer) was started in 1932.

The first building cost index was compiled in 1942, with the base period set at 1935. This index measures the price development of factors of production in building and construction: wages, materials, and planning. The first series for the volume index of industrial production dates back to 1954. This index measures the change in the volume of goods produced in manufacturing industry relative to base period.Describing share prices on the stock exchange, the Unitas index was launched in 1927. The first index describing wages and salaries was the wage earnings index 1938=100, which follows the change in the average gross wages paid to employees (the index does not take account of changes in taxation or in indirect labour costs). Data on the incomes of wage earners in industry and agriculture have been published since the early twentieth century. Kansallis Okaske (1970) Statistical data on the development of housing rents are available from 1925 onwards. Price and index series on owner-occupied flats are available from 1970. Price indices on real estate transactions (detached houses and plots of land for detached houses) have been compiled since 1985.

2.3 Theory of price indices

According to Frank Reilly (1997) Stock market indices may be classed in many ways. A broad-base index represents the performance of a whole stock market — and by proxy, reflects investor sentiment on the state of the economy. The world's most regularly quoted market indices (Appendix I) are broad-base indices comprised of the stocks of large companies listed on a nation's largest stock exchanges, such as the American Dow Jones Industrial Average and S&P 500 Index, the British FTSE 100, the French CAC 40, the German DAX, the Japanese Nikkei 225 and the Hong Kong Hang Seng Index.

An index may also be classified according to the method used to determine its price. In a Price-weighted index such as the Dow Jones Industrial Average and the NYSE ARCA Tech 100 Index, the price of each component stock is the only consideration when determining the value of the index. Thus, price movement of even a single security will heavily influence the value of the index even though the dollar shift is less significant in a relatively highly valued issue, and moreover ignoring the relative size of the company as a whole. In contrast, a market-value weighted or capitalization-weighted index such as the Hang Seng Index factors in the size of the company. Thus, a relatively small shift in the price of a large company will heavily influence the value of the index. In a market-share weighted index, price is weighted relative to the number of shares, rather than their total value. (Brown 1997)

Brown 1997, further notes that, traditionally, capitalization- or share-weighted indices all had a full weighting i.e. all outstanding shares were included. Recently, many of them have changed to a float-adjusted weighting which helps indexing. The concept may be extended well beyond an exchange. The Dow Jones Wilshire 5000 Total Stock Market Index, as its name implies, represents the stocks of nearly every publicly traded company in the United States, including all U.S. stocks traded on the New York Stock Exchange and most traded on the NASDAQ and American Stock Exchange. The Europe, Australia, and Far East Index (EAFE), published by Morgan Stanley Capital International, are listing of large companies in developed economies in the Eastern Hemisphere. Russell Investment Group added to the family of indexes by launching the Russell Global 10000 which covers 80 countries and all stocks with a market capitalization greater than $200 million.

According to Philip Spencer (1999) Toronto Canada the alternative to using an arithmetic average is calculating the geometric mean, or average, which is the standard practice when looking at historical results. Because it takes compounding into account, a geometric mean tends to be more accurate about what the actual rate of return was over the period being considered. And in most cases, the result will be lower than the arithmetic average.

2.4 Arithmetic mean versus geometric mean

When estimating the average rates of change based on historical data, the vast majority of the analysts favour two approaches in order to calculate the historical mean: the arithmetic mean and the geometric mean. Both means assume a standard and constant method of transforming the initial value of given historical data to the terminal value of a given investment horizon. Given annual data, the arithmetic mean assumes that each year's return is a constant number (the arithmetic average of historical data). Similarly, the geometric mean assumes that a constant annualized measure of the proportional change in value occurs until the terminal value. In other words, it assumes that the initial value grew at a constant rate of return.(Frank Reilly (1997)

It is well known that the mathematics of geometric mean require positive numbers. On the other hand, financial rate of returns could be any number, positive or negative. Therefore, a transformation is required in order to make our data applicable to all means.

Mathematically speaking, the arithmetic mean is defined as the sum of the values of a random variable divided by the number of values. (Ibbotson,2002) Accordingly, the geometric mean of a set of T positive values is defined as the T_{th} root of the product of all the values of the set. A second and more practical way to calculate the geometric mean is to take the antilog of the arithmetic average of the logarithms of r's, the exact relationship between the two means will depend on volatility and time period measured. The larger the volatility, the larger the difference between the two means. Equality holds if and only if all members of the data set are equal. Assuming that the past is indicative of the future, the arithmetic mean is a better measure of expected future return. Geometric mean is a better measure of past performance over some specified period of time (Francis and Ibbotson, 2002).

The difference between the two approaches basically arises due to the variance of returns. Arithmetic returns respond to volatility, and do not measure the actual return by investors over a period of more than one year. Hence the more variable returns have been, the more arithmetic means will depart from actual returns. When earning a constant annual return, the geometric mean will be the same as the arithmetic mean. The difference between arithmetic and geometric mean returns can be considerable. Ibbotson (2002), examining returns in U.S. capital markets over the period 1920-2001, reports that the arithmetic mean large company stocks return is18.69% greater than its geometric counterpart. The corresponding figure for bonds was 29.63% greater.

Geometric mean return should be used for measuring historical returns that are compounded over multiple time periods. Arithmetic mean return should be used for future-oriented analysis where the use of expected values is appropriate. Deciding which measure of mean tendency to report will depend on the type of data collected and the distribution of the results. The geometric mean is not as sensitive to extreme figures and skewness as the arithmetic is. In general, the arithmetic mean is appropriate when values follow a more-or-less normal distribution with no outliers. Ibbotson (2002)

In financial literature, various ways to produce unbiased estimates have been suggested. The most classical are those of Blume (1974). Blume initially, and Cooper (1996) later, showed that the arithmetic mean of historical returns is a less biased estimate than the geometric mean. Cooper's reasoning further assumes that returns are serially independent. However, when returns are negatively serially correlated the arithmetic average is not necessarily superior as a forecast of long-term future returns. Historical evidence suggests that the stock market is mean-reverting (Poterba and

Summers, 1988). That is, periods of high returns tend to be followed by periods of lower returns. In such a case the geometric mean is a better indication of long-term future prospects. Damodaran (1999) reaches to the conclusion that the arithmetic mean return is likely to over state the premium since his empirical studies indicate that returns on stocks are negatively correlated over time. The statistical nature of the problem is such that the choice of mean ultimately will depend on the predictability of returns over longer time periods and the distribution of these returns. The more unpredictable the return, the better the case for using the arithmetic average.

In mathematical and financial literature, there have been several suggestions of using mixtures of arithmetic mean and geometric mean. Blume (1974) examined the above-mentioned bias problem under the assumption that returns are independently and normally distributed. For an investment horizon of N time periods, he found that the arithmetic mean overestimates the true compound rate of return and the geometric mean underestimates it. Blume's remedy was to suggest using both arithmetic and geometric means of historical data to form an unbiased estimator of the expected return.

Jacquier's et al. (2003) says: "An unbiased forecast of the terminal value of a portfolio requires compounding of its initial value at its arithmetic mean return for the length of the investment period. Compounding at the arithmetic average historical return, however, results in an upwardly biased forecast. This bias does not necessarily disappear even if the sample average return is itself an unbiased estimator of the true mean, the average is computed from a long data series, and returns are generated according to a stable distribution. In contrast, forecasts obtained by compounding at the geometric average will generally be biased downward. The biases are empirically significant. For investment horizons of 40 years, the difference in forecasts of cumulative performance can easily exceed a factor of 2. And the percentage difference in forecasts grows with the investment horizon, as well as with the imprecision in the estimate of the mean return. For typical investment horizons, the proper compounding rate is in between the arithmetic and geometric values."

Many scholars have dealt with the existence of bias of estimates based on either the arithmetic mean or the geometric one. To quote a few, see Blume (1974), Cooper (1993), Indro and Lee (1997), Jacquier et al. (2003 and 2005). Blume (1974) explains that even if returns are independent and normally distributed there will still exist an upward (downward) bias based on variance (time) for the arithmetic (geometric) mean when used as long-run estimates of future returns When the number of future periods (N) is larger than the number of historical observations (T) geometric mean will be downward biased. When N>1 arithmetic mean will be upwards biased. He therefore suggests that the weighted average of the arithmetic mean and geometric mean, given in (8), should be used in order to not over state and understates the true return. Cooper (1993) focuses upon correction of estimation errors in US data from 1926 to 1992 by measuring real returns and adjusting to allow for serial correlation in returns. He suggested using (10). The unbiased estimates of discount rates which he tentatively arrives at are far closer to the arithmetic than the geometric mean.All those who investigated the bias problem agree that, as Booth (2006) states it very accurately, "in all cases the arithmetic return is the best estimate of next period's rate of return while the geometric return is only one estimate of what would have been earned over this very long investment horizon: neither are appropriate for investment horizons in between these two extremes".

2.5 A Mean-reversion theory

Mean-reversion is the change of the market return in an opposite direction to a prior change in the market return. (Brown 1997) After a positive change in the actual returns, mean-reversion causes a negative subsequent change and vice versa. This reverting move can occur with different speeds, it can eliminate the prior change in, say, one day or in one year. In a stock market with mean-reversion in returns, the participants will develop expectations about the speed of the reversion. When a market participant observes for instance a positive change in returns, her reaction to this change will depend on her expectation of the reversion speed. If she has a long position and expects the high returns to disappear quickly, she will probably sell in order to realize the high returns. If she has a short position, she will probably keep this position and recover later when prices are lower. She might even sell more short to gain the difference when prices come down again. If she on the other hand expects the reversion speed to be very slow, then in the case of a long position she will probably hold the paper to get high returns. She might even want to buy when she thinks that more positive moves are possible. In the case of a short position she will probably recover earlier as there is the risk that prices will stay high or even rise. That is, after a positive change the expectation of a fast reversion leads to higher selling pressure than the expectation of a slow reversion. The mean-reversion expectations of the market participants are not directly observable; they can only be deducted from their sales. High sales after a positive change in returns indicate a fast expected reversion. Poterba (1988)

Black (1988) proposed that misperceptions in the development of mean reversion expectations can cause stock-market crashes when the participants learn about their error. Black's work was based on a literature that emerged in the late 1980's and discussed the evidence of mean-reversion in stock returns (DeBondt/ Thaler (1985), Summers (1986), Fama/French (1988), Poterba/Summers (1988))

Recent research by Fama and French (1988a, 1988b), Poterba and Summers (1988), and Bekaert and Hodrick (1992) reports significant negative serial correlation in long-term stock returns. One explanation for this statistical phenomenon is that there exists a stationary component in stock prices. The existence of a stationary component in stock prices implies that stock returns should revert to their mean returns in the long run. In this sense, the term mean reversion can be used to describe the existence of a stationary component in stock prices.

In the absence of an equilibrium model for expected stock returns, the link between mean reversion in stock returns and market efficiency is not clear. Nevertheless, there are several interesting implications of mean-reverting stock returns for market efficiency. For example, suppose that (ex-post) stock returns can be decomposed into two parts: (1) an (conditional) expected return component and (2) an unexpected return component. Under this scenario, if an expected return-generating model can be specified that can fully explain the mean reversion phenomenon such that the unexpected return component is serially uncorrelated, then mean-reverting stock returns are consistent with market efficiency. Fama and French (1988a, 1988b) suggest that the stationary component in stock prices is caused by time-varying expected returns and, hence, is not inconsistent with market efficiency. On the other hand, if the assumed expected return-generating model cannot fully account for the mean reversion phenomenon in stock returns, then this is evidence inconsistent with market efficiency. In addition to the empirical finding of the mean reversion phenomenon, there is considerable evidence of time-varying expected returns [e.g., Keim and Stambaugh (1986), Campbell (1987), French, Schwert, and Stambaugh (1987), Fama and French (1988a, 1988b), Fama (1990), and Balvers, Cosimano,and,McDonald(1990)]

Fama and French (1988b) regress current returns on past returns to examine the serial correlation in NYSE stock returns for decile-sized portfolios, industry portfolios, and equally-weighted and value-weighted market portfolios. Their finding of an autocorrelation pattern in stock returns is consistent with the hypothesis that stock prices have a slowly-decaying stationary component. Poterba and Summers (1988) also examine mean reversion in stock prices using a variance-ratio test on monthly data. Their results show that ex-post returns exhibit positive autocorrelation over short horizons, but display strong negative autocorrelation over longer horizons. Poterba and Summers (1988) conclude that their results are consistent with the existence of a stationary components in stock prices.

In a related paper, Summers (1986) hypothesizes that stock prices have two components- a random walk (permanent) component and a stationary (temporary) component. (2). That is, suppose that there is a positive stationary shock (3) at time t so that [P.sub.t] (the stock price at time t) increases and is larger than what it would be without the positive stationary shock. Thus, it is expected that ln [P.sub.t] - ln [P.sub.t-Q] [approximately equal to] [R.sub.t-Q,t] [greater than or equal to] r, where r is the constant drift term from the random walk component and is the grand mean of all stock returns. Assuming that Q is large enough so that [P.sub.t+0] will not be affected by the stationary shock at time t and reverts to the level that is determined by the permanent component, it is expected that ln [P.sub.t+Q] - ln [P.sub.t] [approximately equal to] [R.sub.t,t+Q] [less than or equal to] r .Thus, this stationary shock tends to induce negative autocorrelation in stock returns at some Q. (4) That is, stock returns will fluctuate around the grand mean r. Therefore, the stationary component in stock prices induces mean reversion in (ex-post) stock returns. This stationary component in stock prices should cause stock prices to move around the levels solely determined by the random walk (permanent) component, however, but not around the grand mean of stock prices.

Mean reverting stock returns do not necessarily require ex-post stock returns to have negative serial correlation at all horizons. Therefore, even though positive autocorrelation in ex-post short-term stock returns is consistent with mean-reverting stock returns, this does not necessarily support the mean-reverting stock return hypothesis.

A number of studies have been done on the Nairobi Stock Exchange market but in none them tests the mean reversion of the market.Mutiri (2007) did a study on the relationship between fundamental accounting variables and common stock returns at the Nairobi Stock Exchange; these were; size effect, book value effect, cash flow from operations, debt to equity ratio and dividend yield. Oliech (2002) studied the relationship between size, book to market return at NSE for all listed companies from 1996 to 2000. Muthui(2003) investigated whether there is any significant difference in the returns between low price earnings ratio stocks and high price earnings ratio stocks for companies quoted at the NSE for period 1996 to 2002.

2.6 The index under study

2.6.1 NSE 20 share index

The Nairobi Stock Exchange Index which is the Index under consideration here was established in 1966 and was managed by Dyer and Blair Ltd. This Index is computed using the Geometric mean and it composes 20 stocks. The compositions were revised in 2008, (Appendix II) where Safaricom Ltd was introduced in 2008 to replace TPS Serena, Equity bank to replace Diamond Trust Bank and East Africa Cables to replace Sameer Africa.

Mbaru (2008) a presentation at Nairobi Stock Exchange explained the key parameters for the new index selection criteria. To be included in the index, a listed company would need; to be quoted for at least one year, have a minimum market capitalization of Kshs50 million, and have 20 percent shares available for trading at the stock market(float). Another key consideration is the tradability (liquidity) of the shares tracked by the turnover, number of shares traded, and number of deals concluded on each counter. But he emphasized that market capitalization will be an underlying criteria for inclusion in line with international best practice. Odera (2000) indicated that NSE did not have a clear portfolio selection and revision policy. There was no precise criterion to determine why a particular stock was dropped or why a new one was added to the portfolio.

2.6.2 AIG 27 share index

The AIG 27 shares Index was established in 1998 to compliment the NSE 20 Share Index. The Index is managed by AIG 27 Share Index Investment EA Ltd. The Index uses the Arithmetic method in calculating the Index. It comprises 27 stocks of actively traded stocks (Appendix (III & IV)

2.7 The filter rules

Filter rule has over the years been used across the spectrum as a data analysis tool.
In Finance, Alexander and Blume (1966), and Dryden (1969) considered a trading rule called filter rule and empirically showed that taking transaction costs into account, the filter rule cannot outperform the buy and hold strategy in which an investor simply buys the stock and holds it through the time period under consideration.

According to Reilly, Frank (1997) Filter rule is a set of criteria used to help an investor narrow down which financial instruments or conditions of financial instruments are the most profitable. Most beginner investors feel overwhelmed by the large number of financial products available in each type of market. Filters help narrow down the investor's or trader's search, so the decision of which securities to trade is less complicated. Filters are not limited to finding companies by stock screeners. The technical analysis tools can also help an investor or trader find a particular financial instrument. For example, if a trader wants to find financial instruments that are trading above their 200-day moving average, he or she can use a filter to find such instruments.

Sweeney (1986) used a similar filter rule technique on daily exchange rates for currencies over the April 1973 – December 1980.Filter of 0.5 – 10 % led to trading profits in more than 30% of the cases. The results for the smaller filters were again superior. Sweeney divided his sample into a 2,5 year estimation period by a 5 year post sample period. Filter rules that were profitable in the first year tended to be profitable in the second. The profit from filter trading was significant. Okello (2006) determined filter rule averaging 4.3% ranging from 3.6% lowest and a higher of 4.9% for the NSE stocks.

In science and mathematical field, Filter methods have been used to analyze both linear and nonlinear functions. According to Roger Fletcher and Sven Leyffer (2006) there are a number of filter methods used in the scientific field which can be used in analyzing data; These include Nonmonotone Filter method, Wachter and Biegler Filter, Filter Algorithm, Augmented Lagrangian and Simple reduction Filter rule method. In biological studies reduction filter methods are used in elimination of one sample from the analysis. This study borrows from the mathematical field to analyze the market indices. A simple reduction filter rule is used to analyze two set of data to determine the similarity in the percentage change. Simple reduction filter rule has been used in chemical analysis by obtaining the percentage changes within the data and eliminating the undesired set. Roger Fletcher (2006)

3.0 CHAPTER THREE: METHODOLOGY

3.1 Research design

The main line of inquiry was limited to determining whether NSE 20 Share Index (Geometric Mean) is a long-term biased estimator of the stock market performance. An alternative Arithmetic Mean Index which researches have shown to be a one period unbiased estimator was necessary for comparison with the NSE 20 Share Index. To test for the first objective as a precondition for the second objective a Pearson correlation for stocks between 1998 to 2006 will calculated to test the existence of partial serial correlation.

A simple filter method was used to test for the existence of the downward bias of the NSE 20 Share Index. Filter methods have been used in the scientific field to analyze both linear and nonlinear functions. According to Roger Fletcher and Sven Leyffer (2006) there are a number of filter methods used in the scientific field which can be used in analyzing data; These include Nonmonotone Filter method, Wachter and Biegler Filter, Filter Algorithm, Augmented Lagrangian and Simple Filter rule method. The simpler, Simple Filter rule method was ideal in this case.

3.2 Population and Sample

The research used 1925 daily prices observations for all stocks included in the Nairobi Stock Exchange Index for the period January 1998 to December 2006. 1998 was the ideal starting point since this was the time when the comparative AIG 27 Share Index was started. To attain comparison between the NSE 20 Share Index and AIG 27 Share Index which started in 1998, The NSE 20 Index was rebased at 100 points from 1998.

3.3 Data collection and presentation

The study was wholly based on secondary data filed with NSE secretariat and that maintained by AIG Investment (EA) Limited. These were the daily price indices from 1998 to 2006 both years inclusive. The daily AIG 27 Share indices were obtained from the AIG EA Limited. Since the AIG EA Limited, portfolio fund managers have an Arithmetic Mean Index for evaluating the portfolio performance, we rejected the idea of reconstructing an alternative Arithmetic mean Index to benchmark against the Geometric Mean Index (NSE 20 Index), this because all the 20 stocks in the NSE 20 Share Index were include in the AIG 27 Share Index thus making it similar in terms of sample representation we therefore based our investigation on the said index after rebasing it at 100 points from 1998.

3.4 Data analysis and model specification

Inferential statistics and regression was used to analyze the data. For the first objective the Pearson correlation was calculated to test the existence of partial serial correlation. To attain accuracy and due to the bulkiness of the daily data involved the statistical package for social sciences (SPSS) was used.

Simple reduction filter rule is a mathematical analytical procedure which can be used to determine the similarity in the percentage change of the two sets of data. The study applied the method in testing the second objective. To achieve the accuracy and due the bulkiness of the data involved, we used the statistical package for social sciences (SPSS) to analyze the data. The following procedures were followed.

3.4.1 Testing for short run downward bias

1) Cases where the NSE 20 Index and AIG 27 Index were on a downward trend between 1998 and 2006 were selected.
2) The Daily percentage change for both the NSE 20 Index and AIG 27 Index were then calculated.
3) The results were then analyzed and tabulated for interpretation as follows;

Number of cases where: % Change in NSE 20 Share >% Change in AIG 27 Share Index	Number of cases where: % Change in NSE 20 Share < % Change in AIG 27 Share Index	Number of cases where: % Change in NSE 20 Share = % Change in AIG 27 Share Index
A	B	C

3.4.2 Testing for short run upward bias

1) A sample of 964 where the NSE 20 Index and AIG 27 Index were on an upward trend between 1998 and 2006 were selected. In this case one year period between April 2003 and March 2004 was ideal since there was a steady upward trend.
2) The Daily percentage change for both the NSE 20 Index and AIG 27 Index were then calculated separately.
3) The results were then analyzed and tabulated for interpretation as follows;

Number of cases where: % Change in NSE 20 Share Index >% Change in AIG 27 Share Index	Number of cases where: % Change in NSE 20 Share Index< % Change in AIG 27 Share Index	Number of cases where: % Change in NSE 20 Share Index= % Change in AIG 27 Share Index
A	B	C

3.4.3 Long -term bias test results

1) A sample of 1925 daily prices between 1998 and 2006 were selected.
2) The Daily percentage change for both the NSE 20 Index and AIG 27 Index were then calculated separately.
3) The results were then analyzed and tabulated for interpretation as follows;

Number of cases where: % Change in NSE 20 Share Index >% Change in AIG 27 Share Index	Number of cases where: % Change in NSE 20 Share Index< % Change in AIG 27 Share Index	Number of cases where: % Change in NSE 20 Share Index = % Change in AIG 27 Share Index
A	B	C

4.0 CHAPTER FOUR: EMPIRICAL RESULTS AND INTERPRETATION

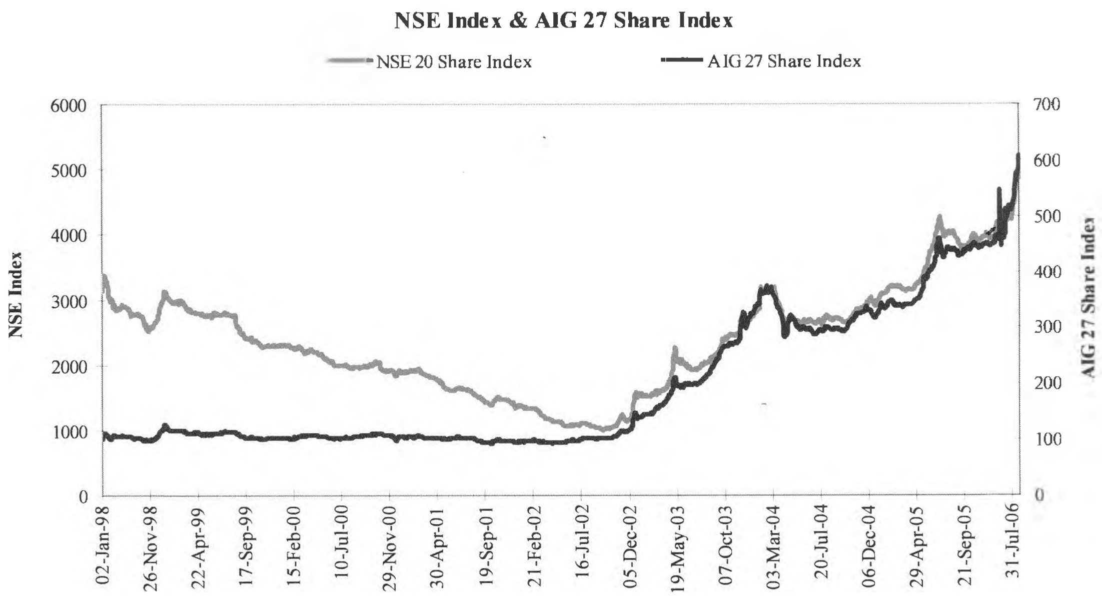
4.1 Testing for mean reversion

The research used 1925 daily prices observations for all stocks included in the Nairobi Stock Exchange 20 Share Index. The data was then divided into 16 runs referred in the SPSS output result as Lags. Each lag had 120 daily prices observations. These gave a cross period comparison a representative sample.

```
RESULTS

Partial Autocorrelations:   NSEINDEX

   Pr-Aut-   Stand.
Lag  Corr.   Err. -1   -.75   -.5 -.25   0    .25  .5   .75   1

  1    .096   .023                      .⇔.*
  2    .001   .023                      .*.
  3   -.048   .023                      *⇔.
  4    .016   .023                      .*.
  5   -.019   .023                      .*.
  6   -.058   .023                      *⇔.
  7    .020   .023                      .*.
  8   -.010   .023                      .*.
  9    .014   .023                      .*.
 10    .101   .023                      .⇔.*
 11    .066   .023                      .⇔*
 12   -.021   .023                      .*.
 13   -.006   .023                      .*.
 14    .012   .023                      .*.
 15   -.026   .023                      *⇔.
 16    .018   .023                      .*.

Plot Symbols:      Autocorrelations *     Two Standard Error Limits.

Total cases:  1927      Computable first lags:  1924
```

The results above show that at 16 lag points the NSE stocks produce seven negatively correlated points and nine positively correlated points. The presence of the negatively correlated points clearly indicated the up and down swings of the market, that is a period of upward movement is always followed by a downward movement, thus the mean reversion of the Nairobi Stock Exchange Market. The results can be supported by the graphical representation of stock movements as shown below:

Fig 1



4.2 Short - term downward bias test results

Table I

Number of cases where: % Change in NSE 20 Share Index >% Change in AIG 27 Share Index	Number of cases where: % Change in NSE 20 Share Index < % Change in AIG 27 Share Index	Number of cases where: % Change in NSE 20 Share Index = % Change in AIG 27 Share Index
A = 665	B = 248	51 = C

Max A = 3×10^{-2} - Min = 7.3×10^{-4}
Max B = 2.1×10^{-2} - Min = 1.07×10^{-4}

The above results were obtained through the application of the statistical package for social sciences (SPSS) to analyze the data.

Table one above illustrates that out of the sample of 964 daily Index data analyzed, for a downward trend, the percentage change of NSE 20 Index was higher in 665 days compared to 248 days when the AIG Index percentage change was higher than the NSE Index. NSE percentage change was equal the AIG Index percentage change in n = 51. Further the SPSS result show that the slope range in A was a Maximum of 3×10^{-2} to a Minimum of 7.3×10^{-4}. While the slope range for B was a Maximum of 2.1×10^{-2} to a Minimum of 1.07×10^{-4} This indicates that the downward slope of NSE 20 Share Index is more pronounced than that of the AIG Index thus showing existence of a downward short – run bias in the NSE 20 Share Index (Geometric Mean)

4.3 Short – term upward bias test results

Table II

Number of cases where: % Change in NSE 20 Share Index >% Change in AIG 27 Share Index	Number of cases where: % Change in NSE 20 Share Index < % Change in AIG 27 Share Index	Number of cases where: % Change in NSE 20 Share Index = % Change in AIG 27 Share Index
A= 127	B= 164	C = 12

Max A …… 2.9×10^{-16} - Min 2.0×10^{-18}
Max B…… 1.98×10^{-16} - Min 5.0×10^{-18}

The above results above were obtained through the application of the statistical package for social sciences (SPSS) to analyze the data.

Table two above illustrates that out of the sample of 303 daily Index data analyzed, for upward trend, the percentage change of NSE 20 Index was higher in 127 days compared to 164 days when the AIG Index percentage change was higher than the NSE Index. NSE 20 Share Index percentage change was equal the AIG 27 Share Index percentage change in 12 cases. However, the slope result from SPSS show the range for A is a Maximum of 2.9×10^{-16} to a Minimum of 2.0×10^{-18}. While that one of B is a Maximum of 1.98×10^{-16} to a Minimum of 5.0×10^{-18}, testing this result at 95 percent confidence interval of the mean difference (see appendix V) show that the difference in both cases is so close to zero thus making the difference in percentage change to be so negligible. This indicates therefore that the NSE 20 Share Index bias disappears as the market takes an upward trend, and in this case a better measure of performance.

4.4 Long -term bias test results

Table III

Number of cases where: % Change in NSE 20 Share >% Change in AIG 27 Share Index	Number of cases where: % Change in NSE 20 Share < % Change in AIG 27 Share Index	Number of cases where: % Change in NSE 20 Share = % Change in AIG 27 Share Index
777	804	344

Samples of 1925 days were taken for the long – run period out of which 777 cases the percentage change in NSE 20 Share Index was higher than that of the AIG 27 Share Index percentage change while 804 cases had the AIG 27 Share Index percentages change being higher than that of NSE 20 Share Index percentage change.

The result above is represented by the Dec 2002 to July 2006 curve in fig I above. NSE 20 Share Index curve tend to follow the same path as the AIG Share Index curve. These show that the NSE 20 Share Index corrects itself in the long run when the market moves up and down (mean reverting). The previous result show that the NSE market is mean reverting and the bias test of the NSE 20 Share Index indicates that the index corrects itself in the long run whenever the market reverts thus leading to a conclusion that using a Geometric mean calculated Index in a mean reverting market therefore can be better guide to measure of performance than the Arithmetic mean based Index.

5.0 CHAPTER FIVE: SUMMARY, CONCLUSIONS, LIMITATIONS AND RECOMMENDATIONS

5.1 SUMMARY

The objective of the study was to determine whether the Nairobi Stock Exchange (NSE) is mean reverting and as to whether there exist a short and long term bias of the NSE indices. To achieve these objectives two approaches were used. First a spatial correlation coefficient was calculated and a graph (fig.1) drawn to interpret the result obtained. Second the simple filter rule was used to test for the bias of the NSE Indices.

The test for short run bias show that Geometric mean method gives a biased result on downward trend but the bias reduces and the index corrects itself in the long run when the market reverts. In circumstances where the market reverts the Geometric mean method therefore becomes a good choice for measure of performance in the long run.

5.2 CONCLUSIONS

The negative value of partial autocorrelation indicates that the NSE market mean reverts, that is period of downward movement tend to be followed by period of upward movement showing that the market overreacts to news, that is, following the first dramatic reaction to a shock, the market falls back to normal.Testing for the bias of the NSE indices, The results indicated that there is downward bias for the NSE 20 Share index (geometric mean) in the short – run period. Testing for the short run upward bias the result indicated that NSE 20 Share Index and AIG 27 Share Index have similar percentage change as indicated in table II of page 27. For the long – run bias test, the result showed that NSE 20 Share Index short run bias tend to disappear in the long – run thus becoming a better measure of market performance in the long run. This is well demonstrated in fig 1 page 26 where the NSE 20 Share Index and AIG 27 Share Index curves are overlapping on an upward trend between December 2002 to July 2006. The two Indices therefore give similar results in this period thus showing the same degree of change in the movement of the stock market.

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The negative value of partial autocorrelation indicates that the NSE market mean reverts, that is period of downward movement tend to be followed by period of upward movement showing that the **market overreacts to news, that is, following the first dramatic reaction to a shock, the market falls back to normal.** Testing for the bias of the NSE indices, the results indicated that there is downward bias for the NSE 20 Share index (geometric mean) in the short – run period. Testing for the short run upward bias the result indicated that NSE 20 Share Index and AIG 27 Share Index have similar percentage change as indicated in table II of page 27. For the long – run bias test, the result showed that NSE 20 Share Index short run bias tend to disappear in the long – run thus becoming a better measure of market performance in the long run. This is well demonstrated in fig 1 page 26 where the NSE 20 Share Index and AIG 27 Share Index curves are overlapping on an upward trend between December 2002 to July 2006. The two Indices therefore give similar results in this period thus showing the same degree of change in the movement of the stock market.

The results in this study therefore indicate that there is a tendency for the ex-post excess return for both the NSE 20 share index and AIG 27 share index to revert to their means. That is the period of upward movement will be followed by period of downward movement. The result seems to be challenging the efficient market hypothesis (EMH), that forms a central part of modern portfolio theory. Efficient market hypothesis holds that markets are time independent: that past returns cannot be predictive of future returns, whereas mean reversion test for the NSE market shows the contrary.

The theoretical implication of the result therefore is that for small markets like the Nairobi Stock Exchange which is highly predictive, the Geometric mean becomes an ideal method of calculating the market index. The Arithmetic mean will not be suitable for such mean reverting market as the result departs from the actual with time. The current NSE 20 Share Index therefore suits the market contrary to Kibbet (2006) and Odera (2000) findings.

The serial correlation test shows that mean reversion in the Nairobi stock market is a strong phenomenon in modern times. One possible policy implication of the negative serial correlation in the data is that the market overreacts to news, that is, following the first dramatic reaction to a shock, the market falls back to normal. The view is consistent with Beveridge and Nelson permanent/transitory components model, which basically says that stock markets are driven by a fundamental component that reflects the efficient market price and behaves like a random walk, whereas there is also a temporary component that captures deviations from efficiency and this component reverts to something that is close to zero.

5.3 LIMITATIONS OF THE STUDY

The Nairobi Stock Exchange market is a small and apparently speculative and may not give a good comparison with established stock exchanges in the world, where similar study have been carried out. The Nairobi Stock Exchange market currently has 58 listed companies while the world's major developed markets have more than five hundred listed companies. The study covered the Kenyan case only and we could not conclude whether the mean reversion is a universal phenomenon. There were also some periods where companies observed to have been suspended from trading confirmed to be included in the Index. The non exclusion of these companies from index calculation could have affected the value of the index thus the spatial autocorrelation.

5.4 RECOMMENDATIONS

The solution to bias is not abandoning all indices as misleading, but rather being aware of the biases any particular index may introduce and letting that knowledge guide in use of the index. The use of multiple indices is therefore necessary so as to eliminate the bias related to period under consideration. In analysis of data, the choice of period and methodology can influence the outcome, as seen in this result the use of daily data gave a different result from the earlier researches which had used the weekly data. The problem of data bulkiness should not limit one from using daily data as data analysis software are now available to give accurate results.

The results obtained here show that the mean reversion phenomenon at NSE seems to contradict the Efficient Market Hypothesis. This shows that the market is predictive; however such inefficiency is limited to the timing differences. We would not determine with certainty how long the market will be up before a reversion takes place or how long it will be down before the upward trend. This opens room for more studies on reversal timing trends.

The difficulty of deciding over which period to look for the effect of mean reversion highlights a particular problem, Presumably if we had just looked at annual periods we would have found that the returns in the year 2005 were generally above average and all returns in the 1992 generally below average. This would seem to may be suggest an element of positive partial autocorrelation if we change the time step. In summary there seems to be some arbitrariness in the choice of time period of returns under the autocorrelation definition of mean reversion, further studies are therefore necessary to determine a mean reversion that is invariant under choice of time interval. Observing that mean reversion involves some negative autocorrelation followed by some positive autocorrelation is not particularly helpful. We also recommend further studies on mean reversion using an overall market index instead of a representative index.

In the test for bias it has been seen in this study that the use of different methodology can yield different results. It is therefore recommendable that use of different methodology such as GARCH MODEL be used to test for mean reversion in the NSE to see if similar results will hold.

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APPENDICES

Appendix 1

World Major Indices

Index	Computation	Weighting	Stocks
S&P 500	Arithmetic Mean	Market Capitalization	500
NASDQ Composite	Arithmetic Mean	Market Capitalization	All Share
Financial Times Ordinary (FTO)	Geometric Mean	Equally Weighted	30
Financial Times-Actuaries	Arithmetic Mean	Market Capitalization	All Share
New York Stock Exchange Composite	Arithmetic Mean	Market Capitalization	1,700
Hang Seng Index	Arithmetic Mean	Market Capitalization	33
Dow Jones 30	Arithmetic Mean	Price Weighted	20

Appendix II

NSE 20 Share Index composition

Agriculture Sector	Commercial Sector	Financial Sector	Industrial Sector	AIMS
Sasini Rea Vipingo	CMC Kenya Airways Nation Media Group TPS Serena	Barclays Diamond Trust Bank KCB ICDC Investments Standard Chartered	Kengen Bamburi Cement BAT Kenya Mumias Sugar Co. E.A.BL Sameer KPLC Total Kenya	Express Ltd

Appendix III

AIG 27 Index Compositions

Agriculture Sector	Commercial Sector	Financial Sector	Industrial Sector
Uniliver	CMC	Barclays	Athi River Mining
Sasini	Kenya Airways	CFC Bank	BOC Kenya
Rea Vipingo	Nation Media	Diamond Trust Bank	Bamburi Cement
	TPS Serena	Housing Finance	BAT Kenya
		KCB	EA Portland
		ICDC Investments	EA Breweries
		NBK	Sameer Africa
		NIC Bank	KPLC
		Standard Chartered	Kengen
			Mumias
			Total Kenya

Appendix IV

	AIG (EA) 27	NSE 20
Formulae	Arithmetic Mean	Geometric Mean
Weighting	Market Capitalization	Equally Weighted
Return	Total Return, captures both capital gains and dividends	Simple Return, only captures capital gains
Composite	27 Stocks	20 Stocks

Appendix V

Paired Samples Correlations

		N	Correlation	Sig.
Pair 1	VAR00001 & VAR00002	303	.838	.000

Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	VAR00001	8.101E-03	303	1.036E-02	9.419E-04
	VAR00002	7.512E-03	303	8.560E-03	7.782E-04

Paired Samples Test

		Paired Differences					t	df	Sig. (2-tai ed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference				
					Lower	Upper			
Pair 1	VAR00001 - VAR00002	5.89E-04	5.662E-03	5.147E-04	-4.30E-04	1.608E-03	1.145	302	.25