OBJECTIVES OF THIS CHAPTER

This chapter discusses in details the research work undertaken in regard to determining:

- What are the measures of risk adjusted return used in this research and why?
- What are the measures of fund manager's decision making abilities used in this research and why?
- What are the measures of nature of price co-movement used in this research and why?
4.1 EVOLUTION OF MODERN PORTFOLIO THEORY & PERFORMANCE MEASURES

Performance evaluation is the assessment of a fund manager's results, which involves, first, determining whether the money manager added value by outperforming the established benchmark (performance measurement) and, second, determining how the money manager achieved the calculated return (performance attribution analysis).

The primary objective of mutual fund managers is to maximise the performance of their schemes over time. How effectively do they achieve this objective, can be gauged by employing various portfolio performance evaluation measures and finding out which mutual fund manager(s) provide(s) the highest risk adjusted returns. Prior to 1950s, the investment community was concerned about risk but there was no specific measure of the term. The first measure relates back to 1952 to the modern portfolio theory of Harry Markowitz. He derived measures of the expected rate of return and the expected risk of an asset as well as a portfolio. He showed that the variance of the returns was a measure of risk under a reasonable set of assumptions and derived a formula for computing the variance of the returns of a portfolio. This formula for the variance of a portfolio not only indicated the importance of diversifying investments to reduce the total risk of a portfolio, but it also showed how to diversify effectively (Reilly, 1994).

Modern portfolio theory was introduced by Harry Markowitz through his paper "Portfolio Selection," which appeared in the 1952 Journal of Finance. Thirty eight years later, he shared a Nobel Prize with Merton Miller and William Sharpe for what has subsequently become a broad theory for portfolio selection.

Prior to Markowitz's work, investors focused on assessing the risk and reward of individual securities in constructing their portfolios. Standard investment advice was to identify those securities that offered the best opportunities for gain with the least risk and then construct a portfolio of those securities. Following this advice, an investor might
conclude that stocks of a particular industry offered good risk-reward characteristics and thus compile a portfolio entirely of such stocks. Intuitively, this would however be foolish. Markowitz formalised this intuition. Detailing on the mathematics of diversification, he proved that investors should focus on selecting portfolios based on their overall risk-reward characteristics instead of merely compiling portfolios from securities that each individually has attractive risk-reward characteristics. In a nutshell, inventors should select portfolios, not individual securities. He further introduced the concept of efficient frontier of portfolios and also discussed the use of the expected returns-variance of returns, which is extensively used as a hypothesis to explain investment behavior (Markowitz, 1956).

James Tobin expanded on Markowitz's work by adding a risk-free asset to the analysis. This made it possible to leverage or deleverage portfolios on the efficient frontier. By combining a risk-free asset with a portfolio on the efficient frontier, Tobin constructed new portfolios whose risk-return profiles were superior to those of portfolios on the efficient frontier. This led to the notions of super-efficient portfolio and the capital market line (Tobin, 1958).

Subsequently in 1963, William Sharpe first suggested the single index model. It is a simple asset pricing model that shows that the performance of each stock is in relation to the performance of a broad based market index. To simplify analysis, the single-index model assumes that there is only one macroeconomic factor that causes the systematic risk affecting all stock returns and this factor can be represented by the rate of return on the broad based market index. According to this model, the expected excess return of any stock can be decomposed into the expected return of the individual stock due to firm-specific factors, commonly denoted by its alpha coefficient ($\alpha$), the expected excess return due to macroeconomic events that affect the market, commonly termed as excess returns.
due to systematic risk and the unexpected return due to microeconomic events that affect only the stock, commonly termed as returns due to unsystematic risk (Sharpe, 1963).

Although the single index model was essentially developed in order to simplify the Markowitz model, yet this model established the foundation on which the concepts of the capital asset pricing model was formalised by Sharpe in 1964. The capital asset pricing model makes strong assumptions that lead to interesting conclusions. Not only is the market portfolio located on the efficient frontier, but it is actually Tobin's super-efficient portfolio on which it is located. According to the capital asset pricing model, all investors should hold the market portfolio, leveraged or de-leveraged with positions in the risk-free asset. The capital asset pricing model also relates the expected return of an asset/ portfolio to its beta and establishes a linear relationship between the expected return and the beta of an asset/ portfolio (Sharpe, 1964).

The capital asset pricing model states that the expected returns of an asset depend on its systematic risk only. Assets or portfolios with greater systematic risk have higher expected returns than those with lower systematic risk. This means a fund manager can simply boost the returns of his/ her portfolio by merely increasing the systematic risk of the portfolio. This poses a problem for anyone who wants to assess a fund manager's performance. Naturally it becomes quite difficult to distinguish a manager who achieved high returns merely by taking high risk from one who was successful at market timing or stock picking. Early studies of fund managers' performance, including Cowles (1933), Friend et al (1962) and Horowitz (1963), failed to address this problem. They assessed fund managers' performance without any adjustment for the risks that they shouldered in order to achieve such performance.

Not only did the capital asset pricing model highlighted this problem, but it also provided a framework for assessing and adjusting returns of a portfolio with due diligence to the
risk of the portfolio. Between 1965 and 1970, a number of papers were published on fund managers' performance evaluation, suggesting various risk adjusted performance metrics based on the capital asset pricing model, primarily to support testing of the emerging efficient market theory.

Among such various risk adjusted performance metrics, the first notable one was developed in 1965 by Jack Treynor. The Treynor model measured performance based on systematic risk. Building on the capital asset pricing model, Treynor introduced a risk-free asset that rational, risk-averse investors would always prefer to invest in along with assets at risk. The Treynor model used beta as a proxy for measuring systematic risk and used the security market line as a benchmark for gauging fund managers’ performance (Treynor, 1965).

In 1966, William Sharpe introduced the Sharpe ratio, which he termed as reward-to-variability ratio. This measure is based on the efficient market theory and the capital asset pricing model and was built on Harry Markowitz's mean variance paradigm, which assumes that the mean and standard deviation of the distribution of one period return are sufficient statistics for evaluating the prospects of a portfolio. The reward-to-variability ratio uses the standard deviation of returns as the measure of risk and evaluates the fund manager on the basis of both rate of return and degree of diversification. The ex ante Sharpe Ratio takes into account both the expected differential return and the associated risk, while the ex post version takes into account both the average differential return and the associated variability. However, neither incorporates information about the correlation of a portfolio or strategy with other assets, liabilities or previous realisations of its own return and for this reason, the ratio may need to be supplemented in certain applications (Sharpe, 1966).
The Jensen intercept is similar to the Sharpe ratio because it also uses as its benchmark the capital asset pricing model. The Jensen intercept is the difference between the actual return of a portfolio and that which could have been earned on a benchmark portfolio with the same systematic risk, as measured by beta. It thus measures the ability of active fund management in increasing the returns above those that are purely a reward for bearing market risk. Caveats apply however since it will only produce meaningful results if it is used to compare two portfolios which have similar betas (Jensen, 1968).

Subsequently in 1973 Treynor and Black developed the Information ratio, also known as the appraisal ratio. This is a popular and widely used performance measure and is regarded as one of the most important measures in the investment management industry (Grinold, 1989). This ratio indicates how much additional excess return over the benchmark can be obtained per additional unit of residual risk. Hence it is a ratio for the excess return of a portfolio relative to a specified benchmark divided by the volatility of the excess returns of the portfolio. The measure, therefore, is able to show how much additional return has been generated per unit of additional risk, which is important information in the field of active management. Therefore, it is possible to quantify how much value is added or destroyed by active fund management (Treynor & Black, 1973).

Among the latest developments in fund managers’ evaluation, a notable one is the Eugene Fama model. This model is an extension of Jenson model. This model compares the performance, measured in terms of returns, of a fund with the required return commensurate with the total risk associated with it. The difference between these two is taken as a measure of the performance of the fund and is called net selectivity. The net selectivity represents the stock selection skill of the fund manager, as it is the excess return over and above the return required to compensate for the total risk taken by the fund.
manager. Higher value of which indicates that fund manager has earned returns well above the return commensurate with the level of risk taken by him (Fama, 1992).

4.2 RATIONALE FOR USING SHARPE, TREYNOR & JENSEN MODELS AS MEASURES OF RISK ADJUSTED RETURN

4.2.1 Sharpe Ratio As A Measure Of Risk Adjusted Return

4.2.1.1 Introduction To Sharpe Ratio

The Sharpe Ratio developed by Nobel laureate William F. Sharpe is a measure for calculating risk-adjusted return. This ratio has become the industrial standard for the same. William Forsyth Sharpe born June 16, 1934 was an American economist. He is the STANCO 25 Professor of Finance, Emeritus at Stanford University's Graduate School of Business and the winner of the 1990 Nobel Memorial Prize in Economic Sciences. He created the Sharpe ratio for risk-adjusted investment performance analysis. He has also contributed to the development of the binomial method for the valuation of options, the gradient method for asset allocation optimization, and returns-based style analysis for evaluating the style and performance of investment funds. The Sharpe Ratio was published in The Journal of Portfolio Management, fall 1994.

4.2.1.2 Concept Of Sharpe Ratio

The Sharpe ratio is often used to compare the change in a portfolio's overall risk-return characteristics when a new asset or asset class is added to it. For example, a portfolio manager is considering adding an allocation towards a hedge fund to his existing equally weighted investment portfolio of stocks which has a Sharpe ratio of 0.67. If the new portfolio's allocation is 40:40:20 stocks, bonds and a diversified hedge fund allocation (perhaps a fund of funds), the Sharpe ratio increases to 0.87 (for example). This indicates that although the hedge fund investment is risky as a standalone exposure, it actually improves the risk-return characteristic of the combined portfolio and thus adds a
diversification benefit. If the addition of the new investment lowers the Sharpe ratio, then it should not be added to the portfolio.

The Sharpe ratio can also help explain whether a portfolio's excess returns are due to smart investment decisions and meticulously calculated asset allocation or a result of too much of risk. Although one portfolio or fund can enjoy higher returns than its peers, it is only a good investment if those higher returns do not come with an excess risk. So, to summarise the concept is greater a portfolio's Sharpe ratio, the better is its risk-adjusted performance. A negative Sharpe ratio indicates that a risk-less asset would perform better than the security being analysed.

4.2.1.3 Measure Of Sharpe Ratio

The Sharpe ratio uses the standard deviation of risk premiums as the measure of risk and evaluates the fund manager on the basis of both rate of return and quantum of risk.

\[
\text{Sharpe Ratio} = \frac{\text{Mean (Fund Risk Premium)}}{\text{Standard Deviation (Fund Risk Premium)}}
\]

4.2.1.4 Interpretation Of Sharpe Ratio

The Sharpe ratio is the average return earned in excess of the risk-free rate per unit of volatility or total risk. Subtracting the risk-free rate from the mean return, the performance associated with risk-taking activities can be isolated. One intuition of this calculation is that a portfolio engaging in "zero risk" investment, for example, the purchase of U.S. Treasury bills (for which the expected return is the risk-free rate), has a Sharpe ratio of exactly zero. Generally, the greater the value of the Sharpe ratio, the more attractive is the risk-adjusted return.

Since this ratio uses standard deviation as its measure of risk, it is most appropriately applied when analysing a fund that is an investor's sole investment. The Sharpe ratio can be used to compare directly how much risk each of the two funds had to bear to earn excess return over the risk-free rate. For example, a mid-cap growth fund may have a
Sharpe ratio of 0.40. Meanwhile, the average Sharpe ratio for all mid-cap growth funds is 0.29. This means that this individual fund currently has had better risk-adjusted performance than the average mid-cap growth fund.

4.2.1.5 Criticisms And Limitations Of Sharpe Ratio

Risk and Return are both equally important components that need to be looked into before planning an investment. While return can be easily quantified, risk cannot. Today, standard deviation is the most commonly used measure of risk, while the Sharpe ratio is the most commonly used risk vs. return measure. The Sharpe ratio has been around since 1966, but its life has not passed without controversy. Even its founder, William Sharpe, has admitted the ratio is not without its problems.

- The Sharpe ratio is a good measure of risk for large, diversified, liquid investments, but for others like hedge funds; it can only be used as one of a number of risks vs. return measures.
- The Sharpe ratio uses the standard deviation of risk premiums in the denominator as its substitute of total portfolio risk, which makes an assumption that risk premiums are normally distributed. Evidence has shown that returns (vis-à-vis risk premiums) on financial assets tend to deviate from a normal distribution and may make interpretations of the Sharpe ratio misleading and incorrect.
- A variation of the Sharpe ratio is the Sortino ratio, which removes the effects of upward price movements on standard deviation to measure only return against downward price volatility and uses the semi-variance in the denominator.
- The Sharpe ratio can also be tampered with or used to their advantage by hedge fund managers or portfolio managers seeking to boost their pseudo risk-adjusted returns history. This can be done by.
a. Lengthening the measurement interval. This will result in a lower measure of volatility. For example, the annualized standard deviation of daily returns is generally higher than of weekly returns, which is, in turn, higher than of monthly returns.

b. Compounding the monthly returns but calculating the standard deviation from the non-compounded monthly returns.

c. Writing out-of-the-money puts and calls on a portfolio. This strategy can potentially increase the return by collecting the option premium without paying off for several years. Strategies that involve taking on default risk, liquidity risk, or other forms of catastrophe risk have the same ability to report an upwardly biased Sharpe ratio.

d. Smoothing of returns. Using certain derivative structures, infrequent marking to market of illiquid assets, or using pricing models that understate monthly gains or losses can reduce reported volatility.

e. Eliminating extreme returns. Because such returns increase the reported standard deviation of a hedge fund, a manager may choose to attempt to do away with the best and the worst monthly returns each year to reduce the standard deviation.

4.2.2 **TREYNOR RATIO AS A MEASURE OF RISK ADJUSTED RETURN**

**4.2.2.1 INTRODUCTION TO TREYNOR RATIO**

The Treynor ratio is a ratio developed by Jack Treynor that measures returns earned in excess of that which could have been earned on a riskless investment that has no diversifiable risk per each unit of market risk.
4.2.2.2 **Concept Of Treynor Ratio**

The Treynor ratio is similar to the Sharpe ratio. Both the ratios conclude that measure of return is the excess over the risk-free investment. However the two differ in their definitions of risk. The Sharpe ratio uses standard deviation to define volatility risk, whereas the Treynor ratio uses beta as a measure of market or systematic risk. While the standard deviation is a measure of the total volatility both upside as well as downside, the beta measures only the portfolio's sensitivity to the market movement. The Treynor ratio is useful in determining how a particular investment contributes to a diversified portfolio.

4.2.2.3 **Measure Of Treynor Ratio**

The Treynor ratio uses the security market line as a benchmark for gauging fund managers’ performance and measures risk premium per unit of systematic risk.

\[
\text{Treynor Ratio} = \frac{\text{Mean (Fund Risk Premium)}}{\text{Beta (Fund Risk Premium)}}
\]

In other words, the Treynor ratio is a risk-adjusted measure of risk premiums based on the systematic risk. It is also known as the "reward-to-volatility ratio".

4.2.2.4 **Interpretation Of Treynor Ratio**

Generally speaking, the higher the Treynor ratio the better it is. One hopes the risk premium that is the excess return over the risk-free rate is large. However, one should be cautious of Treynor ratios that appear abnormally high. If a Treynor ratio is too large, it could be the result of the beta in the denominator being very small. Such a scenario might indicate an incorrectly specified benchmark.

4.2.2.5 **Criticisms And Limitations Of Treynor Ratio**

Although Treynor ratio is a popular and common method of judging fund managers’ abilities, the Treynor ratio is not free from its own share of drawbacks.

- Like all benchmark relative metrics, choosing the proper benchmark as a standard is the key. However, this creates a bit of a perplexity if the Treynor ratio seeks to
measure how the addition of the investment impacts the risk of the portfolio. If one has a broadly diversified portfolio covering many different asset classes, what would be the appropriate benchmark for the portfolio is the question.

- Like the Sharpe ratio, the Treynor ratio does not quantify the value added of active portfolio management. It is a criterion for ranking only. A ranking of portfolios based on the Treynor Ratio is only useful if the portfolios under consideration are sub-portfolios of a broader, fully diversified portfolio. If this is not the case, portfolios with identical systematic risk, but different total risk, will be rated the same. The portfolio with a higher total risk is less diversified and therefore has a higher unsystematic risk which is not priced in the market.

- An alternative method of ranking portfolio management is Jensen's Alpha, which quantifies the added return as the excess return above the security market line in the capital asset pricing model. As these two methods both determine rankings based on systematic risk alone, they will rank portfolios identically.

- Perhaps the best use for the Treynor ratio lies in evaluating a multi-manager line-up. If the investor is planning to have several managers representing each Treynor Ratio of the major asset classes, then one can first specify the correct benchmark for each given asset class, then calculate Treynor ratios for each of the managers within each asset class and then examine how different combinations of similar managers work together.

4.2.3 Jensen’s Alpha As A Measure Of Risk Adjusted Return

4.2.3.1 Introduction To Jensen’s Alpha

Jensen's alpha was first used as a measure in the evaluation of mutual fund managers by Michael Jensen in 1968. The Jensen’s alpha is supposed to be 'risk adjusted', which means it takes account of the relative risk factor of the asset.
Many academics believe financial markets are so efficient that repeated earning of positive alpha is a rare event unless it happens by chance. Still, Alpha is widely used to evaluate mutual fund, hedge fund and portfolio managers’ performance, often in combination with the Sharpe ratio and the Treynor ratio.

4.2.3.2 Concept of Jensen’s Alpha

Jensen's alpha also known as Jensen's Performance Index or ex-post alpha is used to determine the abnormal return of a security or portfolio of securities over the theoretical expected return. It is a version of the standard alpha based on a theoretical performance index instead of a market index.

The security could be any asset, such as stocks, bonds, or derivatives. The theoretical return is predicted by a market model, most commonly the capital asset pricing model (CAPM). The market model uses statistical methods to predict the appropriate risk-adjusted return of an asset. The CAPM for instance uses beta as a multiplier.

Jensen’s alpha is the difference between the actual return earned by the security and the theoretical return predicted by the market model.

Alpha is used in finance to represent two things:

A measure of performance on a risk-adjusted basis.

- Alpha which is considered the active return on an investment, measures the performance of an investment against a market index used as a benchmark, since they are often considered to represent the market’s movement holistically. The excess return of a fund relative to the return of a benchmark index is the fund’s alpha.

- Alpha is most often used for mutual funds and other similar investment types. It is often represented as a single number (like 3 or -5), but this signifies a percentage measuring how the portfolio or fund performed compared to the benchmark index.
(i.e. 3% better or 5% worse). Alpha is also often referred to as “excess return” or “abnormal rate of return.”

A measure of the abnormal rate of return:

- Alpha measures the abnormal rate of return on a security or portfolio in excess of what would be predicted by an equilibrium model like the capital asset pricing model (CAPM). In this context, alpha is often known as the Jensen index.

4.2.3.3 Measure Of Jensen’s Alpha

In the context of CAPM, calculating alpha requires the following inputs:

- the realized return (on the portfolio),
- the market return,
- the risk-free rate of return and
- the beta of the portfolio.

\[
\text{Jensen Intercept} = \text{Mean (Fund Risk Premium)} - \{\text{Beta (Fund)} \times \text{Mean (NIFTY Risk Premium)}\}
\]

In other words, it is calculated as the difference between the actual return of a portfolio and that which could have been earned on a benchmark portfolio with same amount of systematic risk.

4.2.3.4 Interpretation Of Jensen’s Alpha

This is based on the concept that riskier assets should have higher expected returns than less risky assets. If an asset's return is even higher than the risk adjusted return, that asset is said to have "positive alpha" or "abnormal returns". Investors are constantly seeking investments that have higher alpha.

The fundamental idea is that to measure the performance of an investment manager one must look not only at the overall return of a portfolio, but also at the risk of that portfolio. For instance, if there are two mutual funds that both have a 12% return, a rational investor will want the fund that is less risky. Jensen's alpha is one of the ways to help
determine if a portfolio is earning the proper return for its level of risk. If the value is positive, then the portfolio is earning excess returns. In other words, a positive value for Jensen's alpha means a fund manager has outperformed or beat the market with his or her stock selection skills.

4.2.3.5 Criticisms & Limitations Of Jensen’s Alpha

While alpha has been an important factor of investing and receives a lot of attention from investors and advisors alike, there are a couple of important limitations that one should take into consideration before attempting to use alpha.

- One such drawback is that alpha is used in the analysis of a wide variety of fund and portfolio types. Since the same term can apply to investments of such differing natures, there is a tendency for people to attempt to use alpha values to compare different kinds of funds or portfolios with one another. Because of the complexities of large funds and portfolios, as well as of these forms of investing in general, comparing alpha values is only useful when the investments contain assets in the same asset class.

- Additionally, because alpha is calculated relative to a benchmark deemed suitable for the fund or portfolio, when calculating alpha it is necessary that an appropriate benchmark is chosen. Since funds and portfolios vary, it is a possibility that there is no suitable pre-existing index, in which case advisors will often use algorithms and other models to simulate an index for comparative purposes.
4.3 RATIONALE FOR APPLYING FAMA MODEL & INFORMATION RATIOS AS INDICATORS OF FUND MANAGERS’ DECISION MAKING ABILITIES

4.3.1 Eugene-Fama Model As A Measure Of Fund Manager’s Decision Making Abilities

4.2.1.1 INTRODUCTION TO EUGENE FAMA MODEL

The Net Selectivity Measure, formulated by Eugene Francis Fama, is an absolute measure of performance of the Fund Managers. Fama is an American economist and Nobel laureate in Economics, often referred to as "The Father of Finance", and best known for his path breaking work on portfolio theory, asset pricing and stock market behavior. The Net Selectivity Measure is calculated as the annualized return of the fund, less the yield of an investment without risk, deducting the standardized expected market premium times the total risk of the portfolio under review.

4.3.1.2 CONCEPT OF EUGENE FAMA MODEL

The Eugene Fama model is an extension of the Jenson model. This model compares the performance, which is measured in terms of returns, of a portfolio with the required return commensurate with the total risk associated with it. The difference between these two measures is considered as a measure of the performance of the fund and is referred to as net selectivity.

The net selectivity is the proxy for the stock selection skill of the fund manager, since it is the excess return over and above the return required to compensate for the total risk undertaken by the fund manager. Higher value of this indicates that the fund manager has earned returns well above the return required to commensurate with the level of risk taken by him/ her.
4.3.1.3 Measure of Eugene Fama Model

Eugene Fama Net Selectivity Measure provides for an analytical framework, which enables for a detailed analysis of scheme performance.

Selectivity comprises of “diversification” and “net selectivity”. Diversification indicates the excess return required for getting diversifiable risk, whereas Net Selectivity is the return that is achieved beyond the return which is attributable to incurring non-diversifiable and diversifiable risk.

Hence, Fama’s net selectivity ratio represents the stock selection skills of the fund manager, as it is the excess return generated above the return required to compensate for the total risk taken by the fund manager:

\[
\text{Fama Ratio} = \frac{\text{Mean (Fund Risk Premium)} - \left\{ \text{Mean (NIFTY Risk Premium)} \times \frac{\text{SD(Fund)}}{\text{SD(NIFTY)}} \right\}}{}
\]

4.3.1.4 Interpretation of Eugene Fama Model

From the above derivation it can be said that:

The Fama's Index gives the excess return obtained by the manager that could not have been obtained by investing in the market portfolio. It compares the extra return obtained by the portfolio manager carrying a specific risk with the extra return that could have been obtained with the same amount of systematic risk.

4.3.1.5 Criticisms and Limitations of Eugene Fama Model

In case of Eugene Fama model, the accuracy and reliability of this measure is based on the quality of the market proxy.
4.3.2 Information Ratio As a Measure of Fund Manager’s Decision Making Abilities

4.3.2.1 Introduction to Information Ratio

The Information Ratio, developed in 1973 by Treynor & Black, is one of the most important performance measures in the investment management industry. It is a ratio for the excess return of a portfolio relative to a specified benchmark divided by the volatility of the excess returns. The measure is able to show how much additional return has been generated per unit of additional risk, which is important information in the field of active management.

4.3.2.2 Concept of Information Ratio

The information ratio (IR) is a ratio of portfolio returns above the returns of a benchmark which is usually an index, to the volatility of those returns. The information ratio (IR) analyses a portfolio manager's ability to generate excess returns with respect to a benchmark, but also attempts to identify the consistency of the portfolio manager. This ratio will identify if a manager has beaten the benchmark by a lot in a few months or a little every month.

The information ratio is the more general form of the Sharpe ratio. It is used as a risk adjusted measure of the relative performance of a portfolio. It is easy to calculate given the fact that historical price data and pre-calculated information ratios for funds are widely available. The information ratio deducts the effect of market movements from returns and adjusts for the risk taken. This makes it a single number that neatly summarises the element of performance that can be attributed to good fund management. It also has the advantage that it does not depend on the period over which it is measured. This means that when comparing a fund that only has a short history with one that has a long history,
once can directly compare the information ratios calculated using the full histories of both funds, using the most accurate numbers for each.

**4.3.2.3 Measure of Information Ratio**

The information ratio shows how much abnormal return per unit of unsystematic risk is being generated by the portfolio which could have being diversified away by holding a market portfolio.

\[
\text{Information Ratio} = \frac{\text{Alpha (Fund Risk Premium)}}{\text{Unsystematic Risk (Fund Risk Premium)}}
\]

**4.3.2.4 Interpretation of Information Ratio**

The higher the Information ratio, the more consistent a manager is and consistency is an ideal trait. A high IR can be achieved by having a high return in the portfolio, a low return of the index and a low tracking error. This can be better substantiated by an example.

Manager A might have returns of 13% and a tracking error of 8% while Manager B might have returns of 8% and tracking error of 4.5%. The index has returns of -1.5%.

Now Manager A's IR = \([13-(−1.5)]/8 = 1.81\) and Manager B's IR = \([8-(−1.5)]/4.5 = 2.11\).

In the above example Manager B had lower returns but a better Information ratio. A high ratio means a manager can achieve higher returns more efficiently than one with a low ratio by taking on additional risk. Additional return could be achieved through leveraging.

So, in conclusion, the higher the information ratio, the better it is. If the information ratio is less than zero, it means the active manager was not able to fulfill the first objective of outperforming the benchmark. Holistically speaking, an information ratio in the 0.40-0.60 range is considered quite commendable. Information ratios of 1.00 for long periods of time are a rarity. Typical values for information ratios vary by asset class.

**4.3.2.5 Criticisms and Limitations of Information Ratio**

The information ratio is a benchmark-relative statistic. It is not impossible for a manager to have a high information ratio but still show significant losses if the benchmark is down.

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One of the main criticisms of the Information Ratio is that it considers arithmetic returns and ignores leverage. This can lead to the Information Ratio calculated for a manager being negative when the manager produces alpha to the benchmark and vice versa. A better measure of the alpha produced by the manager is the Geometric Information Ratio.

4.4 RATIONALE FOR CONSIDERING COINTEGRATION & ERROR CORRECTION MODEL AS PARAMETERS FOR EVALUATING THE NATURE OF PRICE CO-MOVEMENT

4.4.1 Cointegration As A Parameter For Evaluating The Nature Of Price Co-Movement

4.4.1.1 INTRODUCTION TO COINTEGRATION

Cointegration, developed by Engle and Granger in 1987, is an econometric technique for testing the relationship between non-stationary time series variables. If two or more series each have a unit root, that is $I(1)$, but a linear combination of them is stationary, $I(0)$, then the series are said to be cointegrated. Both Robert Engle and Clive Granger shared the Bank of Sweden Prize in Economic Sciences in Memory of Alfred Nobel in 2003, for Granger’s contribution to the development of cointegration.

4.4.1.2 CONCEPT OF COINTEGRATION

The concept of cointegration can be illustrated by an example, a stock market index and the price of its associated futures contract. While both follow a random movement, they will be in a long-run equilibrium and deviations from this equilibrium will be stationary. Another humorous example can be of two drunks having two random walks wandering around. The drunks are strangers to each other, so there’s no meaningful relationship between their paths. But suppose instead there is a drunk walking with her dog. This time there is a connection. We will notice that although each path individually is still an unpredictable random walk, given the location of one of the drunk or dog, we have a pretty good idea of where the other is. Therefore the distance between the two is fairly
predictable. If the dog wanders too far away from his owner, she'll tend to move in his
direction to avoid losing him, so the two stay close together despite a tendency to wander
around on their own. We describe this relationship by saying that the drunk and her dog
form a cointegrating pair.

In more technical terms, if we have two non-stationary time series X and Y that become
stationary when differenced such that some linear combination of X and Y is stationary,
then we say that X and Y are cointegrated. That is, while neither X nor Y alone moves
around a constant value, some combination of them does, so we can think of cointegration
as describing a particular kind of long-run equilibrium relationship.

4.4.1.3 Measure Of Cointegration

Mathematically speaking, cointegration is said to exist if the residuals from a regression
analysis of non-stationary series is stationary. Engle–Granger two-step method states that if
two variables are cointegrated, a linear combination of them must be stationary.

The Engle–Granger Two–Step Modelling Method (EGM)

Among a number of alternative methods, the EGM, originally suggested by Engle and
Granger in 1987, has received appreciation in the recent times. One of its benefits is
that the long-run equilibrium relationship can be modeled by a straightforward
regression involving the levels of the variables. The long-run (cointegrating) regression
can be expressed as:

\[ C_t = \beta Y_t + u_t \]

Where, both \( C_t \) and \( Y_t \) are nonstationary variables and integrated to order one \([C_t \sim I(1) \text{ and } Y_t \sim I(1)]\). In order for \( C_t \) and \( Y_t \) to be cointegrated, the necessary condition is that the
estimated residuals from the above regression equation should be stationary \([u_t \sim I(0)]\).

Since the variables in the above equation are non-stationary, one should place little faith
in the standard error estimates in the cointegrating regression. Therefore, less importance
can be attributed to the standard statistical tests on $R^2$ or $t$-statistics of the estimated coefficients unless a correction procedure is employed to eliminate the bias.

The second step involves estimating a short-run model with an error-correction mechanism (ECM) by the Ordinary Least Square (OLS) method. According to the Granger Representation Theorem (GRT), if a number of variables, such as $C_t$ and $Y_t$, are cointegrated, then there will exist an error-correction mechanism relating these variables and vice versa. Conditional on finding cointegration between $C_t$ and $Y_t$, the estimate of $\beta$ from the first step long-run regression may then be imposed on the following short-run model with the remaining parameters being consistently estimated by the OLS method.

Thus, we retrieve the estimate of $\beta$ from the above equation, and insert it in place of $\beta$ in the error-correction term $(C_t - \beta Y_t)$ in the following short-run equation:

$$\Delta C_t = \alpha_1 \Delta Y_t + \alpha_2 (C_t - \beta Y_t)_{t-1} + \epsilon_t$$

Where, $\Delta$ represents first-differences and $\epsilon_t$ is the error term. Alternatively, in practice, since $C_t - \beta Y_t = u_t$, one can substitute the estimated residuals from the first equation in place of the error-correction term, as the two will be identical. Note that the estimated coefficient $\alpha_2$ in the short-run the second equation should have a negative sign and be statistically significant. Note also that, to avoid an explosive process, the coefficient should take a value between $-1$ and $0$. According to the GRT, negative and statistically significant $\alpha_2$ is a necessary condition for the variables in hand to be cointegrated. In practice, this is regarded as a convincing evidence and confirmation for the existence of cointegration found in the first step. It is also important to note that, in the second step of the EGM, there is no danger of estimating a spurious regression because of the stationarity of the variables ensured. A combination of the two steps then provides a model incorporating both the static long-run and the dynamic short-run components.
4.4.1.4 INTERPRETATION OF COINTEGRATION

The concept of Cointegration has a wide repertoire of application. Firstly, the statistical concept of cointegration is required to make sense of regression models with non-stationary data. It is most often associated with economic theories that imply equilibrium relationships between time series variables. A test of cointegration can be thought as a pretest to avoid “spurious regression” with non-stationary time series. Cointegration is said to exist between a mutual fund scheme and a suitable benchmark if they have a long term, equilibrium relationship between them. This relationship is expressed as follows:

\[ \text{Fund NAV}_t = \beta_0 + \beta_1 \times \text{NIFTY Price}_t + U_t \]

4.4.1.5 CRITICISMS AND LIMITATIONS OF COINTEGRATION

Cointegration is one of the greatest tools used by contemporary economists and financial researchers in identifying and studying long run equilibrium relationships between related variables. However, users of cointegration have to keep the following issue in mind while applying this concept in their research studies:

- Cointegration tests very often fail to recognize causal relations.
- Similarly, on the other hand, cointegration approach does not always avoid the peril of accepting spurious relationships as causal relations.
- Also many a times it happens that a little problem of misspecification in the form of the relation between truly cointegrated economic variables leads to an existence of no cointegration among the variables.
4.4.2 Error Correction Model As A Parameter For Evaluating The Nature Of Price Co-Movement

4.4.2.1 Introduction To Error Correction Model

In an extremely influential and important paper titled “Co-integration and Error correction: Representation, Estimation and Testing”, Engle and Granger in March 1987 showed that cointegration implies the existence of an Error Correction Model. Error correction models are multiple time series models that can be used to estimate the following quantities of interest for all variables:

- Short term effects of X on Y
- Long term effects of X on Y (long run multiplier)
- The speed at which Y returns to equilibrium after a deviation has occurred.

ECMs are useful for estimating both short term and long term effects of one time series on another. Although, ECMs are useful models when dealing with integrated data, they can also be used with stationary data as well.

4.4.2.2 Concept Of Error Correction Model

The error correction model (ECM) links the long-run equilibrium relationship implied by cointegration with the short run dynamic adjustment mechanism that describes how the variables react when they move out of long-run equilibrium. Thus ECM makes the concept of cointegration useful for modelling financial time series. The tight linkage between cointegration and error correction models stems from the Granger representation theorem. According to this theorem, two or more integrated time series that are cointegrated have an error correction representation, and two or more time series that are error correcting are cointegrated. In short, the two concepts are isomorphic, as each implies the other.
4.4.2.3 Measure Of Error Correction Model

\[ \Delta \text{Fund NAV}_t = \alpha_0 + \alpha_1 \times \Delta \text{NIFTY Price}_t + \alpha_2 \times U_{t-1} + \varepsilon_t \]

4.4.2.4 Interpretation Of Error Correction Model

From the Cointegrating equation the following can be concluded:

\[ Y_t = \beta_0 + \beta_1 X_t + U_t. \]

\( \beta_1 \) represents the proportion of change in the independent variable that gets reflected in the dependent variable in the long run.

- The equilibrium effect that \( X \) has on \( Y \) \( \rightarrow \) The causal effect that occurs over future time periods.

Additionally from the Error Correction Model the following can be concluded:

\[ \Delta Y_t = \alpha_0 + \alpha_1 \Delta X_t + \alpha_2 U_{t-1} + \xi_t \]

\( \alpha_1 \) represents the proportion of change in the independent variable that gets reflected in the dependent variable in the current period.

- The immediate effect that \( X \) has on \( Y \) \( \rightarrow \) The simultaneous or short-term effect

\( \alpha_2 \) denotes the proportion of discrepancy in the long run equilibrium relationship of the previous period that gets adjusted in the current period.

- The rate at which the long term effect that \( X \) has on \( Y \) occurs

4.4.2.5 Criticisms and Limitations Of Error Correction Model

The Engle-Granger two step method has several limitations, as follows:

- Firstly, it identifies only a single cointegrating relation, among many such relations. This requires one of the variables, \( Y_{1t} \), to be identified as "first" among the variables in \( Y_t \). This choice which is usually arbitrary, affects both test results and model estimation.

- Secondly, the method is a two-step procedure, with one regression to estimate the residual series, and another regression to test for a unit root. Errors in the first
estimation are necessarily carried into the second estimation. The estimated, rather than observed, residual series requires entirely new tables of critical values for standard unit root tests.

- Finally, the method estimates cointegrating relations in two steps. As a result, model estimation also becomes a two-step procedure.

4.5 SELECTIVE IMPORTANT AND RELEVANT ASPECTS OF DATA ANALYSIS

4.5.1 Sampling Scheme

Judgmental sampling is a method of non random sampling where personal knowledge and opinion are used to identify the items from the population that are to be included in the sample. Such samples are very convenient. However, the feasibility of conducting rigorous statistical analysis with judgmental sample(s) is a question of validity. Since the study focused on performance of the ten largest large cap mutual fund schemes by asset size as on January 2011 (beginning of the period of study) this was a case of judgmental sampling.

However, given the fact that the research was undertaken with an objective of enabling the retail investors in identifying whether they should follow the same investment strategies or take discriminatory stances in case of bear and bull phases, it was imperative to consider the mutual fund schemes that were managing a significant amount of investors’ corpus. From that perspective, selecting the mutual fund schemes based on highest average assets under management (AAUM) was logical and the best method of sampling possible in the given research context.

4.5.2 Survivorship Bias

Survivorship bias, or survival bias, is the logical error of concentrating on people or things that "survived" some process and inadvertently overlooking those that did not because of their lack of visibility. This can lead to false conclusions in several different ways.
Survivorship bias can lead to overly optimistic beliefs because failures are ignored, such as when companies that no longer exist are excluded from analyses of financial performance. It can also lead to the false belief that the successes in a group have some special property, rather than just coincidence. For example, if the three of the five students with the best college grades went to the same high school that can lead one to believe that the high school must offer an excellent education. This could be true, but the question cannot be answered without looking at the grades of all the other students from that high school, not just the ones who ‘survived’ the selection process.

Since the large cap mutual fund schemes have been identified from the list of average assets under management (AAUM) at the beginning of the sampling period, hence this study is free of survivorship bias.

4.5.3 **Details About Periodicity Of Analysis**

All analysis has been performed at weekly rests. A week, for the purpose of this analysis, means a span of five days starting on Monday and ending on Friday. Wherever Monday was a trading holiday, the next trading day has been considered. Wherever Friday was a trading holiday, the previous trading day has been considered (Refer to Table 4.5.3.1)

Also although Friday 28 December 2012 was a trading day yet Monday 31 December 2012 was considered as the concluding day for the concerned week since it was the last trading day of the sample period.

Although markets were open on certain Saturdays, yet the same has been ignored because of lack of availability of net asset value (NAV) details of some of the selected mutual fund schemes. Details of these above mentioned date are mentioned as below:

1. Saturday 7 January 2012.
2. Saturday 28 April 2012 and
4.5.4 Relevance of Benchmarking Large Cap Mutual Fund Schemes with NIFTY

Benchmarking is a critical issue in regard to analysis of performance of mutual fund schemes. For researchers in this field, a common dilemma is whether to use an existing index as the benchmark or to create a custom one. The most important advantage of a custom benchmark over a standard market benchmark is that it accounts for the unique characteristics of the fund manager. If the fund manager specialises in small cap growth stocks then the benchmark should also be made up of small cap growth stocks. In fact, the ideal benchmark should be able to explain all of the returns generated by the manager that come from the various systematic factors e.g., style, market movements etc.

In the current research work, NIFTY has been used as a benchmark. The choice seems ideal on the basis of the following arguments.

- NIFTY is composed of 50 large cap stocks of the National Stock Exchange; hence NIFTY becomes a logical match with large cap mutual fund schemes in regards to benchmarking.

- Correlation analysis between the logarithmic returns of the selected large cap mutual fund schemes and Nifty for the in-sample period shows existence of very high correlation. Refer to Figure 4.5.4.1 for a time series plot of the returns of selected large cap mutual fund schemes and NIFTY. The diagram shows stationarity of the data and justifies acceptance of correlation value as a reliable statistic. Refer to Table 4.5.4.1 for the respective correlation values along with p values under the null hypothesis of no correlation.

Further, during the analysis, cointegration analysis has been performed amongst the rebased net asset value (NAV) of the selected mutual fund schemes and the rebased prices of NIFTY for the in-sample period. The cointegration analysis too highlights existence of a
long term relationship between most of the selected mutual fund schemes and NIFTY, which augments well with the correlation analysis and the choice of the benchmark.

4.5.5 **Errors, Powers & Significance Levels Considered**

In statistics, a Type I Error means the probability of rejecting a true null hypothesis whereas a Type II Error means the probability of failing to reject a false null hypothesis. The Power of a Test, on the contrary, means the probability of correctly rejecting a false null hypothesis. Thus Power of a test = 1 – Type II Error.

Statistical rules recommend that the Power of a test can be increased by increasing the significance level. This is so since higher the significance level, higher is the Power of the test. Conversely, a lower significance level signifies, lower Power of a test, higher probability of a Type II Error and simultaneously a lower probability of Type I Error.

In the context of the current research work, if a true null hypothesis is rejected (i.e. Type I Error) then it signifies that an investor will invest in an underperforming fund. Conversely, if a false null hypothesis is failed to be rejected (i.e. Type II Error) then it signifies that an investor will miss out a good investment opportunity. Hence a Type II Error is preferred over a Type I Error.

So significance level for all statistical tests performed under the current research had been kept moderate in order to accommodate a relatively lower probability of Type I Error. The significance level had been kept at 95%, although in social sciences mostly alpha is considered at 99%.

4.5.6 **The Issue Of Finite Population Multiplier**

In statistics, if the population is finite and the sampling is done without replacement, then the standard error of the mean is calculated with the help of the Finite Population Multiplier.
However, when the size of the population is very large relative to the size of the sample, the finite population multiplier takes a value close to 1 and has no effect on the calculation of the standard error.

Since the current research work is on time series data, thus it can be said that the population (return series, which can be annually, quarterly, daily etc) is infinite. So the Finite Population Multiplier is not required.

On the other hand, it can also be argued that the size of the population (total number of bull/ bear periods till date) is very large relative to the size of the sample (one bull and one bear period). This further negates the need of a Finite Population Multiplier.

4.6 EVALUATION OF RELEVANT RESEARCH WORKS TO AID DATA ANALYSIS

4.6.1 INTRODUCTION

Analysis can be both qualitative as well as quantitative in nature. Parametric analysis is specific in terms of application. Yet, the approach, methodology and interpretation of any analytical method would significantly be influenced by the context and background of the research work undertaken.

In this section, the issues (complementary as well as contradictory) relating to the analytic methods used have been addressed through an exhaustive literature review of mutual fund performance evaluation methods and measures. Given the extent of research work already undertaken in this field, the existing literature has rich vastness in itself. It was a challenging task to select and present a few. The ones presented herein do in no way however indicate their supremacy over the ones not presented.

4.6.2 BROAD OBSERVATIONS

The following few segments acknowledges the various literatures that have significantly helped in depicting the analytical approaches of the research work. Initially, the various relevant literatures from newspaper articles, websites, magazines and journals etc. that
have discussed the broad issues related to approaches towards measuring beta of a mutual fund scheme have been extensively reviewed and subsequently presented in a brief manner. Subsequently a few literatures which explore the issue of conducting a one tailed test of hypothesis have been reviewed and briefly presented along with. Thereafter this review puts forward the opinions in context to dealing with the issue of a low Durbin Watson value in the cointegrating equation and follows up with a synopsis of the research works in regard to certain computational issues of the error correction model.

4.6.3 APPROACH TOWARDS MEASURING BETA OF A MUTUAL FUND

Beta i.e. sensitivity of the returns of a mutual fund scheme to the returns of the benchmark is an extremely important measurement for a quantitative evaluation of mutual fund performance. Thus the question how to measure beta in real life, is an enduring one and has been the subject matter of interest for several researchers over the last few decades.

4.6.3.1 FINDINGS OF THE REVIEW

Handa, Kothari & Wasley (1989) studied the impact of size effect i.e. the length of the return interval used in estimating betas. In their study, evidence from cross-sectional regressions of returns on monthly and annual betas is inconsistent with beta changes stemming only from the higher standard errors of the longer-interval betas. They provided evidence that the size effect becomes statistically insignificant when risk is measured by betas estimated using annual returns.

Daves, Ehrhardt and Kunkel (2000) while evaluating systematic risk for the purpose of capital budgeting used the Capital Asset Pricing Model approach for the purpose of estimating the firm’s cost of equity. The beta value, which is a necessary input for the Capital Asset Pricing Model is estimated through a time series regression. Their study examined which return interval and estimation period the financial manager should
select when estimating beta. The results showed that the financial manager should select the daily return interval and an estimation period of three years or less.

**Armitage & Brzeszczynski (2011)** compared beta estimates obtained from ordinary least square regression with estimates corrected for heteroscedasticity of the error term using ARCH models, for 145 UK shares. The differences found were mainly less than 0.10, for betas calculated using daily returns.

**Ryu (2011)** studied the distortions in financial measures while using high frequency stock price data. In her study, using mean square error as the measure of accuracy in beta estimation, she found out that the optimal pair of sampling frequency and the trailing window was empirically found to be as short as 1 minute and 1 week, respectively. Moreover, the realized beta obtained from the optimal pair outperformed the constant beta from the CAPM when overnight returns were excluded. The comparison further strengthened the argument that the underlying beta is time-varying.

**4.6.3.2 PRIMA FACET CONCLUSION**

Daily returns have been used for beta calculation in this research work. This is because historical beta can be calculated even with only two pairs of data sets. Moreover the beta which has being calculated in this research work is for evaluation purpose and not forecasting. Finally evidence of bias in beta (for the short period) is primarily associated with high risky/volatile stocks, which large cap stocks essentially are not.

**4.6.4 SALIENT FEATURES OF PERFORMING ONE TAIL TEST OF HYPOTHESIS**

The main problem in conducting a test of hypothesis in any popular statistics/econometrics software is that all these packages provide an option to run a two tailed test of hypothesis. The problem is not very serious in case of tests of hypothesis where the nature of the statistical distribution is symmetric in nature. However, if the distribution is asymmetric, the problem aggravates.
4.6.4.1 **Findings Of The Review**

An article by **SPSS Tutorial** discussed how to use SPSS version 12.0 to perform one-sample t-tests. The article specified that SPSS generates a two-tailed significance (the two-tailed p value.) But if the hypothesis is a one tailed hypothesis, then there is no option to specify a one-tailed test in SPSS. In that situation the table of critical t values has to be referred to determine the applicable critical value.

Another help guide in **IBM Support Portal** specified that SPSS has no specific procedure or dialog box to run a one-tailed test for differences of means. The procedure for the one-tailed test is the same as for the two-tailed test. There are two issues here, though. First is to have an idea of which direction the t-statistic has to go. If one expects that the first group has a higher mean than the second group, then one needs to look for a positive t-statistic (since SPSS will use the mean of group 1 minus the mean of group 2 as the numerator in computing the t statistic). The significance for such one tailed test is the displayed significance divided by two. Since the t statistic has a symmetrical distribution, the "significant" tails will have the same probability (e.g. in a two-tailed test, a .05 criteria reflects that the .025 tails will reflect significance). Since a one tail test looks at only one of the two tails, the researcher should divide the significance in half to determine if the t statistic is significant or not.

4.6.4.2 **Prima Facet Conclusion**

SPSS has no specific procedure or dialog box to run a one-tailed test for differences of means. However since the t statistic has a symmetrical distribution, a one tail test looks at only one of the two tails. Thus the researcher should divide the significance in half to determine if the t statistic is significant or not.
4.6.5 **Considerations Regarding Low Durbin Watson Values in Cointegration**

In order to be considered valid, an ordinary least square (OLS) regression needs to generate residuals that are not auto correlated. A measure of autocorrelation is the Durbin Watson value. A Durbin Watson value close to 2 means no autocorrelation while a Durbin Watson value close to 0 & 4 means positive and negative autocorrelation respectively. According to Granger and Newbold, an $R^2 > d$ is a good thumb rule to suspect an invalid (spurious) regression.

However, in case of the cointegrating equation between two variables that share a long term equilibrium relationship, the abovementioned is not a necessary condition. What follows is a discussion on the same based on notable published research work.

4.6.5.1 **Findings of the Review**

In an article published by the Warwick University, on cointegration, the conclusion was drawn that the Durbin Watson statistic for the cointegrating equation does not make any statistical sense: "...The traditional diagnostic tests from the cointegrating equation are unimportant as the only important question is the stationarity or otherwise of the residuals..." However, the Durbin Watson statistics can be improved if some alternative to the ordinary least square (OLS) regression method is used: "...The estimates from OLS in the cointegrating equation, although consistent, can be substantially biased in small samples, partly due to serial correlation in the residuals. The bias can be reduced by allowing for some dynamics. In stage (i) we can estimate, with OLS, an ADL model..."

In a discussion paper, Dolado, Gonzalo & Marmol (1999) discussed that residual autocorrelation is applicable not for the cointegrating equation but only in the error correction model. They argued that the sufficient condition in the cointegrating equation is that the cointegrating residuals are I (0) i.e. stationary. They also pointed out to the fact that given the super consistency of the beta term in the cointegrating relation, their
asymptotic distributions will be identical to using the true value of the beta. However, all the variables in the error correction model are I(0) i.e. stationary and hence conventional modeling strategies (e.g., testing the maximum lag length, residual autocorrelation or whether the estimated value of the coefficients is zero, etc.) can be applied to assess model adequacy. They further pointed that instead of using the ordinary least square (OLS) regression method, if some other method like Fully Modified OLS, Dynamic OLS etc could have been used in determining the cointegrating relation, then the problem would have been minimized. Refer to the following excerpt: "The procedure, denoted as a fully modified ordinary least squares estimator (FM-OLS), is based upon a correction to the OLS estimator by which the error term $zt$ is conditioned on the whole process \{$Dy_t$\} _{t = 0, ± 1,... and, hence, orthogonality between regressors and disturbance is achieved by construction..."

In one of his lecture series, Nielsen (2005) presents an example of a valid cointegrating equation that shows a horribly low Durbin Watson statistic. However the R squared value was less than the Durbin Watson statistic.

In his blog on econometrics, Giles (2012) shows a horribly low Durbin Watson statistics for a valid cointegrating regression equation. This time even the R squared value is more than the Durbin Watson statistic. Going forward the author admits to the severe autocorrelation among the residuals and tries to fix the same by adding lagged values of the dependent as well as independent variables in the cointegrating equation. However in the comments section the following question-answer seems interesting:

Question made by a visitor: "Is there a need to correct for autocorrelation in the residuals of the cointegrating regression? Wouldn't the OLS estimates of the regression be *super consistent* as long as cointegration exists? Am I right in saying that since we are not
making any inference on the coefficients of the cointegrating regression, there is no need to correct for autocorrelation?"

Response provided by Giles. “In general, that's correct. However, in my example I was interested in the long-run relationship itself (beyond using it to test for cointegration). To get a sensible inference about the long term relationship, I really needed to allow for the autocorrelation.”

4.6.5.2 **Prima Facet Conclusion**

Autocorrelation of residuals is a deterrent factor towards validation of an ordinary least square (OLS) regression. However, as long as the Error Correction Model is satisfying all necessary conditions of statistical validation, a cointegrating equation with a low Durbin Watson statistics is valid and acceptable.

4.6.6 **Methods Of Validating The Parameters Of Error Correction Models**

The usual statistical properties regarding validity of the regression are not applicable in regard to the cointegrating equation. Hence the parameters of the cointegrating equation cannot be used for statistical inference. However, given the fact that all the constituent variables of an Error Correction Model are I (0) i.e. stationary in nature, it can hence be intuitively used for inferential purpose. A review regarding validity and applicability of this hypothesis is presented below.

4.6.6.1 **Literature Review**

In their highly popular article *Kremers, Ericsson & Dolado* (1992) delved into the issue of contrasting inferences about the presence of cointegration that often appear in empirical investigations. The most common observation is that in applying the commonly used 'two-step' procedure proposed by Engle and Granger (1987), the Dickey-Fuller unit-root test only marginally rejects the null hypothesis of no cointegration, if it rejects at all. By contrast, the coefficient on the error-correction term in the corresponding dynamic model
of the same data is 'highly statistically significant', strongly supporting cointegration. Since both procedures are tests of cointegration, the existence of such a contrast raises inquisitiveness? Kremers et al tried to generate a plausible explanation centering on an implicit common factor restriction imposed when using the Dickey-Fuller statistic to test for cointegration. If that restriction is invalid, the Dickey-Fuller test remains consistent, but loses power relative to cointegration tests that do not impose a common factor restriction, such as those based upon the estimated error correction coefficient. In their article, they examined the asymptotic and finite sample properties of the two procedures for a simple, single-lag, bivariate process and found that even with more lags and more variables, the reason for the low power of the Dickey-Fuller test remains. They concluded that the error correction based test is preferable because it uses available information more efficiently than the Dickey-Fuller test.

In a research paper, Turner & Kanioura (2003) generated critical values for a test for cointegration based on the joint significance of the levels terms in an error correction equation. They showed that the appropriate critical values were higher than those derived from the standard F-distribution. Subsequently they compared the power properties of this test with those of the Engle-Granger test and Kremers et al’s t-test based on the t-statistic from an error correction equation. Their results revealed that F-test has a higher power than the Engle-Granger test but lower power than the t-form of the error correction test. However, the F-form of the test has the advantage that its distribution is independent of the parameters of the problem being considered.

Rocha (2006) verified a claim made by Jansen (1996) and Jansen and Schulze (1996), that an error correction model would be the correct specification to estimate saving-investment correlations. In her paper she also verified how serious is the potential bias from using regressions in levels and in first differences instead of an error correction
model. Throughout her paper, the t test was used for statistically validating the parameters of the Error Correction Model.

In a lecture series presentation by Barunik (2010/11), he referred to an alternative test of cointegration other than the Dickey Fuller test of stationarity of residuals. The alternative test suggested was the test developed by Sargan and Bhargava in 1983 in which the null hypothesis refers to testing for a Durbin Watson value equal to zero signifying no cointegration with the alternative hypothesis being the Durbin Watson value being more than zero signifying existence of cointegration. This test is applicable only if the residuals follow a first order auto regression.

4.6.6.2 PRIMA FACET CONCLUSION

The tight linkage between cointegration and error correction models stems from the Granger representation theorem. According to this theorem, two or more integrated time series that are cointegrated have an error correction representation, and two or more time series that are error correcting are cointegrated (Engle and Granger 1987). In short, the two concepts are isomorphic, as each implies the other. Hence based on the representation theorem and the findings of the above mentioned literatures, the error correction based test of cointegration would be preferred to the Dickey–Fuller test of stationarity of cointegration residuals. Also the parameters of the error correction model would be statistically validated by testing through the t test.

4.6.7 FINDINGS DERIVED FROM EVALUATION OF RELEVANT RESEARCH WORKS

The objective of the abovementioned literature review was to determine certain baseline norms relating to carrying forward the analytical aspects of the research work. In that regard, the literature review established the following considerations that have been incorporated in the analytical methods adopted subsequently:

- Beta would be calculated based on daily data.
• For undertaking one tail test of hypothesis, the p value generated by SPSS would be divided by two (2), provided the underlying test statistic follows a symmetric distribution.

• In case of cointegration analysis, a low Durbin Watson statistics would not be a cause of concern as long as the residuals of the cointegrating equation are stationary.

• The error correction based test of correlation would be preferred to residual based test of correlation.

• The parameters of the Error Correction Model can be statistically validated by t test.
OUTCOMES OF THIS CHAPTER

The research work undertaken, as elaborated in this chapter, had helped in establishing the following understandings:

- The Sharpe and Treynor ratios and the Jensen’s alpha were used as measures of risk adjusted return. Sharpe ratio is often used to compare the change in a portfolio's overall risk-return characteristics when a new asset or asset class is added to it. On the other hand, the Treynor ratio is useful in determining how a particular investment contributes to a diversified portfolio. Jensen’s alpha is the difference between the actual return earned by the security and the theoretical return predicted by the market model with the same level of risk.

- The Eugene Fama model and the Information ratio were used as measures of fund manager’s decision making abilities. The Eugene Fama model gives the excess return over and above the return required to compensate for the total risk undertaken by the fund manager. Higher value of this measure indicates that the fund manager has earned returns well above the return required to commensurate with the level of risk taken by him/her. The information ratio shows how much abnormal return per unit of unsystematic risk is being generated by the portfolio which could have being diversified away by holding a market portfolio.

- Cointegration and Error Correction Model have been used for evaluating the nature of price movement. The concept of Cointegration is most often associated with economic theories that imply equilibrium relationships between time series variables. Error Correction Models, on the other hand, are multiple time series models that are useful for estimating both short term and long term effects of one time series variable on another.