Major Project Report on

DETERMINANTS AND PREDICTION OF MUTUAL FUNDS PERFORMANCE

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CERTIFICATE

This is to verify that the Project Report titled "**DETERMINANTS AND PREDICTION OF MUTUAL FUND PERFORMANCE**", is a bonafide work carried out by Deepanshu Sharma of EMBA 2018-20 and submitted to Delhi School Of Management, Delhi Technological University, Bawana Road, Delhi-110042 in partial fulfillment of the requirement for the award of the Degree of Masters of Business Administration (Executive).

Signature of Guide	**Signature of Head (DSM)**
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DECLARATION

I, **Deepanshu Sharma** student of EMBA 2018-20 of Delhi School Of Management, Delhi Technological University Bawana Road Delhi -110042 declare that Dissertation Report on **"DETERMINANTS AND PREDICTION OF MUTUAL FUNDS PERFORMANCE"** submitted in partial fulfillment of Degree of Masters Of Business Administration (Executive) is the original work conducted by me.

The information and data given in the report is authentic to the best of my knowledge. This report is not being submitted in any other university for award of any other Degree, Diploma and Fellowship.

Place: Delhi

Date: **DEEPANSHU SHARMA**

ACKNOWLEDGEMENT

Accomplishment of a task with desired feat demands devotion to work and prompting direction, co-operation from seniors.

At the outset I would like to thank Dr. Deep Shree, Assistant Professor, Delhi School of Management for her backing and specialized methodology in supervising me through the watchful details of the project.

I would be failing in my duty if I do not express my deep sense of gratitude to Dr Rajan Yadav, H.O.D and all the faculty members for their valuable advice and guidance in this project.

EXECUTIVE SUMMARY

Mutual funds are a very important and distinct segment of the financial market. Mutual funds group money from different investors and spend in different investment foundations like stocks, shares, bonds etc. A specialized fund manager manages these, and earnings are paid in form of dividends. Some arrangements guaranteed fixed returns that are less in risk and some offer dividends built on the market variations and prices. Mutual funds have to be contributed in units and the buying or sale is reliant on NAV (Net Asset Value), taking into respect the exit and entry load aspects into account. There are several funds and arrangements accessible in mutual fund marketplace. People recognize how much risk they can digest and based on that have to choose arrangements.

With the rising risk wish, increasing pay, and swelling consciousness, mutual funds in India are attractive and a favored choice to invest in. During the period of last 4-5 years, there has been a visible rise and an intense growth in the Indian MF industry with many private actors adding and bringing worldwide capability to the Indian MF Industry. Risk may be defined as the chance of differences in actual return. Return is defined as the gain in the worth of asset. The return on an investment portfolio aids an investor to assess the financial performance of the investment. This study aims to perform an analysis on some of the mutual fund schemes that are available in India and to provide an insight into the determinants that affect the mutual fund performance in different time span. The study also tries to make use of data analytics to predict the performances of selected mutual fund schemes and to indicate/recommend the schemes which are good investment options for an individual in the short span as well as for the long term.

TABLE OF CONTENTS

1. INTRODUCTION

1.1 Concept of Mutual Fund

Mutual funds are multinationals who group money through investors at great and propose to trade and acquire back its shares on a continuous way and utilize the money therefore raised up to benefit from securities of different firms. The shares these MF's consist are very liquid and utilized to purchase or redeem and/or selling out stocks at NAV value. Mutual funds own stocks of numerous firms and obtain bonuses in place of them and the earnings are dispersed among the investors. Mutual funds remain considered as foundations for helping small investors with paths to invest in the capital marketplace. As small investors usually don't have adequate time, information, skill along with ways to openly access the capital market, they rely on an intermediate, which commences learned investment conclusions and delivers significant assistances of specialized skill. Mutual funds derived into existence in the year 1963 under public segment. The first corporation to start the mutual funds was UTI and its first arrangement was us-64, it was like a domination status in the field and was an certain frontrunner.

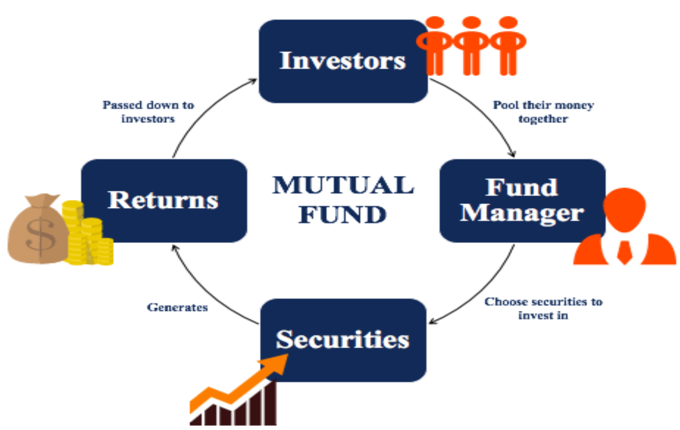


Figure 1: Mutual Fund – Participation Procedure

Procedure of participating in MF consists of:-

- Pulling cash with the Fund Manager
- Capitalize in different securities by Fund Manager
- Returns produced by securities
- Deliver back returns

1.2 Reason for Growth of Mutual Fund

Nowadays there are numerous ways and also choices to invest in, going from recurrent deposits to postal saving schemes. But investment in mutual funds has developed quiet enormously and still rising. The causes for such evolution in mutual funds can be credited to the detail that outlay in them can be done with ease. Nowadays time is a big restriction for individuals, limited individuals have the time to shadow stocks and know the instabilities involved in share market. It is correctly said that stock market is stake. So individuals today need somebody to look afterwards their moneys and propose them concerning their investments. In this condition mutual funds arise to their saving.

Initially a specialized and capable fund manager manages mutual funds. Although investors have the capability and know-how to evaluate and recognize a financial tool but still and methodical and intelligent result making ability of a fund manager is very helpful and vital bearing in mind the knowledge. And also the investors are protected from the job of keeping track of their moneys, not only this since mutual funds let to spend in varied stocks it decreases the risk load. Many firms nowadays have arrangements like stable equity funds which aid them to decrease the risk form. Primary major benefit of mutual funds is the investor can participate with minor volumes every time he has corpus funds with him and also they can be cashed simply as and when the investor needs if he is participating in open ended funds.

Risk and Return Tradeoff

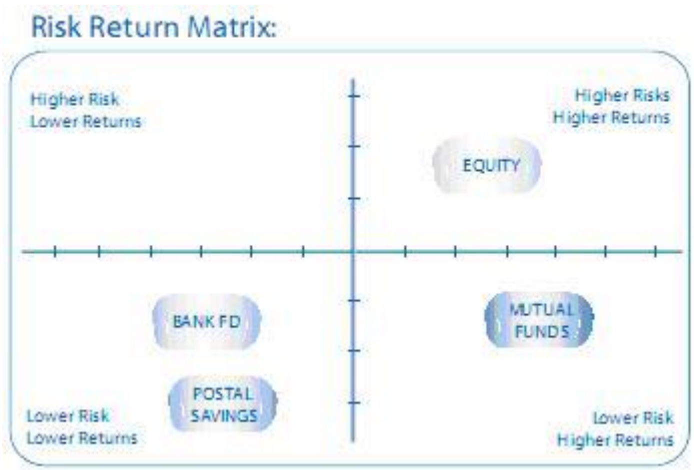


Figure 2: Risk Return Matrix for various investment methods

The risk and return trade-off depicts when financier is ready to go for greater threat then similarly he can assume greater yields and vice versa if relating to lesser threat tools, which will be satisfied by lower yields. A individual moving forward to participate in capital protected funds and the profit-bonds can produce extra return if we compare it to deposits in bank but then again the threat related also rises in the similar amount. Investors select MF's as one of the prime resources of participating, as they deliver expert supervision, broadening, ease and liquidness. But it does not mean that MF's investments are completely free of risk.

1.3 History - Indian MF Industry

Mutual fund sector started in India in the year 1963 through creation of UTI or the Unit Trust of India, through inventiveness of the Indian Govt and Reserve Bank. MF industry's history in India can be generally distributed into four separate stages:-

Phase 1 - Formation and Development of Union Trust

Phase 2 - Admission of Public Sector Funds

Phase 3 - Rise of Private Sector Funds

Phase 4 - Evolution and SEBI Guidelines

In India mutual funds derived into presence in the year 1963 with UTI (unit trust of India). The scheme was the lone mutual fund at that period which was public held and relished a domination rule till a lengthy period. It was overseen under UTI act; 1963, the principal mutual product from UTI was UTI Master Share in 1986. Earlier that the first arrangement tossed by UTI was US-64 followed by CGGF in 1986. In the year 1987 banks and other monetary organizations were permitted to established mutual funds. RBI (reserve bank of India) was made the supporter of mutual funds and as public segment groups came under the purview of RBI they came under the guidelines of RBI. And later on they were together brought below the rules of SEBI and RBI. State Bank Of India (SBI) was the first bank-sponsored mutual fund shadowed by LIC & CAN BANK.

But till that time UTI was the undoubted frontrunner in the marketplace. And later when the upsurge of liberalization arrived in India, in 1993 private sector mutual funds were permitted to arise up. The first private sector mutual fund was JV and JM Kothari pioneer was the main private sector mutual fund, in 1996. The upcoming of private sector mutual funds fetched ground-breaking artifact range, decent administration methods, and investor overhauling methods. With added and more mutual funds with extensive product choice coming up consumers became choosy. In 1996 mutual funds dividends were prepared tax free in the fingers of investor.

Indian MF business is observing a speedy evolution as a effect of growth in infrastructure, rise in individual monetary resources, and growth in overseas involvement. With the rising risk hunger, increasing salary, and growing alertness, mutual funds within India are attractive and a favored invest choice when compared to other asset mechanism like Fixed Deposits, Postal savings that are viewed harmless but provide reasonably low returns, according to “Indian Mutual Fund Industry”. Mutual Fund Industry is instrumental part in the money marketplace nowadays and the quickest rising businesses in the nation.

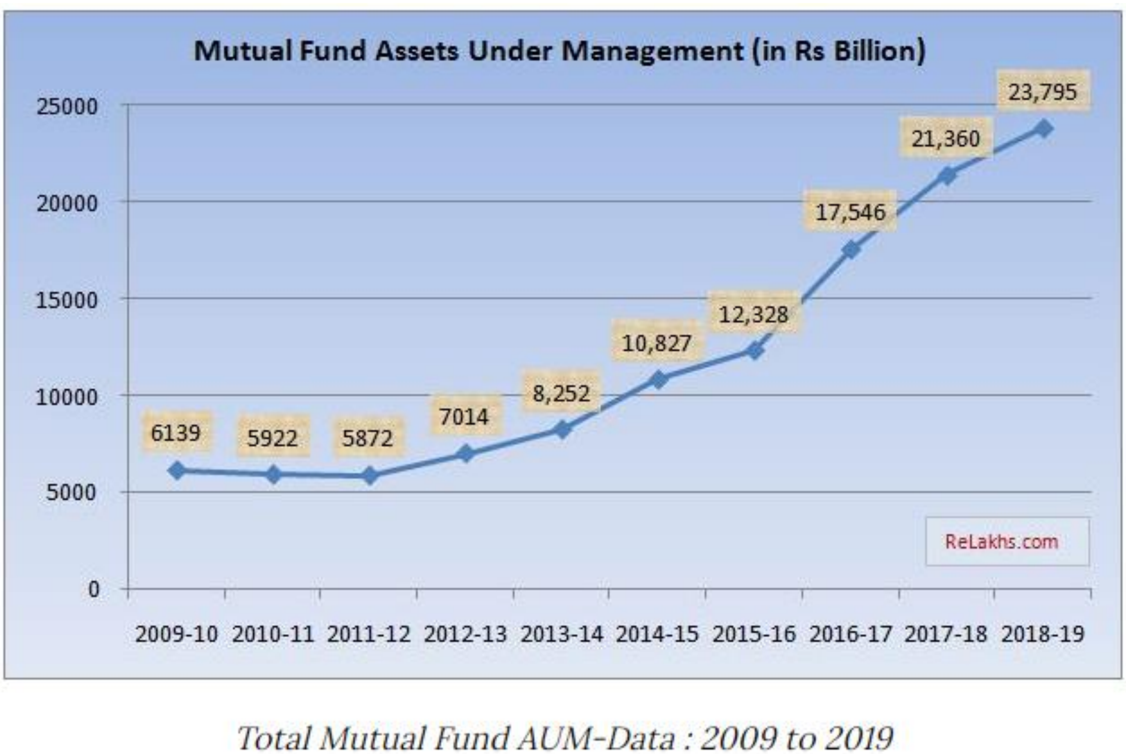


Figure 3: Rise of Mutual Fund AUM

Ten years ago, the entire assets in management (AUM of the Indian mutual fund industry were Rs4.13 trillion (1 trillion equals 1 lakh crore). Over the succeeding five years, the industry raised at a multiple annual growth rate (CAGR) of 15% to take the total AUM to Rs8.2 trillion as on 31 December 2013. Afterward, the Indian mutual fund industry took off like never previously, compounding at 23% CAGR, and winning the total AUM as on 31 December 2018 to Rs22.86 trillion. In just 10 years, Assets under Management of the Indian MF Industry has grown 5.5 time.

As on October 31, 2019 the Assets Under Management (AUM) amounted at ₹26,13,666 crore. As on October 31, 2019 the entire amount of books or folios according to parlance of Mutual Fund stood at 8.63 crore or 86.3 million while the amount of folios under Equity, Hybrid and Solution Oriented Arrangements stood at 7.71 crore or 77.1 million where most of the investment is from retail sector.

1.4 Mutual Fund Industry Worldwide

According to the Investment Company Institute, Mutual fund assets globally at end of 2018 were $46.7 trillion. The nations with the biggest mutual fund activities were:

- United States with $21.0 trillion
- Luxembourg with $4.7 trillion
- Ireland with $2.8 trillion
- Germany with $2.2 trillion
- France with $2.1 trillion
- Australia with $1.9 trillion
- Japan with $1.8 trillion
- China with $1.8 trillion
- United Kingdom with $1.7 trillion

- Brazil with $1.2 trillion

1.5 Objectives of the Study

- To provide a passing idea about the welfares obtainable from investment in Mutual Fund schemes
- To provide an hint of the kinds of arrangements offered
- To study selected mutual fund arrangements
- The elementary purpose of the current study is to provide an understanding of the factors that affect mutual fund performance and the degree to which these factors influence the overall objective
- Perform an study/analysis on mutual fund schemes in India and predict the top performing funds in short and long term, provide best investment options
- Sightsee the new progresses in the mutual funds schemes in India

2. MUTUAL FUND STRUCTURE AND FEATURES

2.1 Types of Mutual Fund Schemes

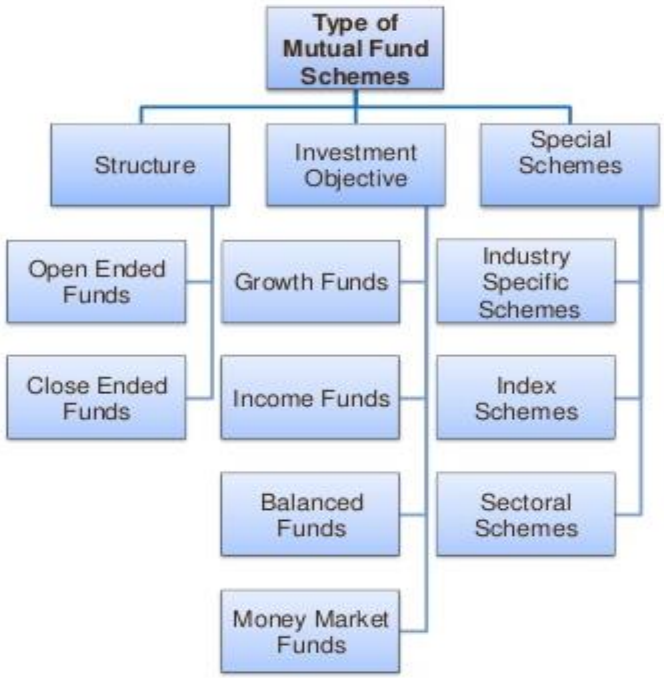


Figure 4: Types of Mutual Fund Schemes

<u>Structure based MF schemes</u>

a) **Open-Ended:** Open-Ended arrangement is up to be subscribed throughout the year. Investors can purchase/trade the units at Net Asset Value or "NAV" linked amount at any period

b) **Close-Ended Funds**: Close-Ended arrangements/ funds are exposed to subscription merely within a definite period, mostly at period of original public offering/issue. Close Ended arrangement are listed on stock exchanges where the investor can purchase/trade the units of Close Ended arrangements. Interval Funds chains together the features of Close-Ended and Open-Ended funds

Investment based MF schemes

a) **Growth Funds**: The aim of such an arrangement is delivering wealth rise over the short/medium to lengthy period. Such kind of arrangement is an perfect arrangement for people looking for wealth increase for a extended time
b) **Income Funds:** This arrangement aims to deliver fixed and stable salary to people
c) **Balanced Funds:** The aim of such an arrangement is to deliver together development and secure pay to investors
d) **Money Market Funds:** The aim of such arrangement is to deliver relaxed liquidness, steady pay and protection of pay

Mutual Fund schemes by Special Schemes

a) **Industry Specific Schemes**: Such an arrangement participate merely in the businesses stated in the proposal file of the arrangement
b) **Index Schemes:** These arrangements links with the BSE Sensex performance or NSE performance
c) **Sectorial Schemes**: The arrangement participate mainly in a stated businesses or initial public offering
d) **Tax Saving Schemes:** The aim of such an arrangement is to suggest tax discounts/rebate to the people below definite requirements of the Indian IT Laws

Mutual Funds are also categorized on the foundation of nature as :-

- **Equity Fund:** Such kind of funds devote a concentrated portion of their quantity into equity assets. The construction of Equity fund may be varied for varied arrangements and the fund manager viewpoint on various diff stocks. These funds are also sub-categorized subject depending on their aim to investment as Differentiated Equity, Mid-Cap, Sector particular funds, ELSS
- **Debt Fund:** The aim of these schemes/funds is to engage in debt papers. Government establishments, private firms, banks and monetary organizations are particular chief producers of debt papers. By capitalizing in debt tools, debt funds carry minimal risk and deliver steady pay to the investors
- **Balanced Funds:** Balanced funds as name suggests are combination of equity and debt funds which invest together in equities plus fixed income instruments which are in sync with defined asset aim of the scheme. Balanced Funds try to deliver the finest of both the domains to investors

2.2 Key Drivers for growth of Mutual Fund

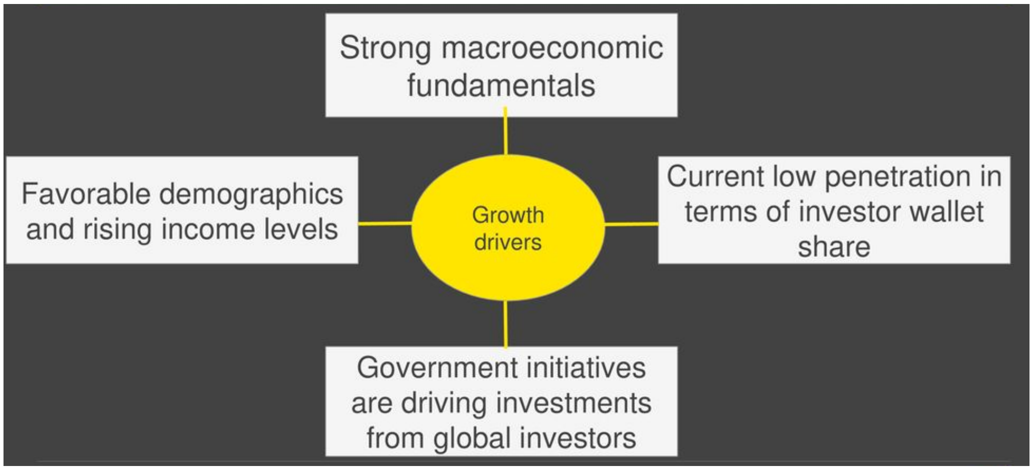


Figure 5: Drivers of Mutual Fund Growth

2.3 Mutual Funds – Parameters for selection

a) **Your Target/Aim**: The basic idea to jolt down before participating in fund is to find out if your aim equals with the arrangement. It is necessary, as any clash will automatically disturb potential earnings. Likewise, choose arrangements that fulfill precise wants such as retirement plans, kids' strategies, schemes specific to sector, etc

b) **Risk capability and capacity**: This directs the selection of arrangements. Those with zero risk acceptance must drive into debt arrangements, as they're pretty harmless. Violent people can go for equity kind of investments. People who are even extra violent can go for arrangements that participate in particular business or areas

c) **Track record of scheme/Fund Manager**: As you give your tough produced cash to somebody to take care of, it is imperious he copes it well and also vital that the company(fund company) you select has outstanding stats/record, must be expert, uphold visibility in actions

d) **Cost :** Fee involved is controlled, but must view the fund's expense ratio beforehand participating due to reason that the cash is taken from your investments. A greater admission capacity or departure capacity also will eat/take away your earnings. Expense ratio which is greater can be justified only by unmatched yields

2.4 Measuring Risk and Return

A repetitive check on one's mutual funds is vital. It benefits to know where one is and appears to be heading. There are numerous relations that individual must look at to additional decide the arrangement's performance. Particulars of some of these ratios have been described underneath:-

a) **Beta** – It is the extent of MF arrangements instability compared with the standard. Beta ratio would aid to review in what way greatly performance of fund can travel up or down when compared with the stand. Fund having Beta worth > 1 would travel more instable compared to the marketplace. Eg-If marketplace travels up 100 percent a fund having beta worth equal to 1.5 would travel up by 150 percent. Beta worth is fewer than 1 would mean that fund would be less instable compared to std

Beta = (Std Dev of MF scheme/Std Dev of the involved benchmark)* R-Square

b) **Alpha –** It is the measure of MF's performance after risk is modified. Ratio aids to calculate the performance of fund manager. Greater the value of alpha, it's superior value. Optimistic value of alpha statistics show encouraging yields when it is compared with standard and bad value of alpha reflects -ve yields to standard. Example- Value of alpha as 8 would mean arrangement will overtake standard by 8 percent and alpha - 8 the arrangement would underachieve by 8 percent compared to stand

Alpha = Return of MF arrangement – (Return's Risk free rate + (value of beta*(Return of benchmark – Return's risk free rate)

c) **Standard Deviation** – This ratio helps to measure the instability of the yields through funds in comparison to avg yields. It expresses how much the yield can deflect away from the past mean yield. Say if fund is having a 10 percent ARR and a std deviation of 4 percent, its yield will vary from 6 percent-14 percent. The greater the std deviation, more will be instablity is the yields of fund. Choose less instable funds

Variance = (Sum of squared diff b/w each monthly yield and its mean / no of monthly return data)

d) **Sharpe Ratio** – This ratio aids the people to tell if MF distributes the yields with respect to the danger taken through it on comparing a fund having risk free rate of return.

Sharpe ratio= (MF returns – Return's Risk free rate)/ Std deviation of the MF

e) Treynor Ratio – Used to measure the performance of fund compared to the danger taken. Greater the ratio, greater the yields against instability

Treynor ratio = (MF return – return's risk free rate)/ value of Beta for the chosen MF

f) **Jensen's Alpha** - Known as the Jensen's Performance Index, is a measure of the additional yields received by the portfolio compared to yields recommended by the CAPM model

2.5 Advantages through Mutual Funds

Reason for development of MF as the preferred investment tool is due to the various rewards they provide above various other arrangements along with the paths of participating, mainly for the people/investor who have inadequate means accessible in relations of wealth and the skill to perform thorough investigation and marketplace observing. Few benefits are:-

- Diversification of portfolio: Every investor in fund holds a portion in all the fund's assets hence permitting him to grasp an investment portfolio that is diversified even with a low quantity of investment that would else want large investment

- Managed Professionally: Even if the person has a huge quantity of wealth accessible to him, the welfares through the expert supervision services transported via the fund in the administration of the portfolio of investor. The supervision abilities, alongside the wanted examination into obtainable investment choices, confirm a much superior yield than what an individual can achieve himself. Limited people have the ability along with own means to prosper in world moving so rapidly, international and marketplaces that are sophisticated
- Reduced and Diversified Risk: If investor participates straight, all the threat of possible damage is personal, whether placing a deposit or a bank, or the person is involved in purchase of shares or debenture on his personal or some other forms. If capitalizing in the group of funds with other people/investors, the probable damages become mutual with other investors. The risk lessening is one of the imp/major significant profits of a combined tool to invest like MF
- Transaction Costs Reduced: Things that were correct for risk also correct for business charges. Investor consumes complete charges such as brokerage/supervision of involved securities. As he goes over a fund, there is an added advantage of economies of scale, funds pay smaller charges due to greater amounts, an advantage delivered to investors
- Convenience: MF supervision firms propose investor facilities which a straight market investor cannot get. Hence the investor can effortlessly handover their holds from one arrangement to others and get efficient marketplace data
- Benefits on Tax: The earnings dispersed after 31 March'2002 would be topic for taxability in valuation of all holders

3. BIG DATA ANALYTICS IN ASSET MANAGEMENT

From the last 3-4 years, the implementation of advanced analytics to various business issues has begun to add and deliver worth for conventional asset managers—by not substituting human individuals but by allowing them to deploy better decisions rapidly and consistently. Larger sets of organizations are embracing newer analytics techniques and methods at different levels across the asset-mgmt value chain and beyond the conventional alpha-generating methods advised by quant organizations - from escalated sophistication in distribution to healthier investment decision making to ring in changes in middle & back-office productivity. Big data technology with analytics is attracting increased attention, keeping in mind its capability to provide efficient views/insights than conventional platforms and cheaper costs of technology infra. Contrary to hedge funds, asset managers have embraced big data at a late stage, but their attentiveness to it has been rising now. Investors are also focusing in big data tools and techniques to combine with their main investment strategy based on fundamentals.

Big data analytics is quickly changing from the static models and is currently able to effectively react to changes happening in the market as well as at macro level. Funds are developing trading algo's that are making predictions using the historical dataset and statistical probabilities. Organizations are looking to enhance their models of investment by making use of big data and new inputs. These fast and rapid growth in Big-Data analytics have been aided from decline in costs of technology, increased access to ML capabilities and increase in analytics talent pool.

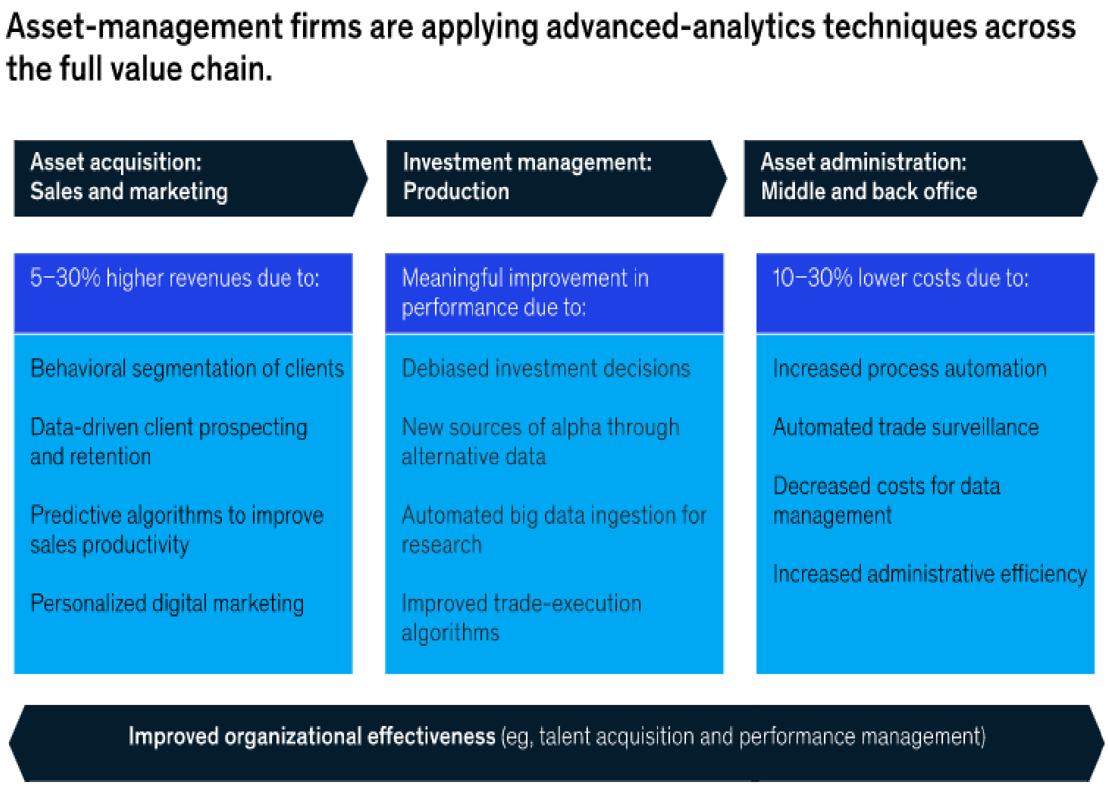


Figure 7: Advanced Analytics Techniques in Asset Management Firms

Currently the asset managers are mainly using and implementing analytics for enhancing distribution across 3 key areas:

- Optimized distribution and better service models – Asset-Managers are creating and establishing greater pool of data with multi-dimensional client features and characteristics to design models of distribution and service that helps to target clients by making use of appropriate channels at the correct time. Instead of depending on the size and type of clientele to find out whether and how to cover the client, managers nowadays are making use of data to attain greater detailed segmentation
- Precision targeting for improved productivity - Asset managers have also started investing in analytics to create client insights for improving the

efforts and sales and marketing productivity. Examples differ from predictive algo's which find out cross selling opportunities to finding and identifying clients at redemption risk for some specific strategies

- Enhanced performance management – Usage of analytics methods is also being carried out by leaders so that the team's overall performance can be effectively managed

On the investments side, managers have been engaging much more in the usage of advanced analytics with focus mainly in 3 key areas:

- Investment decisions debiasing – Elimination of systematic bias from the decision making process of investment. Possessing the capacity to have a wider set of data set and sources of an individual / team's trading background, patterns of communications, features on psychometrics along with time-management practices helps organizations in finding out drivers of perf and other behavior related root causes at much more granularity and at an individual level than earlier
- Usage of alternative data sources to generate alpha - The accessibility to larger quantity of data is adding a premium for possessing data-acquiring powers and the datascience techniques to knit them together for creating predictive models that help to improve decision making
- Research processes enhancement – Application of techniques like the NLP or Natural Language Processing have been able to assist the managers with processing high volume of info more rapidly than earlier—through automation of ingestion and study of public filings and highlighting variations in sentiment which can be used by research analyst to focus on

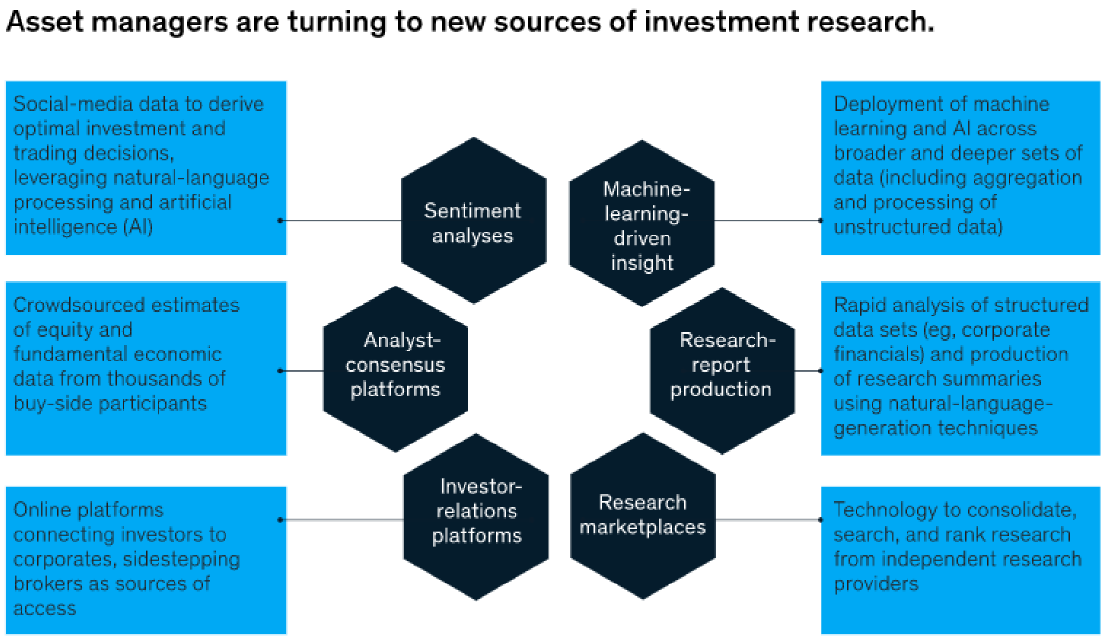
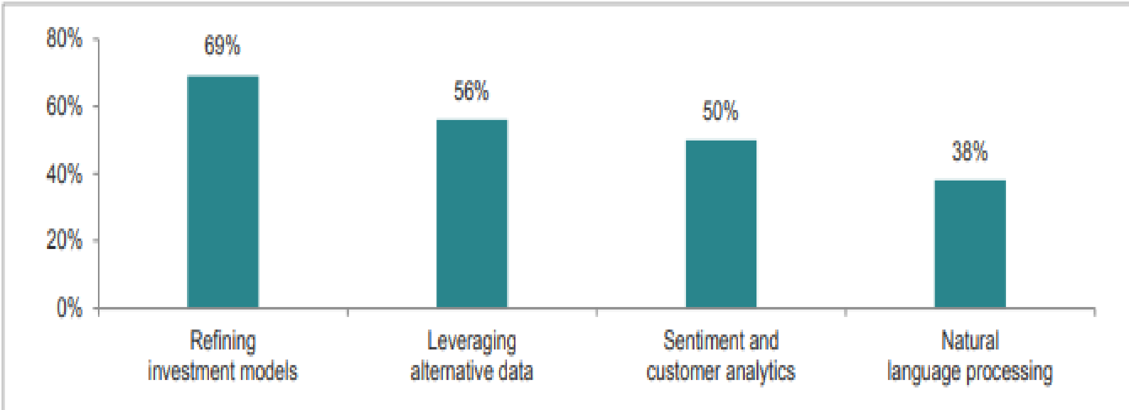


Figure 8: New sources of investment research

3.1 Objectives of using Big Data Analytics

Asset Managers are nowadays seeking applications for Big-Data analytics having scope higher than investment management. The Mktg and Sales teams are trying to utilize investor plus distribution data and additional information to improve customer acquisitions, customer retaining, and conversion rates and improve capital raising. Additionally, teams in compliance have started to invest much more within Big-Data with Analytics in areas like insider trading, fraud management and money laundering. Teams in Risk Mgmt. have moved from traditional VaR analysis to a more robust process of analyzing scenarios. In a survey conducted by CRISIL Global Research and Analytics more than 3/4th of the respondents had ranked generation of alpha value as the major goal for Big-Data analytics investment and 1/4th of respondents had chosen segmentation of market with innovative developments on product side as key priorities.

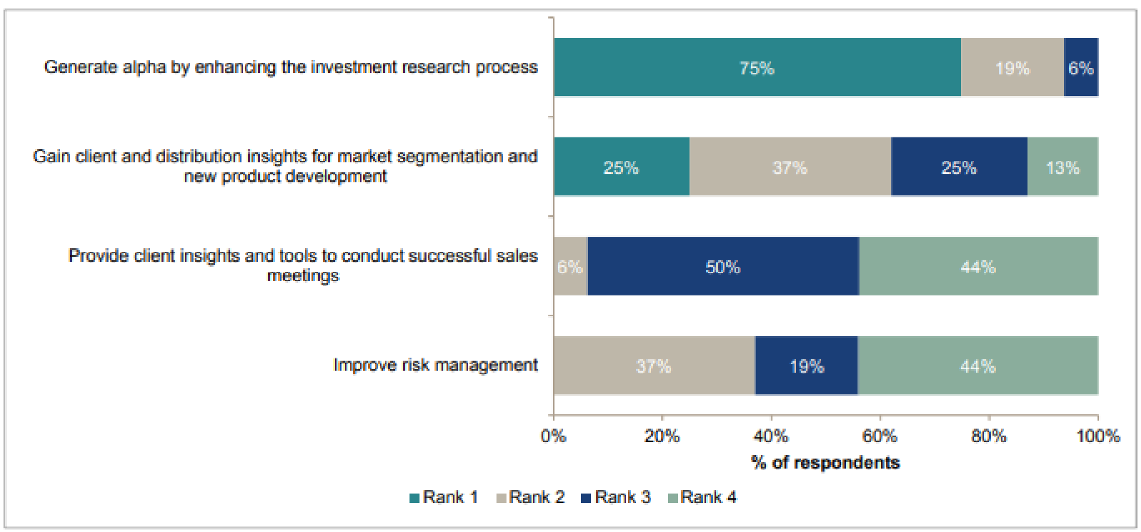
Asset manager priorities in big data analytics



Source: CRISIL Global Research & Analytics; the above are not mutually exclusive

Figure 9: Asset Manager Priorities in Big Data Analytics

Objectives of investing in big data analytics



Source: CRISIL Global Research & Analytics

Figure 10: Investment Objectives – Big Data Analytics

3.2 Key Challenges of using Big Data Analytics

Some of the major challenges with Big Data Strategy are:-

- Securing accessibility to unique and reliable Big-Data - Provided the unique and diverse sources of data, the asset managers must conduct validation on these sources and must also perform due diligence on data vendors along with the used sourcing methodologies. They must ensure that there are no privacy/legal issues. Understandably the cleaning, validation and transformation of raw data might consume up to 80% of the efforts to bring the data into the research process
- Ensuring big data-driven models are reviewed and refined – Periodic validation of models and strategies must be done by asset managers as there can be changes on the regulatory and market environment side. Usage of too many factors can lead to over-fitted models and therefore internal and external teams should be given proper training so that they can relate to Big-Data analytics plus insights in a much better way
- Sensible Implemention of Big-Data strategies – Big Data analytics must be implemented in an incremental fashion using the concept of pilot projects which can be done/executed internally or by using some external consultants or niche partners till the time the advantages and methodology are set/established. As there are multiple sets of data sources, use cases and concepts that are available for testing, the asset managers face hurdles during deciding the areas where time and effort needs to be spent

4. LITERATURE REVIEW

Assessment of performance of Mutual Funds is a favored part of exploration wherever a decent quantity of learning has been performed. The part of study delivers different outlooks of the same.

- One exploration made use of RBSA/Return Based Style Analysis to assess equity MF's present in India using quad optimization of the asset class feature prototype recommended by Sharpe along with inspection of comparative performance of the MF's with relation to style standards. Learning gathered/found that the MF's made encouraging returns monthly on the avg, through the learning phase. The ELSS kind of MF's lagged the the Growth MF's or all funds involved together in respect to yields that were made. The mean yields of the Growth MF's/all the funds were not only important but also optimistic. ELSS MF's also went on to confirm slightly higher volatility - std deviation than the Growth kind of Mutual Funds
- *Meenakshi Garg, Dr. S.L. Gupta, A study of performance evaluation of selected mutual funds in India,* explore the differences in performance indication by different Modern Portfolio Theory statistics, and explore correlation between index based returns and scheme returns
- *Ronald Baganzi, Byung-Gyoo Kim, Portfolio Optimization Modelling for Enhanced Decision Making and Prediction,* explores the portfolio optimization models which include Markowitz's Mean-Variance model, the VaR model and the Mean-Absolute Deviation model to choose the proportion of assets to be held in the portfolio based upon the stock performance with respect to Sharpe Ratio (SR), Risk Parity (RP), Expected Shortfall (ES) or CVaR
- *Gupta and Sehgal (1998)* assessed 80 mutual fund arrangements and their performance over a period of 4 years starting from 1992 till 1996. The education verified the scheme concerning to fund broadening/differentiation, performance uniformity, factor of risk/return along with performance connection. Their learning had observed presence of insufficient diversification within the portfolio and performance steadiness between schemes chosen as sample
- Another learning acknowledged modifications in features of private and public sector backed MF's find the degree of diff in portfolio of securities of private-sector buoyed MF's along with public sector assisted, matching the performance using traditional methods of investment to match private-sector buoyed MF and public-sector assisted. Mostly usage of Sharpe ratio and Jensen alpha, ESDAR was deployed to find out that risk involved in portfolio measured using the private_sector Indian MF's appears to be

outperforming Public_sector backed along with private_sector foreign buoyed MF’s and the general traditional covariance study created differences in performance between 3 class of MF’s in relatives of portfolio diversification/differentiation

- Another research measured if or not the certain MF’s were accomplished to outdo the marketplace on the normal over the studied period . Also, in addition to through investigation the forte of PCM value interrelationships for consecutive periods and the learning also was trying/tried to conclude around the degree to which the forthcoming values of performance of funds were linked to its former through usage of model on single index. The learning represented optimistic signs of info irregularity in marketplace with MF managers possessing greater figures on the full yields of stocks. It was also directed by PCM that on an general, MF’s delivered added yield but also only if the time period unit was longer. Therefore, they had decided that to assess true performance of a specific MF, having a longer time period is much better
- Another training aimed at studying presentation of select equity (open ended) MF through usage of Sharpe Ratio with testing of hypothesis and return recognized on yield. One of the most significant discovery of training was that only 1 Dividend plan and 4 Growth plans were able to produce high yields than those that were generated by the marketplace which is conflicting to the universal view existing in Indian MF marketplace and even Sharpe’s ratio of Growth along with corresponding dividend plans hold testament to the comparatively healthier Growth plan’s performance. Also, the arithmetical tests such as the t-Test, F-test additional verify the important performance alterations among the Dividend and Growth plans.

5. RESEARCH METHODOLOGY

This chapter emphases on research procedure that was adopted in this study. It delivers a thorough explanation of the research method used in this study. Exploration instruments, data gathering and examination methods utilized were presented in the following sections

5.1 Objective

Objective of the learning is to provide an insight into the determinants that can affect the performance of mutual fund schemes and the extent to which these factors can vary/affect the fund's performance in different time spans. The study also focusses on making use of data analytics to predict the mutual fund schemes performance and to indicate/recommend the schemes which are good investment options for an individual in the short term and long term.

5.2 Research Design

This study used Quantitative research design where statistical conclusions are required to gather actionable understandings and where figures deliver a healthier viewpoint to make significant business choices. The study uses linear regression approach and other statistical techniques to understand the correlation between Mutual Fund Performance (dependent variable) and the factors involved (independent variables) and so offer an improved explanation on the subject, and eventually spring a clear image on the usefulness and decision to use it based on the impact. The prediction of Mutual Funds performance in future has also been done by using Logistic Regression approach along with the help of cross validation to classify a scheme as a Good Investment option

5.3 Data Gathering/Collection

The study and analysis performed has been done on the historic returns and other facts that were available over the Internet. Mutual funds were selected randomly from diff fund families and response variable were gathered for various mutual fund schemes with other explanatory variables. The data was collected for Equity, Hybrid and Debt Funds schemes that are being run by top 10 Assets Management Companies in India. Approximately 220 number of Mutual Fund Schemes will be analyzed in this study. The source data was collected, cleaned and transformed to be of practical use. Data collection on various families of mutual fund and different schemes operating in India was done mainly from three data sources:

- Web portal of AMFI - Association of Mutual Funds in India
- MoneyControl.com
- Yahoo Finance
- Financial Express and Fund Bazaar

5.4 Validity/Legitimacy and Reliability/Consistency

To achieve content rationality, parameters used to evaluate included a variety of factors associated with mutual funds. Reliability has been safeguarded by curtailing ways of measurement mistake like information gatherer partiality and collecting information from trusted sources

5.5 Data Analysis

Data Analysis and visualizations were done using the below techniques:-

- Linear Regression using AIC Stepwise Regression Technique
- Logistic Regression
- Scatter Plot / QQ Plot
- Correlation Plot and Correlation Matrix
- Histogram

6. DATA ANALYSIS AND INTERPRETATION

Returns of Mutual Fund schemes are affected by various factors. Purpose/Aim of this study is to analyze data of mutual funds schemes that were selected and investigate factors having significant impact. Using this, the models were constructed and test the importance of individual factors to determine their impact on Mutual Fund

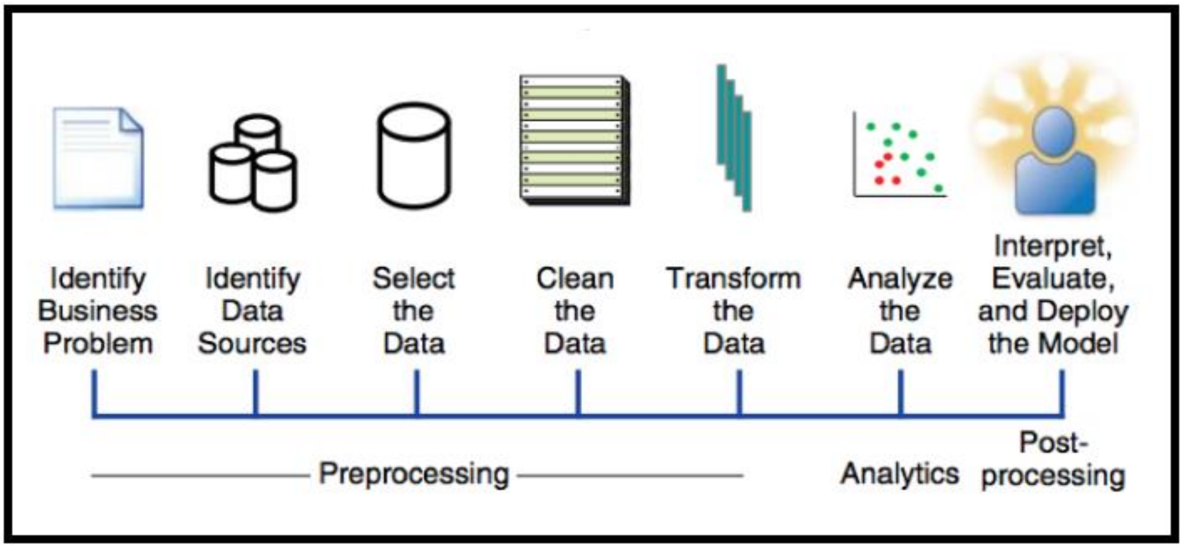


Figure 11: Analytics Process Model

6.1 Identify Business Problem

In the first step, the business problem that needs to be addressed is needed. The Hypothesis statement to carry out the analysis is:-

Ho:Return by Mutual Fund schemes is not dependent on factors involved

H1:Return by Mutual Fund schemes is dependent on factors involved

6.2 Identify Data Sources

The sources of data of potential interest need to be identified. The data which is relevant or not will be decided later by the analytical model based upon the task at hand.

The data was collected for Equity, Hybrid and Debt Funds schemes that are being run by top 10 Assets Management Companies in India. Approximately 220 number of Mutual Fund Schemes will be analyzed in this study. The details of the data collection and sources have been provided below:-

- NAV Details – Sourced from MoneyControl and AMFI Portal
- Risk Return Ratios – Sourced from MoneyControl and Fund Bazaar website
- Assets Portfolio – Sourced from MorningStar and Financial Express website

```
setwd("E:\\Docs\\EMBA - DSM DTU\\Major Project - Final Semester\\")
assets_portfolio<-read.csv('AssetsPortfolio.csv',header=TRUE,stringsAsFactors = FALSE)
historical_returns<-read.csv('HistoricalReturns.csv',header=TRUE,stringsAsFactors = FALSE)
nav_details<-read.csv('NAVDetails.csv',header=TRUE,stringsAsFactors = FALSE)
risk_ratio<-read.csv('RiskRatioReturns.csv',header=TRUE,stringsAsFactors = FALSE)


historical_join <- sqldf("select
                 historical_returns.*
               , risk_ratio.StandardDeviation
               , risk_ratio.Beta
               , risk_ratio.SharpeRatio
               , risk_ratio.JensensAlpha
               , risk_ratio.TreynorsRatio
               from historical_returns
                 left join risk_ratio
                 on historical_returns.SchemeName = risk_ratio.SchemeName")

historical_join <- sqldf("select
                 historical_join.*
               , nav_details.NAV_May212020
               , nav_details.NAV_May212019
               , nav_details.NAV_May212017
               , nav_details.NAV_May212015
               from historical_join
                 left join nav_details
                 on historical_join.SchemeName = nav_details.SchemeName")

historical_join <- sqldf("select
                 historical_join.*
               , assets_portfolio.TurnoverRatio_Percentage
               , assets_portfolio.No_of_stocks_portfolio
               from historical_join
                 left join assets_portfolio
                 on historical_join.SchemeName = assets_portfolio.SchemeName")
```

Figure 12: Creating master dataset named historical_join

6.3 Select the Data

After Mutual Fund schemes were chosen, collection of different independent variables that appeared to sum up the performance as well as overall composition of Mutual Fund schemes was done. The response variables and other explanatory variables were identified for the mutual fund schemes

Response Variables: Annualized 1Y Return, Annualized 3Y Return, Annualized 5Y Return

Explanatory Variables : Crisil Rank, AuM (in Cr), Standard Deviation, Beta, Sharpe Ratio, Jensen's Alpha, Treynor's Ratio, Annualized Holdings Turnover and Number of stocks in portfolio

	SchemeName	Plan	CategoryName	CrisilRank	AuM_in_Cr	YTD_Percent	X1Y_Percent	X2Y_Percent	X3Y_Percent	X5Y_Percent
1	Aditya Birla Sun Life Balanced Advantage Fund	Regular	Dynamic Asset Allocation or Balanced Advantage	2	2357.01	-15.0	-11.0	-3.0	-1.0	5.0
2	Aditya Birla Sun Life Banking & PSU Debt Fund	Regular	Banking and PSU Fund	3	11119.79	4.0	11.0	10.1	8.0	9.0
3	Aditya Birla Sun Life Corporate Bond Fund	Regular	Corporate Bond Fund	3	17647.81	5.0	11.0	10.1	8.0	9.0
4	Aditya Birla Sun Life Credit Risk Fund	Regular	Credit Risk Fund	3	2576.15	0.1	1.0	3.0	4.0	7.0
5	Aditya Birla Sun Life Digital India Fund	Regular	Sectoral/Thematic	4	374.85	-11.0	-7.0	0.1	11.0	7.0
6	Aditya Birla Sun Life Dividend Yield Fund	Regular	Dividend Yield Fund	1	600.32	-21.0	-18.0	-13.0	-8.0	-2.0
7	Aditya Birla Sun Life Dynamic Bond Fund	Regular	Dynamic Bond Fund	2	2096.38	2.0	0.1	3.0	3.0	5.0
8	Aditya Birla Sun Life Equity Advantage Fund	Regular	Large & Mid Cap Fund	2	3901.91	-24.0	-21.0	-12.0	-6.0	2.0
9	Aditya Birla Sun Life Equity Fund	Regular	Multi Cap Fund	3	9861.23	-24.0	-21.0	-10.1	-3.0	4.0
10	Aditya Birla Sun Life Equity Hybrid 95 Fund	Regular	Aggressive Hybrid Fund	1	7536.78	-22.0	-20.1	-10.1	-5.0	2.0
11	Aditya Birla Sun Life Floating Rate Fund	Regular	Floater Fund	5	6133.16	3.0	9.0	9.0	8.0	8.0
12	Aditya Birla Sun Life Focused Equity Fund	Regular	Focused Fund	3	3662.68	-22.0	-19.0	-7.0	-2.0	3.0
13	Aditya Birla Sun Life Frontline Equity Fund	Regular	Large Cap Fund	2	16521.27	-25.0	-22.0	-10.1	-4.0	2.0
14	Aditya Birla Sun Life Government Securities Fund	Regular	Gilt Fund	3	350.64	8.0	16.0	13.0	9.0	10.1

StandardDeviation	Beta	SharpeRatio	JensensAlpha	TreynorsRatio	TurnoverRatio_Percentage	No_of_stocks_portfolio	NAV_May212020	NAV_May212019	NAV_May212017	NAV_May212015
11.93	0.92	-0.23	-3.61	-0.03	303	83	46.7500	52.79	48.19	36.87
4.46	0.49	0.48	1.90	0.04	427	186	266.5815	239.88	210.20	175.21
1.79	0.02	1.89	3.42	2.19	471	196	80.1022	72.31	62.86	52.84
6.23	0.29	-0.21	-1.50	-0.03	177	65	13.8043	13.70	12.20	10.07
18.64	0.84	0.50	3.67	0.11	93	16	48.6500	51.64	35.27	34.40
16.39	0.80	-0.61	-7.25	-0.12	39	55	127.3500	155.28	162.70	139.27
4.94	1.64	-0.35	-6.84	-0.01	687	73	31.7278	31.67	29.26	24.59
19.44	0.94	-0.34	-5.96	-0.07	70	46	314.1400	403.28	376.29	293.05
19.38	0.99	-0.19	-1.60	-0.04	50	65	565.7200	720.99	637.16	483.49
13.73	1.08	-0.46	-7.36	-0.06	81	65	591.0700	746.92	689.08	556.69
2.60	0.18	0.70	1.63	0.10	824	102	251.7507	231.92	200.74	169.41
18.46	0.92	-0.15	-2.23	-0.03	127	27	47.8519	63.27	53.95	43.74
18.37	0.92	-0.24	-3.78	-0.05	61	61	172.0000	237.37	204.70	166.02
6.41	1.12	0.62	0.01	0.03	1315	15	61.1602	52.56	47.05	38.04

Figure 13: Master Dataset from the join of all the individual data files

6.4 Clean the Data

Identify if there are missing value in the data, handle any missing values in the dataset by either filling the missing data with appropriate values or decide to scrap that mutual fund scheme from analysis. Get basic insights from the data; check the values and type of data in the dataset. Analyzing the different features of the dataset and identify the import features to be used in data modelling.

```
#Find missing values in the master dataset
sum(is.na(historical_join))

> sum(is.na(historical_join))
[1] 0
```

Figure 14: Find any missing data in the master dataset

```
> class(historical_join$SchemeName)
[1] "character"
> class(historical_join$Plan)
[1] "character"
> class(historical_join$CategoryName)
[1] "character"
> class(historical_join$CrisilRank)
[1] "integer"
> class(historical_join$AuM_in_Cr)
[1] "numeric"
> class(historical_join$X1Y_Percent)
[1] "numeric"
> class(historical_join$X3Y_Percent)
[1] "numeric"
> class(historical_join$X5Y_Percent)
[1] "numeric"
> class(historical_join$StandardDeviation)
[1] "numeric"
> class(historical_join$Beta)
[1] "numeric"
> class(historical_join$SharpeRatio)
[1] "numeric"
> class(historical_join$JensensAlpha)
[1] "numeric"
> class(historical_join$TreynorsRatio)
[1] "numeric"
> class(historical_join$TurnoverRatio_Percentage)
[1] "integer"
```

Figure 15: Type of data in the master dataset

6.5 Transform the Data

The data that was collected from various sources was interpreted to determine the type of data that was sourced and required transformation so that I had the type of data that was needed while creation of master dataset named historical_join

```
historical_join$AuM_in_Cr <- as.numeric(as.character(historical_join$AuM_in_Cr))
historical_join$TurnoverRatio_Percentage <- as.numeric(as.character(historical_join$TurnoverRatio_Percentage))
```

Figure 16: Transforming data

```
> summary(historical_join)
  SchemeName             Plan             CategoryName          CrisilRank       AuM_in_Cr           X1W_Percent    
 Length:220         Length:220         Length:220         Min.   :1.000   Min.   :   11.91   Min.   :-6.000  
 Class :character   Class :character   Class :character   1st Qu.:2.000   1st Qu.: 1039.28   1st Qu.:-3.000  
 Mode  :character   Mode  :character   Mode  :character   Median :3.000   Median : 2802.89   Median : 0.100  
                                                          Mean   :2.795   Mean   : 6087.03   Mean   :-1.175  
                                                          3rd Qu.:3.000   3rd Qu.: 7566.56   3rd Qu.: 0.100  
                                                          Max.   :5.000   Max.   :87870.22   Max.   : 1.000  
  X1M_Percent        X3M_Percent     X6M_Percent       YTD_Percent       X1Y_Percent        X2Y_Percent         X3Y_Percent     
 Min.   :-12.000   Min.   :-37   Min.   :-42.00   Min.   :-41.0   Min.   :-46.000   Min.   :-30.100   Min.   :-22.000  
 1st Qu.: -3.000   1st Qu.:-25   1st Qu.:-23.25   1st Qu.:-24.0   1st Qu.:-21.000   1st Qu.: -9.000   1st Qu.: -3.000  
 Median : -1.000   Median :-10   Median :-10.10   Median :-10.0   Median : -7.000   Median : -1.000   Median :  2.500  
 Mean   : -1.397   Mean   :-12   Mean   :-10.09   Mean   :-10.6   Mean   : -7.062   Mean   : -1.474   Mean   :  1.374  
 3rd Qu.:  1.000   3rd Qu.:  2   3rd Qu.:  3.00   3rd Qu.:  3.0   3rd Qu.:  8.000   3rd Qu.:  8.000   3rd Qu.:  7.000  
 Max.   :  4.000   Max.   :  5   Max.   :  9.00   Max.   :  8.0   Max.   : 17.000   Max.   : 14.000   Max.   : 11.000  
  X5Y_Percent      StandardDeviation      Beta          SharpeRatio         JensensAlpha      TreynorsRatio     
 Min.   :-11.000   Min.   : 0.010   Min.   :-0.2400   Min.   :-1.20000   Min.   :-14.0000   Min.   :-2.74000  
 1st Qu.:  2.000   1st Qu.: 3.667   1st Qu.: 0.2675   1st Qu.:-0.25500   1st Qu.: -2.2450   1st Qu.:-0.07000  
 Median :  5.000   Median :16.005   Median : 0.8400   Median :-0.03000   Median : -0.0700   Median : 0.01000  
 Mean   :  4.642   Mean   :13.274   Mean   : 0.7030   Mean   : 0.09986   Mean   : -0.8235   Mean   : 0.07282  
 3rd Qu.:  8.000   3rd Qu.:19.172   3rd Qu.: 0.9700   3rd Qu.: 0.19000   3rd Qu.:  1.0600   3rd Qu.: 0.04000  
 Max.   : 10.100   Max.   :55.230   Max.   : 2.7700   Max.   : 2.09000   Max.   : 12.1100   Max.   : 5.42000  
 NAV_May212020      NAV_May212019     NAV_May212017     NAV_May212015     TurnoverRatio_Percentage No_of_stocks_portfolio
 Min.   :   7.244   Min.   :  10.30   Min.   :  11.92   Min.   :   9.33   Min.   :   1.0           Min.   :  3.00        
 1st Qu.:  28.973   1st Qu.:  31.79   1st Qu.:  28.05   1st Qu.:  23.18   1st Qu.:  43.5           1st Qu.: 35.00        
 Median :  48.701   Median :  56.99   Median :  52.48   Median :  42.44   Median : 102.5           Median : 51.00        
 Mean   : 388.250   Mean   : 405.62   Mean   : 350.86   Mean   : 297.25   Mean   : 255.7           Mean   : 55.41        
 3rd Qu.: 173.316   3rd Qu.: 233.28   3rd Qu.: 201.73   3rd Qu.: 166.87   3rd Qu.: 288.0           3rd Qu.: 68.00        
 Max.   :4501.430   Max.   :4412.34   Max.   :3888.44   Max.   :3398.66   Max.   :3768.0           Max.   :196.00        
> 
```

Figure 17: Summary of historical_join master dataset

6.6 Analyze the Data

- <u>The complete analysis of this study has been performed in two parts</u> :-
    1. **PART A** - Determine Feature Importance for Mutual Fund Scheme Performance in Short, Medium and Long Term Investmen
    2. **PART B** - Predicting Top Performing Mutual Fund schemes for Short, Medium and Long Term Investment
- <u>Approach</u> :-
    A. To determine feature importance for Mutual Fund Performance in Short, Medium and Long Term, Linear Regression analysis was

used wherein I tried to find out if there is any relationship between the dependent variable / response variable i.e. Annualized Return by scheme and explanatory variables / features i.e. Crisil Rank, AuM (in Cr), Standard Deviation, Beta, Sharpe Ratio, Jensen's Alpha, Treynor's Ratio, Annualized Holdings Turnover and Number of stocks in portfolio

B. To predict top performing funds for short, medium and long term investment, I have used Logistic Regression approach for modelling the outcome probability of a class – in this case Good Investment/Bad Investment. I have split the respective datasets for short, medium and long term into training set as well as test set with a split ratio of 0.70 i.e 70% data will be attributed to train data while 30% will be attributed to test data

- Assumptions :-

  A. For analysis purpose, I have made the following assumptions with respect to the investment period :-
     - Short Term Investment – 1 Year
     - Medium Term Investment – 3 Year
     - Long Term Investment – 5 Year

  B. For classifying the Mutual Fund Scheme as a Good investment or Bad Investment to be used for prediction, the following values were used :-
     - Standard Deviation – Low (Lower than Average)
     - Beta – Lies between 0 and 1 (Stable Returns)
     - Sharpe Ratio – Greater than 1
     - Jensens Alpha – Greater than 0
     - 1Y Annualized Return must be >= 6% for short term, 3Y Annualized Return must be > 7% for medium term and 5Y Annualized Return must be >=9% for long term investment

6.6.1 ANALYSIS TO DETERMINE FEATURE IMPORTANCE – PART A

Determine Feature importance for Mutual Fund Performance in Short, Medium and Long Term

- **Short Term – Investment Period 1Y**
    - Histogram of 1Year Returns - somewhat skewed however it was relatively normal

```
plotNormalHistogram(historical_join$X1Y_Percent)
```

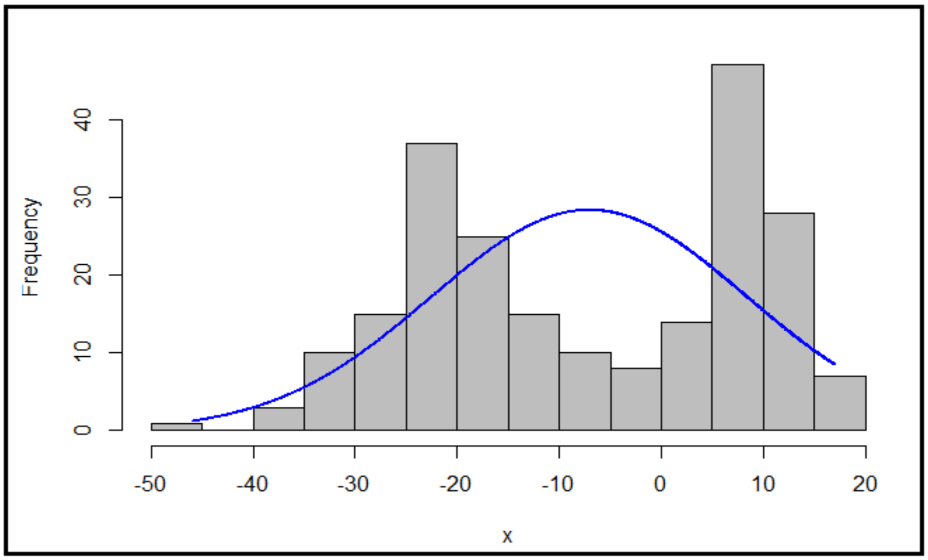


Figure 18: Histogram of Annualized 1Y Return (in%)

```
qqnorm(historical_join$X1Y_Percent,ylab="Sample 1Y Return")
qqline(historical_join$X1Y_Percent,col="red")
```

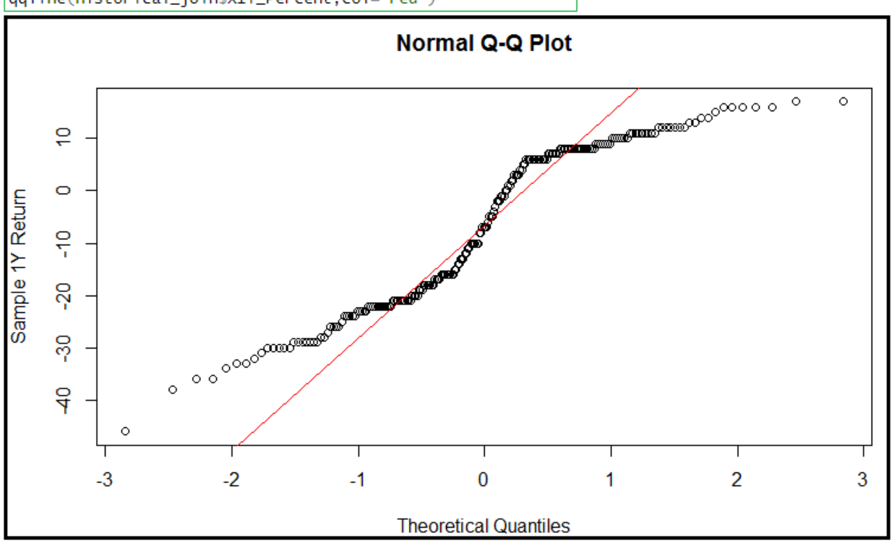


Figure 19: Normal Q-Q Plot of Annualized 1Y Return (in%)

➢ Scatter Plots of -> explanatory variables that appeared correlated in the data. Scatter plots were drawn to find any relationship

```r
#Relation between 1Y return and Crisil Rank
plot(y=historical_join$X1Y_Percent, x=historical_join$CrisilRank,
     col="blue",
     ylim=c(-40, 40), xlim=c(0, 5),
     main="Relationship Btw 1Y Return & Crisil Rank",
     ylab=" Percentage 1Y Return", xlab="Crisil Rank of Scheme")
```

```r
#Relation between 1Y return and Standard Deviation
plot(y=historical_join$X1Y_Percent, x=historical_join$StandardDeviation,
     col="blue",
     ylim=c(-40, 40), xlim=c(0, 60),
     main="Relationship Btw 1Y Return & Standard Deviation",
     ylab=" Percentage 1Y Return", xlab="Standard Deviation of Scheme")
```

```r
#Relation between 1Y return and AuM
plot(y=historical_join$X1Y_Percent, x=historical_join$AuM_in_Cr,
     col="blue",
     ylim=c(-40, 40), xlim=c(0, 90000),
     main="Relationship Btw 1Y Return & AuM",
     ylab=" Percentage 1Y Return", xlab="AuM(in Crs) of Scheme")
```

```r
#Relation between 1Y return and Beta
plot(y=historical_join$X1Y_Percent, x=historical_join$Beta,
     col="blue",
     ylim=c(-40, 40), xlim=c(-3, 3),
     main="Relationship Btw 1Y Return & Beta",
     ylab=" Percentage 1Y Return", xlab="Beta of Scheme")
```

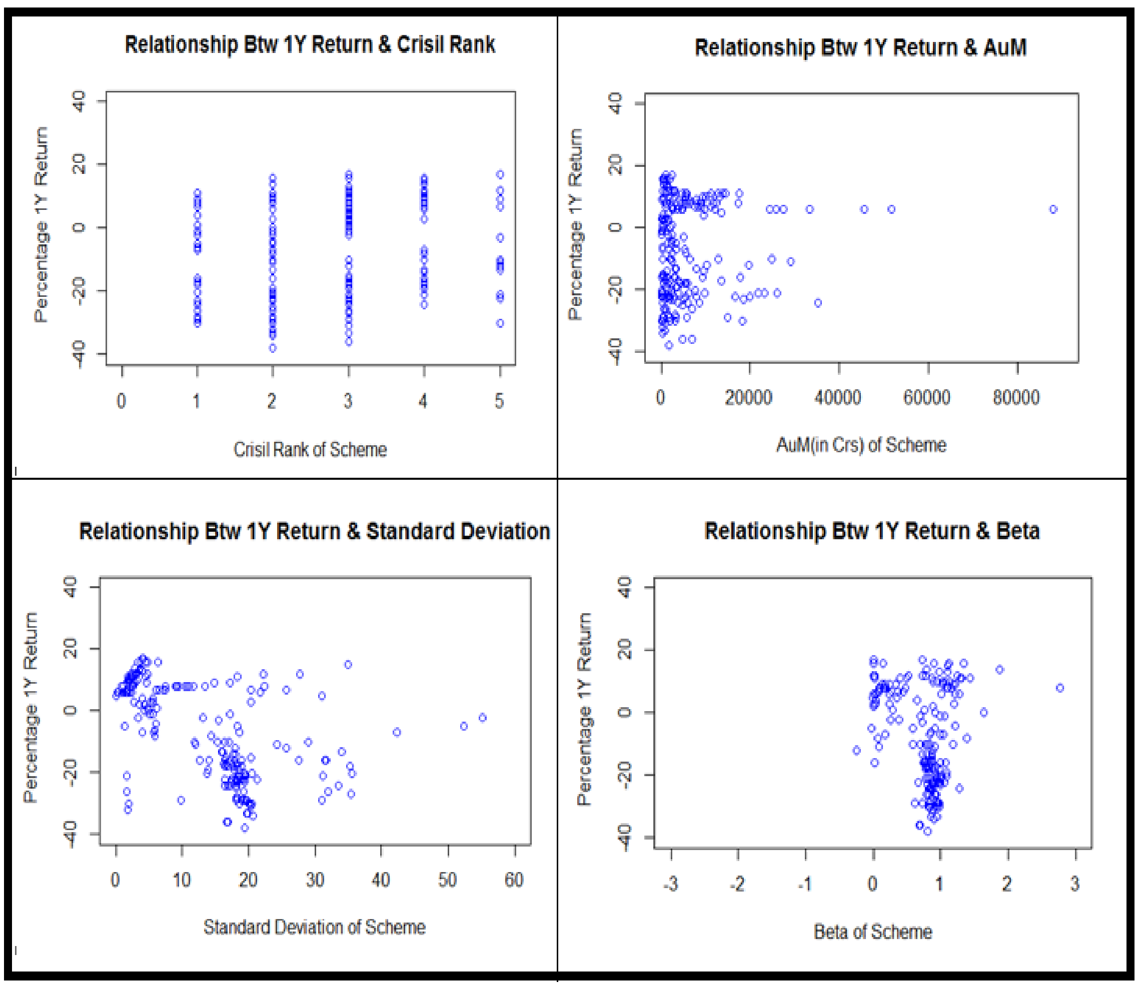


Figure 20: Scatter Plot of Annualized 1Y Return vs Crisil Rank, AuM, Beta and Standard Deviation

```
#Relation between 1Y return and Sharpe Ratio
plot(y=historical_join$X1Y_Percent, x=historical_join$SharpeRatio,
     col="blue",
     ylim=c(-40, 40), xlim=c(-3, 3),
     main="Relationship Btw 1Y Return & Sharpe Ratio",
     ylab=" Percentage 1Y Return", xlab="Sharpe Ratio of Scheme")


#Relation between 1Y return and Jensens Alpha
plot(y=historical_join$X1Y_Percent, x=historical_join$JensensAlpha,
     col="blue",
     ylim=c(-40, 40), xlim=c(-15, 15),
     main="Relationship Btw 1Y Return & Jensens Alpha",
     ylab=" Percentage 1Y Return", xlab="Jensens Alpha of Scheme")


#Relation between 1Y Return and Treynors Ratio
plot(y=historical_join$X1Y_Percent, x=historical_join$TreynorsRatio,
     col="blue",
     ylim=c(-40, 40), xlim=c(-5, 5),
     main="Relationship Btw 1Y Return & Treynor's Ratio",
     ylab=" Percentage 1Y Return", xlab="Treynor's Ratio of Scheme")
```

```
#Relation between 1Y Return and Annualized Holding Turnover
plot(y=historical_join$X1Y_Percent, x=historical_join$TurnoverRatio_Percentage,
     col="blue",
     ylim=c(-40, 40), xlim=c(0, 4000),
     main="Relationship Btw 1Y Return & Annualized Holding Turnover",
     ylab=" Percentage 1Y Return", xlab="Percentage Turnover Ratio of Scheme")


#Relation between 1Y return and Number of Stocks in Portfolio
plot(y=historical_join$X1Y_Percent, x=historical_join$No_of_stocks_portfolio,
     col="blue",
     ylim=c(-40, 40), xlim=c(0, 200),
     main="Relationship Btw 1Y Return & Stocks in Portfolio",
     ylab=" Percentage 1Y Return", xlab="Number of stocks in portfolio")
```

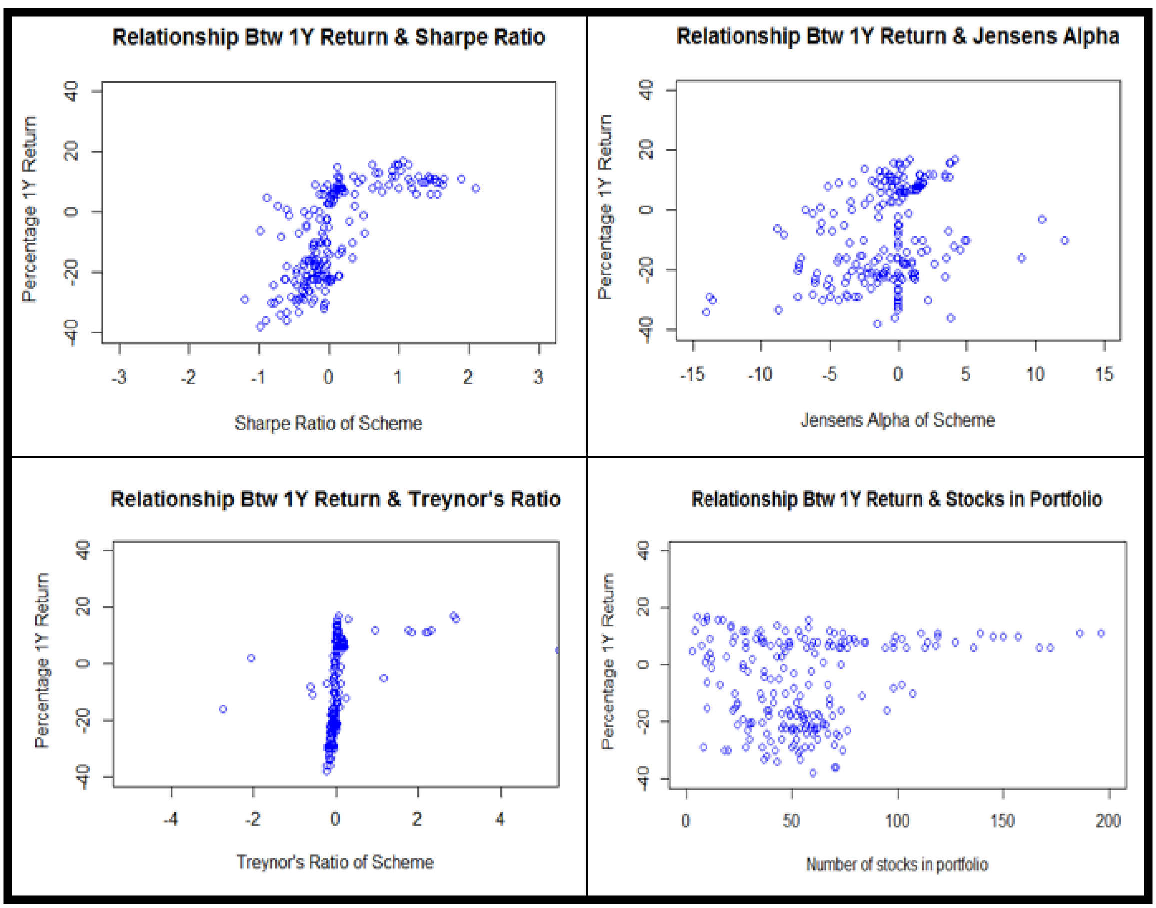


Figure 21: Scatter Plot of Annualized 1Y Return vs Sharpe Ratio, Jensens Alpha, Treynor's Ratio and No of stocks in Portfolio

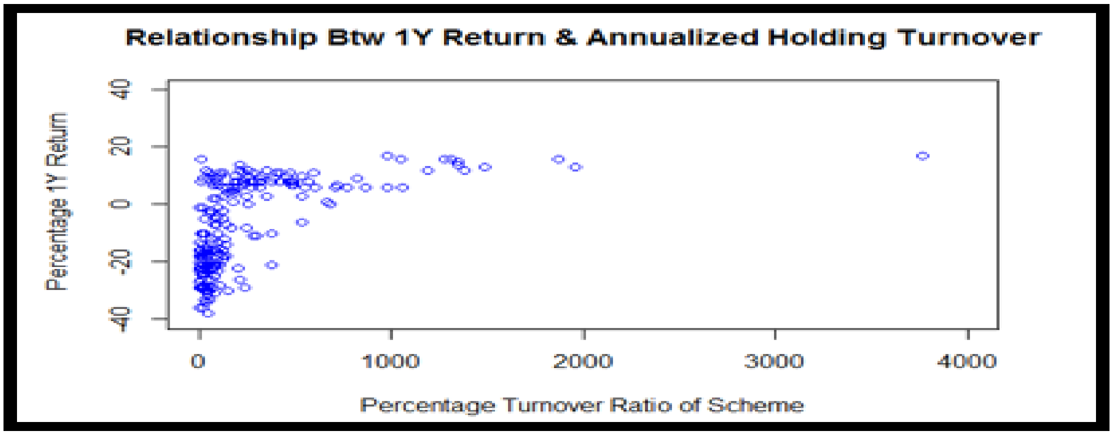


Figure 22: Scatter Plot of Annualized 1Y Return vs Annualized Holding Turnover

➢ Correlation Plot and Correlation Matrix were drawn to understand the correlation of response variable – Annualized 1Y Return with individual explanatory / independent variables that I have considered

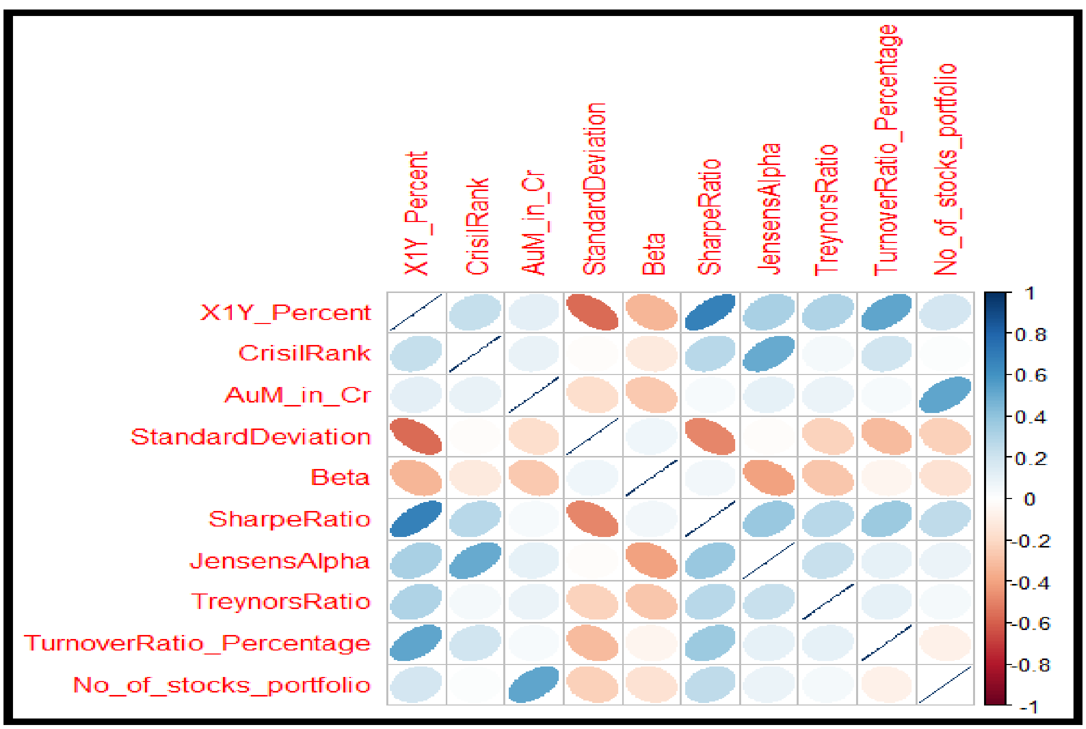


Figure 23: Correlation Plot 1Y – Response v/s Explanatory variables

```
> cor(historic_1year[, c(1:10)])
```

	X1Y_Percent	CrisilRank	AuM_in_Cr	StandardDeviation	Beta	SharpeRatio
X1Y_Percent	1.0000000	0.23697729	0.11097243	-0.56071471	-0.33013666	0.67417178
CrisilRank	0.2369773	1.00000000	0.09708943	-0.01923882	-0.11439060	0.27331235
AuM_in_Cr	0.1109724	0.09708943	1.00000000	-0.17953578	-0.26984890	0.03819755
StandardDeviation	-0.5607147	-0.01923882	-0.17953578	1.00000000	0.06329553	-0.48757622
Beta	-0.3301367	-0.11439060	-0.26984890	0.06329553	1.00000000	0.05457431
SharpeRatio	0.6741718	0.27331235	0.03819755	-0.48757622	0.05457431	1.00000000
JensensAlpha	0.3276449	0.50659559	0.10162812	-0.01345779	-0.40326585	0.37145335
TreynorsRatio	0.3073739	0.04330193	0.08477281	-0.22879641	-0.27150579	0.27102015
TurnoverRatio_Percentage	0.5211990	0.19021977	0.03761012	-0.31930298	-0.05996374	0.36519252
No_of_stocks_portfolio	0.1861887	0.01235628	0.52978046	-0.23206628	-0.15196191	0.25299421

	JensensAlpha	TreynorsRatio	TurnoverRatio_Percentage	No_of_stocks_portfolio
X1Y_Percent	0.32764488	0.30737393	0.52119902	0.18618875
CrisilRank	0.50659559	0.04330193	0.19021977	0.01235628
AuM_in_Cr	0.10162812	0.08477281	0.03761012	0.52978046
StandardDeviation	-0.01345779	-0.22879641	-0.31930298	-0.23206628
Beta	-0.40326585	-0.27150579	-0.05996374	-0.15196191
SharpeRatio	0.37145335	0.27102015	0.36519252	0.25299421
JensensAlpha	1.00000000	0.22343148	0.10343390	0.08432423
TreynorsRatio	0.22343148	1.00000000	0.10657455	0.04895566
TurnoverRatio_Percentage	0.10343390	0.10657455	1.00000000	-0.07869040
No_of_stocks_portfolio	0.08432423	0.04895566	-0.07869040	1.00000000

Figure 24: Correlation Matrix 1Y – Response v/s Explanatory variables

From the Correlation Plot and Correlation Matrix of Short Term, it was observed that the explanatory variables <u>Sharpe Ratio, Turnover Ratio, Jensen's Alpha and Treynor's Ratio had good positive correlation with 1Y Annualized Returns while the variables Standard Deviation and Beta were negatively correlated</u>

- **Medium Term – Investment Period 3Y**

  - Histogram of 3Year Returns is relatively normal

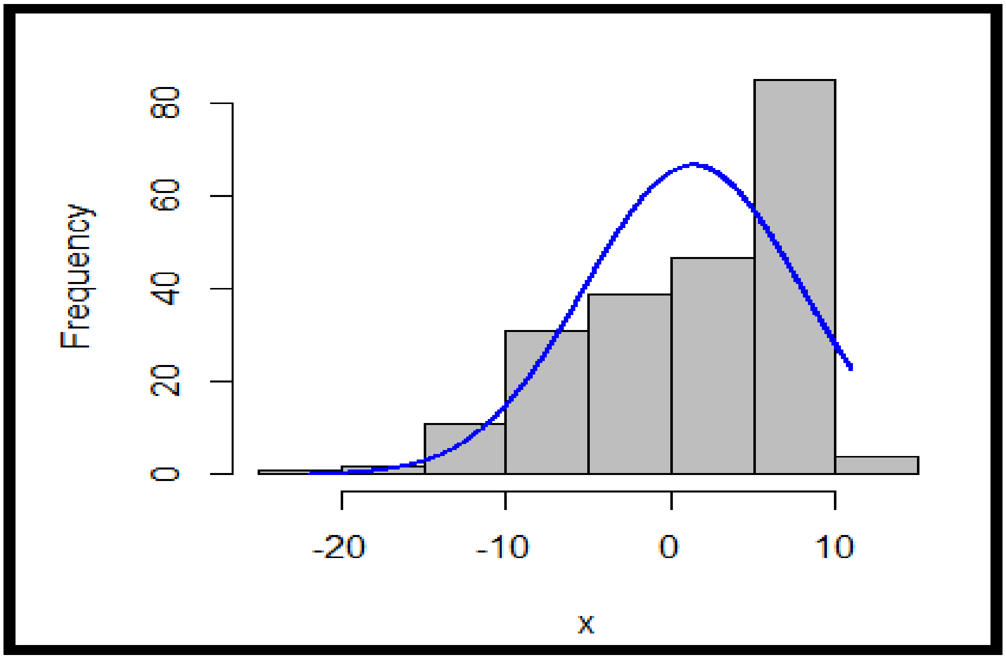


Figure 25: Histogram of Annualized 3Y Return (in%)

```
qqnorm(historical_join$X3Y_Percent,ylab="Sample 3Y Return")
qqline(historical_join$X3Y_Percent,col="red")
```

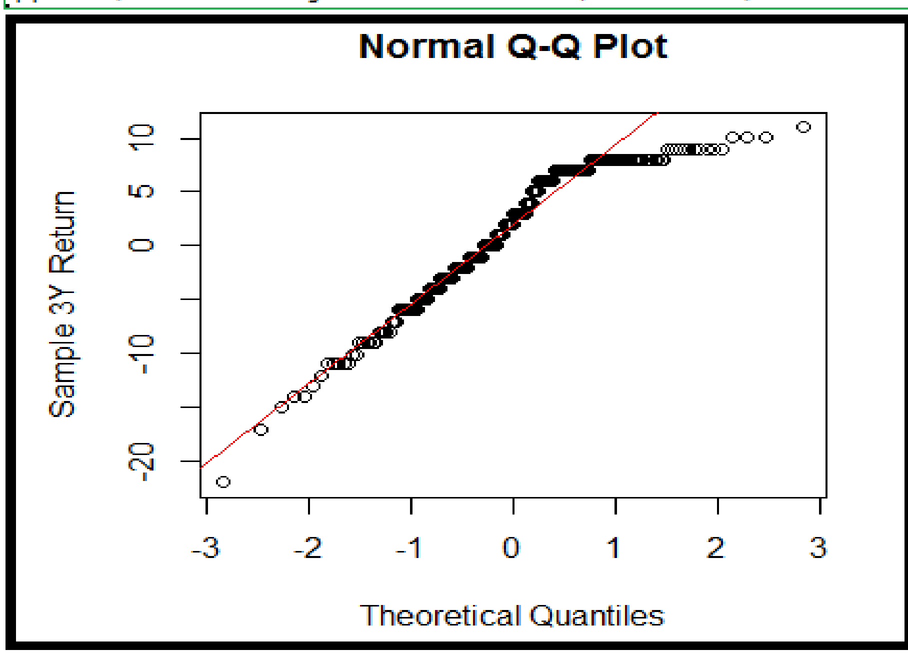


Figure 26: Normal Q-Q Plot of Annualized 3Y Return (in%)

➢ Scatter Plots of -> explanatory variables that appeared correlated in the data. Scatter plots were drawn to find any relationship

```r
#Relation between 3Y return and Crisil Rank
plot(y=historical_join$X3Y_Percent, x=historical_join$CrisilRank,
    col="blue",
    ylim=c(-30, 30), xlim=c(0, 5),
    main="Relationship Btw 3Y Return & Crisil Rank",
    ylab=" Percentage 3Y Return", xlab="Crisil Rank of Scheme")
```

```r
#Relation between 3Y return and Standard Deviation
plot(y=historical_join$X3Y_Percent, x=historical_join$StandardDeviation,
    col="blue",
    ylim=c(-30, 30), xlim=c(0, 60),
    main="Relationship Btw 3Y Return & Standard Deviation",
    ylab=" Percentage 3Y Return", xlab="Standard Deviation of Scheme")
```

```r
#Relation between 3Y return and AuM
plot(y=historical_join$X3Y_Percent, x=historical_join$AuM_in_Cr,
    col="blue",
    ylim=c(-30, 30), xlim=c(0, 90000),
    main="Relationship Btw 3Y Return & AuM",
    ylab=" Percentage 3Y Return", xlab="AuM(in Crs) of Scheme")
```

```r
#Relation between 3Y return and Beta
plot(y=historical_join$X3Y_Percent, x=historical_join$Beta,
    col="blue",
    ylim=c(-30, 30), xlim=c(-3, 3),
    main="Relationship Btw 3Y Return & Beta",
    ylab=" Percentage 3Y Return", xlab="Beta of Scheme")
```

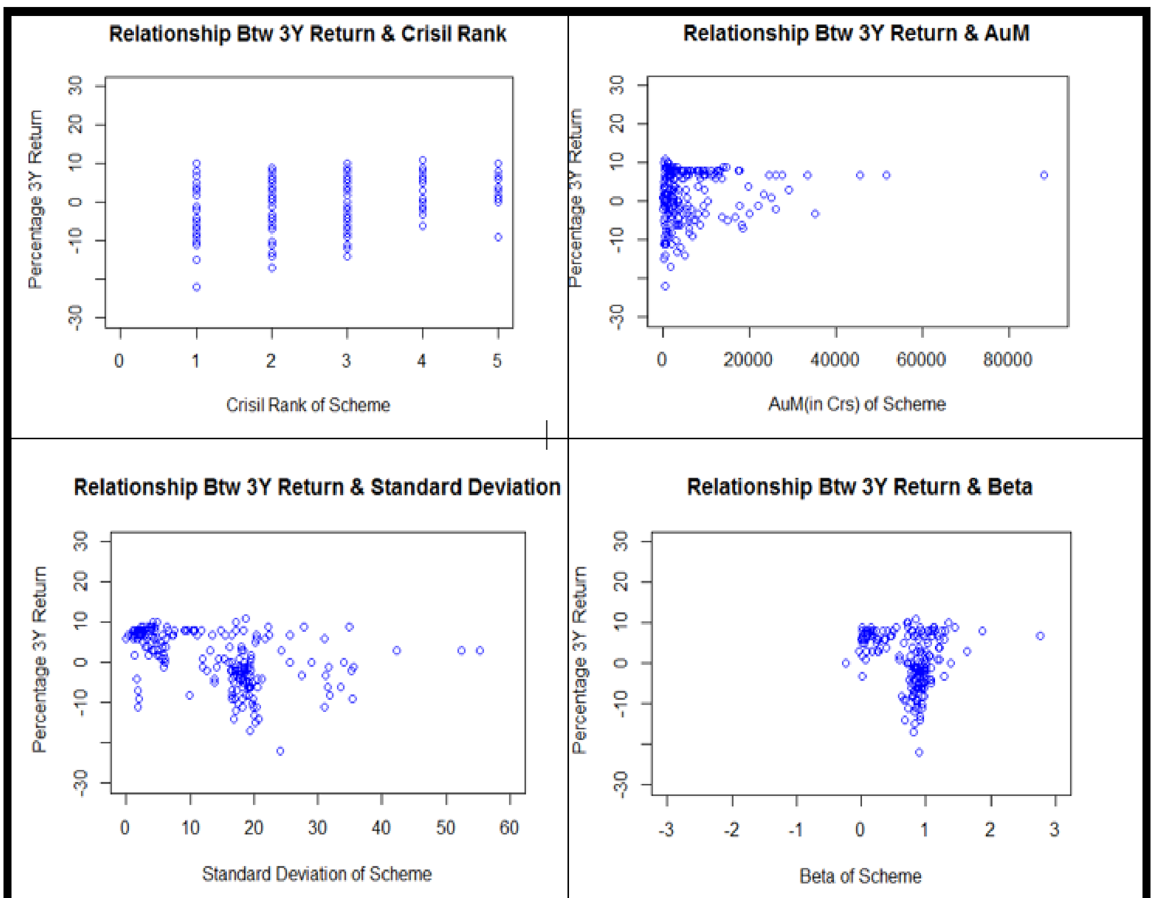


Figure 27: Scatter Plot of Annualized 3Y Return vs Crisil Rank, AuM, Beta and Standard Deviation

```r
#Relation between 3Y return and Sharpe Ratio
plot(y=historical_join$X3Y_Percent, x=historical_join$SharpeRatio,
     col="blue",
     ylim=c(-30, 30), xlim=c(-3, 3),
     main="Relationship Btw 3Y Return & Sharpe Ratio",
     ylab=" Percentage 3Y Return", xlab="Sharpe Ratio of Scheme")

#Relation between 3Y return and Jensens Alpha
plot(y=historical_join$X3Y_Percent, x=historical_join$JensensAlpha,
     col="blue",
     ylim=c(-30, 30), xlim=c(-15, 15),
     main="Relationship Btw 3Y Return & Jensens Alpha",
     ylab=" Percentage 3Y Return", xlab="Jensens Alpha of Scheme")

#Relation between 3Y Return and Treynors Ratio
plot(y=historical_join$X3Y_Percent, x=historical_join$TreynorsRatio,
     col="blue",
     ylim=c(-30, 30), xlim=c(-5, 5),
     main="Relationship Btw 3Y Return & Treynor's Ratio",
     ylab=" Percentage 3Y Return", xlab="Treynor's Ratio of Scheme")
```

```r
#Relation between 3Y Return and Annualized Holding Turnover
plot(y=historical_join$X3Y_Percent, x=historical_join$TurnoverRatio_Percentage,
     col="blue",
     ylim=c(-30, 30), xlim=c(0, 4000),
     main="Relationship Btw 3Y Return & Annualized Holding Turnover",
     ylab=" Percentage 3Y Return", xlab="Percentage Turnover Ratio of Scheme")

#Relation between 3Y return and Number of Stocks in Portfolio
plot(y=historical_join$X3Y_Percent, x=historical_join$No_of_stocks_portfolio,
     col="blue",
     ylim=c(-30, 30), xlim=c(0, 200),
     main="Relationship Btw 3Y Return & Stocks in Portfolio",
     ylab=" Percentage 3Y Return", xlab="No of Stocks in portfolio")
```

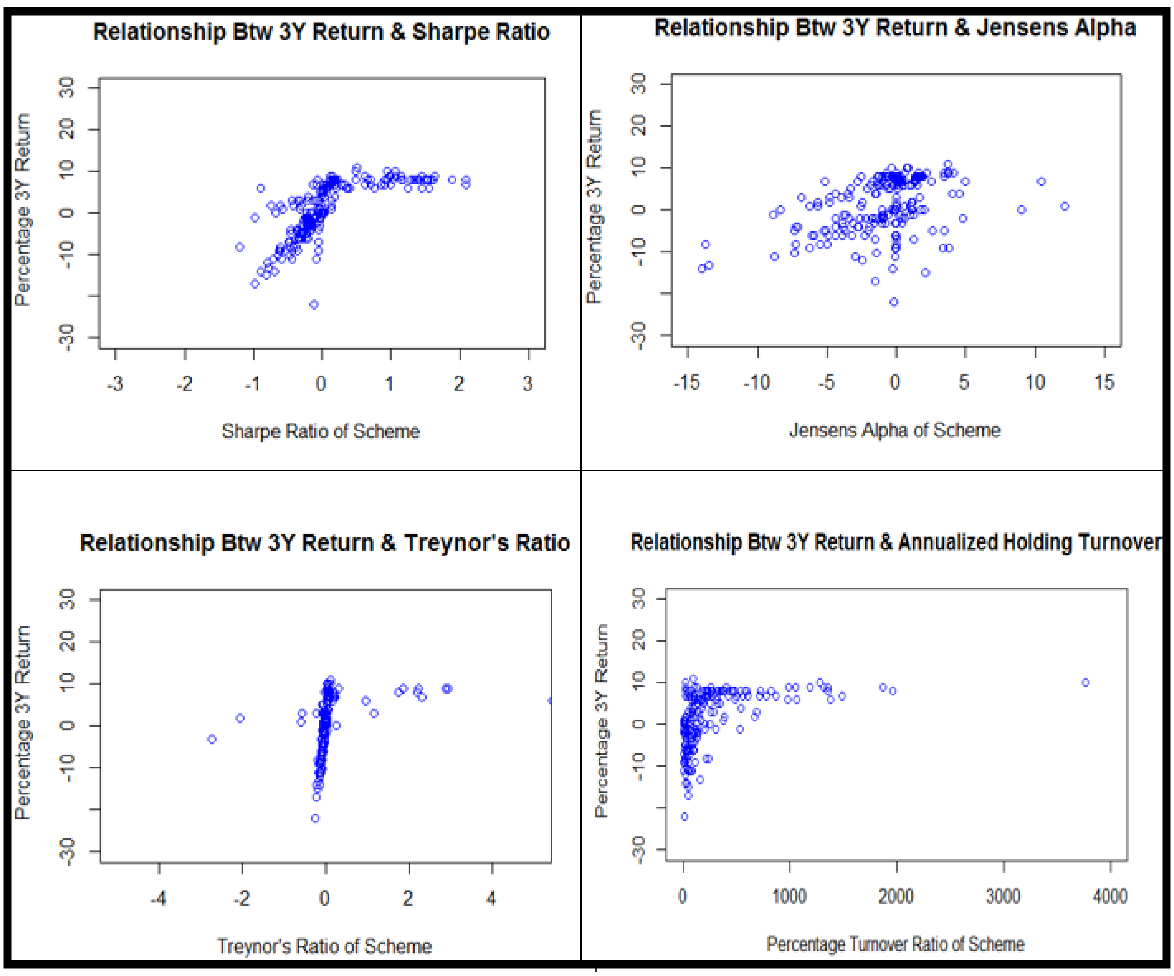


Figure 28: Scatter Plot of Annualized 3Y Return vs Sharpe Ratio, Jensens Alpha, Treynor's Ratio and Annualized Holding Turnover

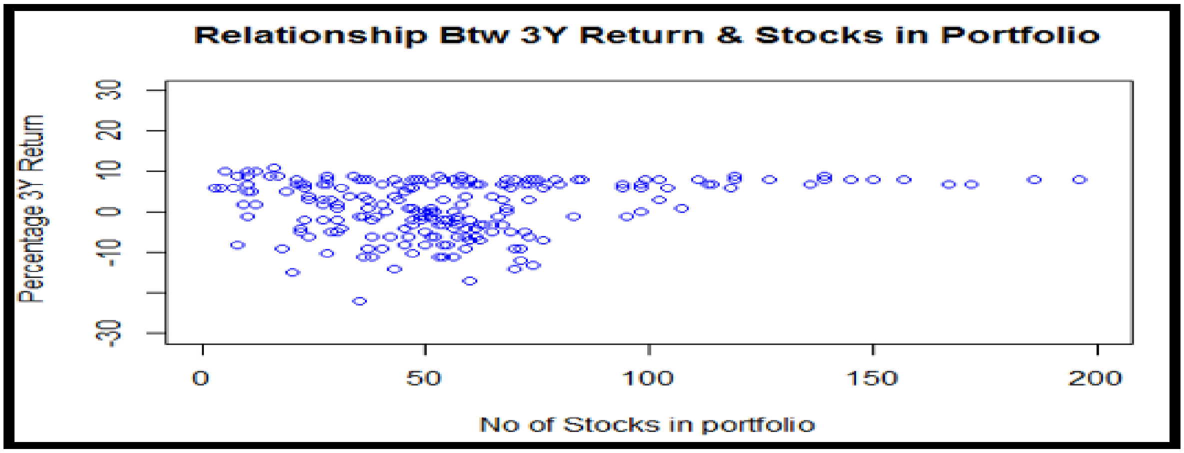


Figure 29: Scatter Plot of Annualized 3Y Return v/s Number of stocks in Portfolio

- Correlation Plot and Correlation Matrix were drawn to understand the correlation of response variable – Annualized 3Y Return with individual explanatory / independent variables that I have considered

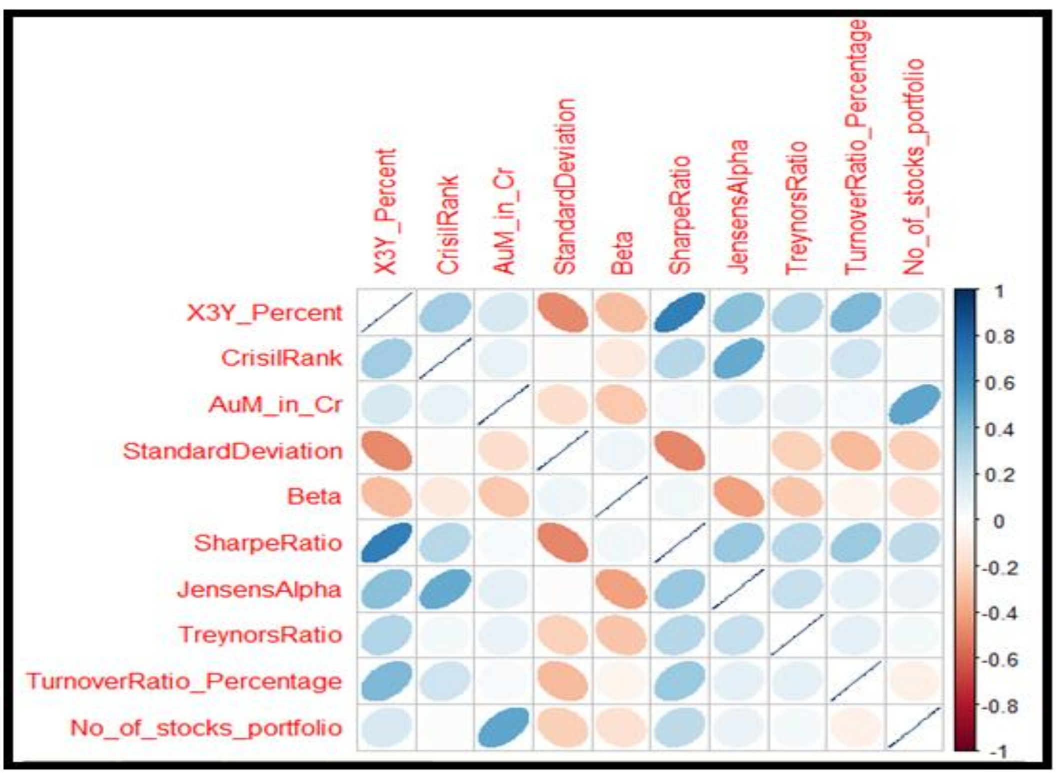


Figure 30: Correlation Plot 3Y – Response v/s Explanatory variables

```
> cor(historic_3year[, c(1:10)])
```

	X3Y_Percent	CrisilRank	AuM_in_Cr	StandardDeviation	Beta	SharpeRatio
X3Y_Percent	1.0000000	0.34223030	0.16852794	-0.47495827	-0.30300723	0.68932054
CrisilRank	0.3422303	1.00000000	0.09708943	-0.01923882	-0.11439060	0.27331235
AuM_in_Cr	0.1685279	0.09708943	1.00000000	-0.17953578	-0.26984890	0.03819755
StandardDeviation	-0.4749583	-0.01923882	-0.17953578	1.00000000	0.06329553	-0.48757622
Beta	-0.3030072	-0.11439060	-0.26984890	0.06329553	1.00000000	0.05457431
SharpeRatio	0.6893205	0.27331235	0.03819755	-0.48757622	0.05457431	1.00000000
JensensAlpha	0.4152509	0.50659559	0.10162812	-0.01345779	-0.40326585	0.37145335
TreynorsRatio	0.2960723	0.04330193	0.08477281	-0.22879641	-0.27150579	0.27102015
TurnoverRatio_Percentage	0.4447932	0.19021977	0.03761012	-0.31930298	-0.05996374	0.36519252
No_of_stocks_portfolio	0.1669060	0.01235628	0.52978046	-0.23206628	-0.15196191	0.25299421

	TurnoverRatio_Percentage	No_of_stocks_portfolio	JensensAlpha	TreynorsRatio
X3Y_Percent	0.44479320	0.16690601	0.41525094	0.29607232
CrisilRank	0.19021977	0.01235628	0.50659559	0.04330193
AuM_in_Cr	0.03761012	0.52978046	0.10162812	0.08477281
StandardDeviation	-0.31930298	-0.23206628	-0.01345779	-0.22879641
Beta	-0.05996374	-0.15196191	-0.40326585	-0.27150579
SharpeRatio	0.36519252	0.25299421	0.37145335	0.27102015
JensensAlpha	0.10343390	0.08432423	1.00000000	0.22343148
TreynorsRatio	0.10657455	0.04895566	0.22343148	1.00000000
TurnoverRatio_Percentage	1.00000000	-0.07869040	0.10343390	0.10657455
No_of_stocks_portfolio	-0.07869040	1.00000000	0.08432423	0.04895566

Figure 31: Correlation Matrix 3Y – Response v/s Explanatory variables

From the Correlation Plot and Correlation Matrix of Medium Term, it was observed that the explanatory variables Sharpe Ratio, Turnover Ratio., Jensen's Alpha., Crisil Rank. and Treynor's Ratio. had good positive correlation with 3Y Annualized Returns while the variables Standard Deviation and Beta were negatively correlated

- **Long Term – Investment Period 5Y**

  - Histogram and QQ Plot of 5Year Returns

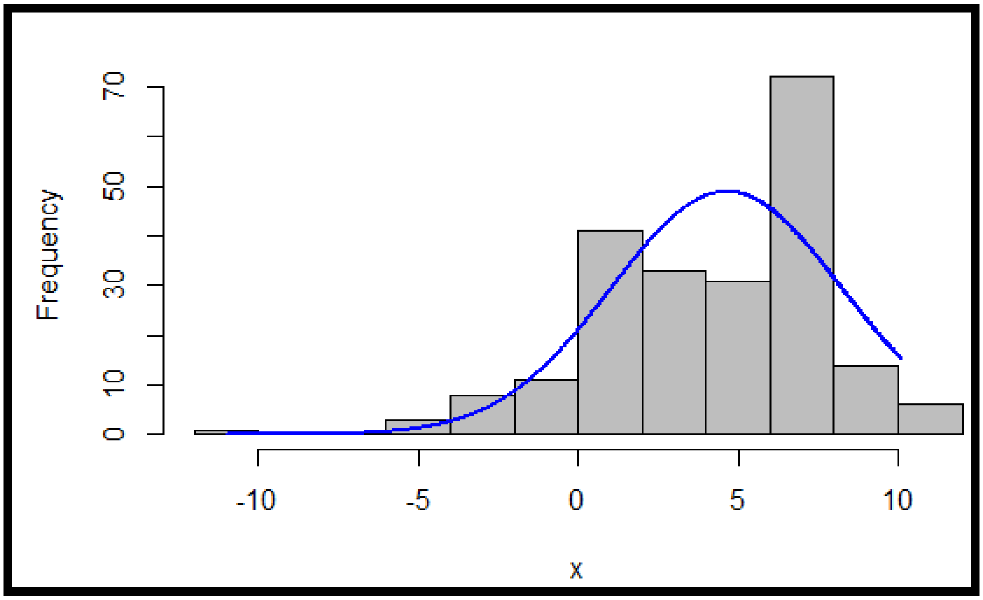


Figure 32: Histogram of Annualized 5Y Return (in%)

```
qqnorm(historical_join$X5Y_Percent,ylab="Sample 5Y Return")
qqline(historical_join$X5Y_Percent,col="red")
```

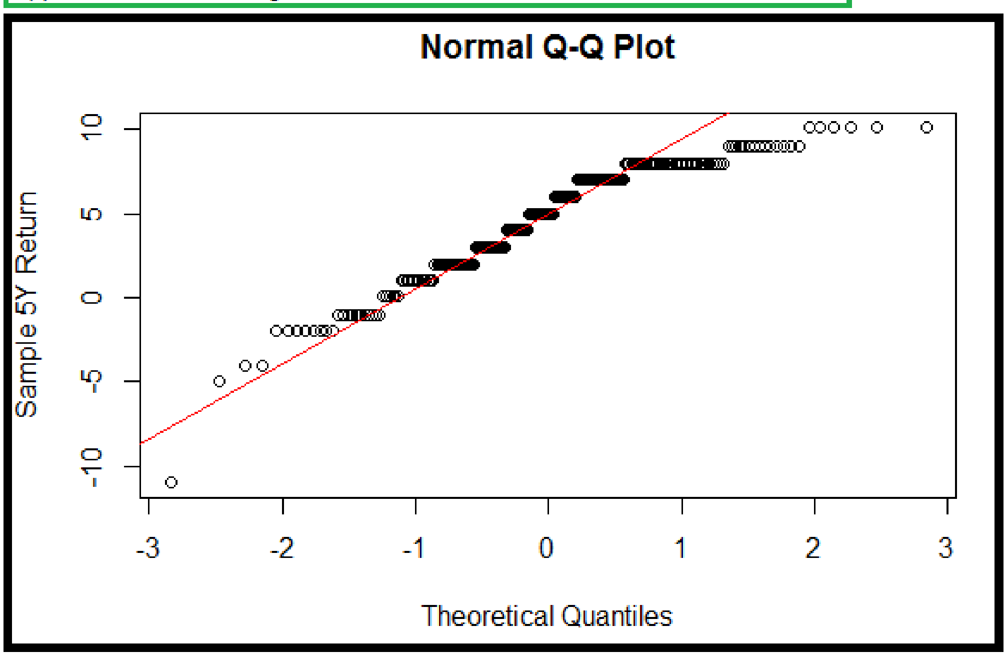


Figure 33: Normal Q-Q Plot of Annualized 5Y Return (in%)

- Scatter Plots of -> explanatory variables that appeared correlated in the data. Scatter plots were drawn to find any relationship

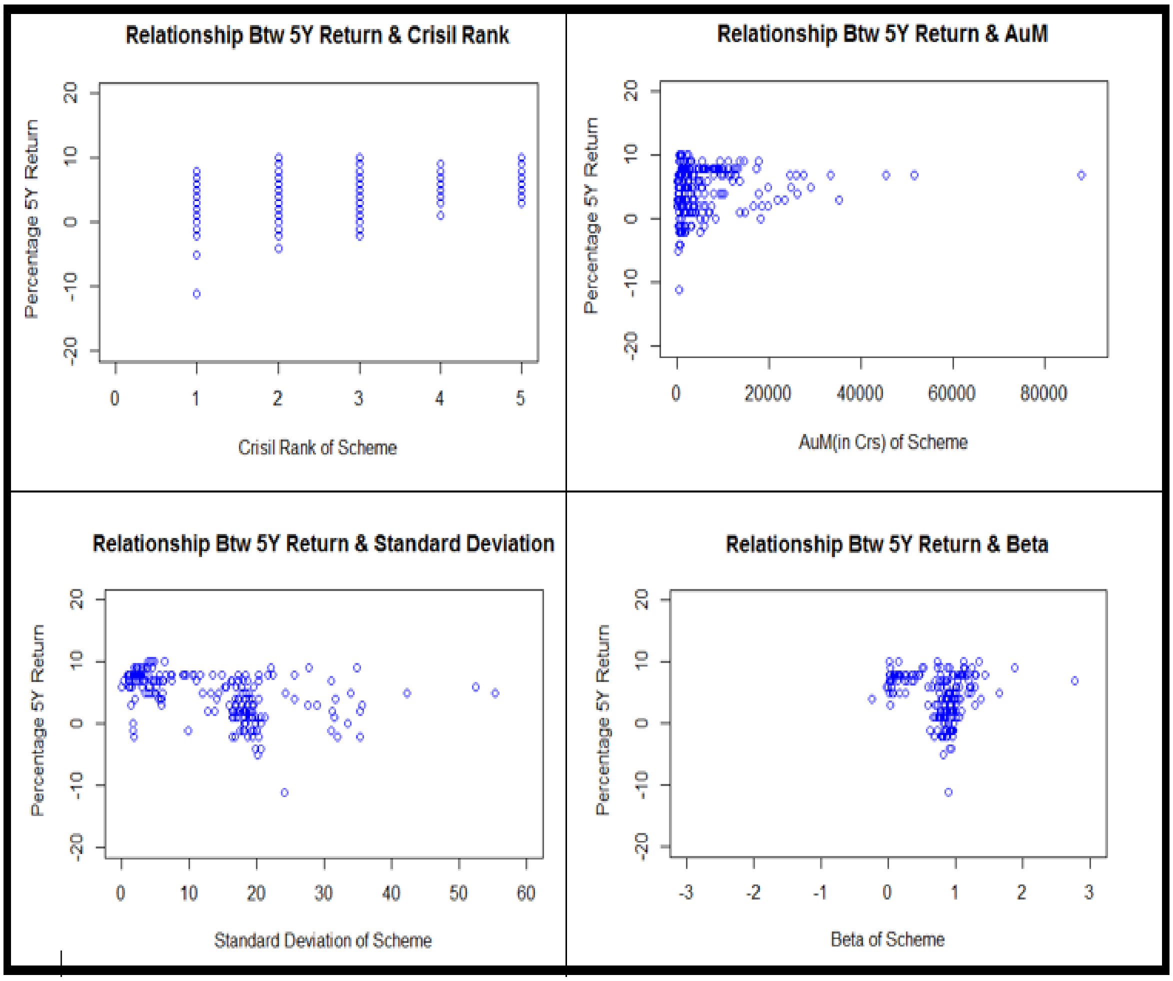


Figure 34: Scatter Plot of Annualized 5Y Return vs Crisil Rank, AuM, Beta and Standard Deviation

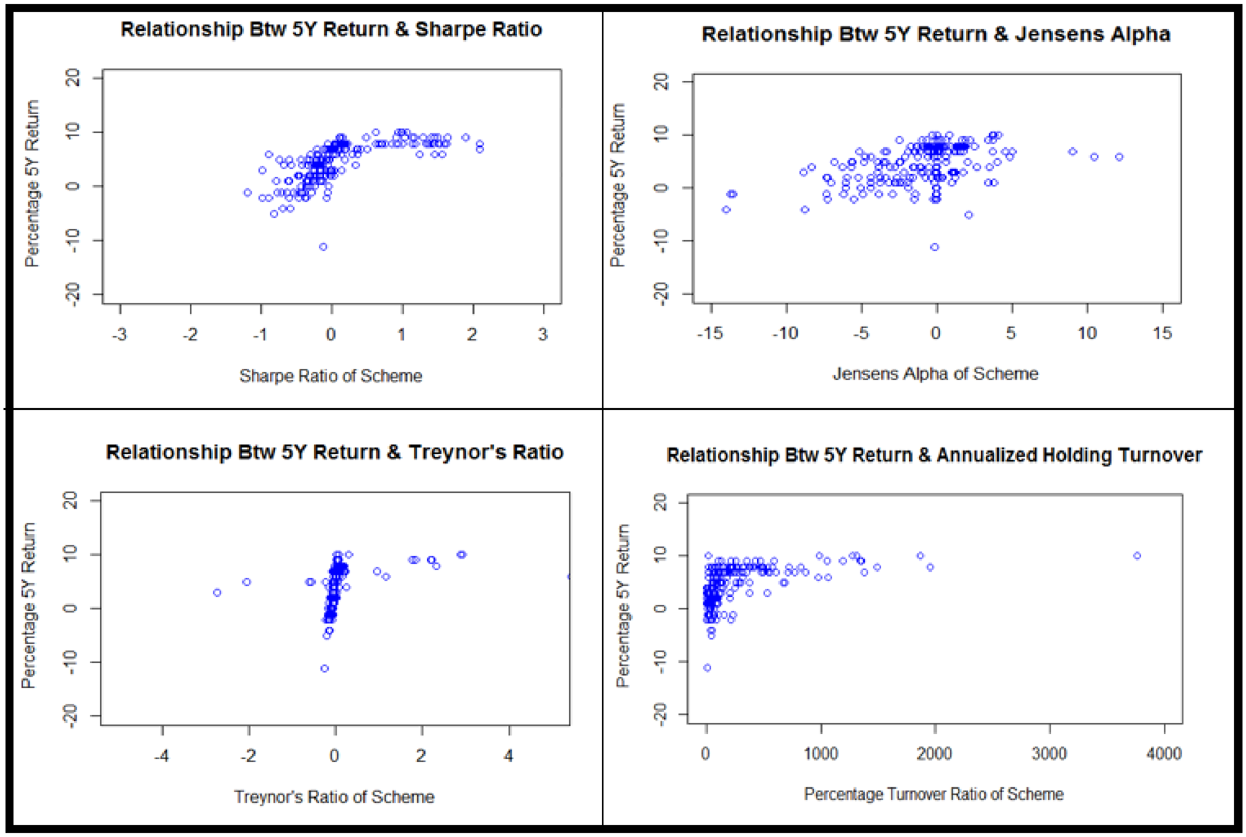


Figure 35: Scatter Plot of Annualized 5Y Return vs Sharpe Ratio, Jensens Alpha, Treynor’s Ratio and Annualized Holding Turnover

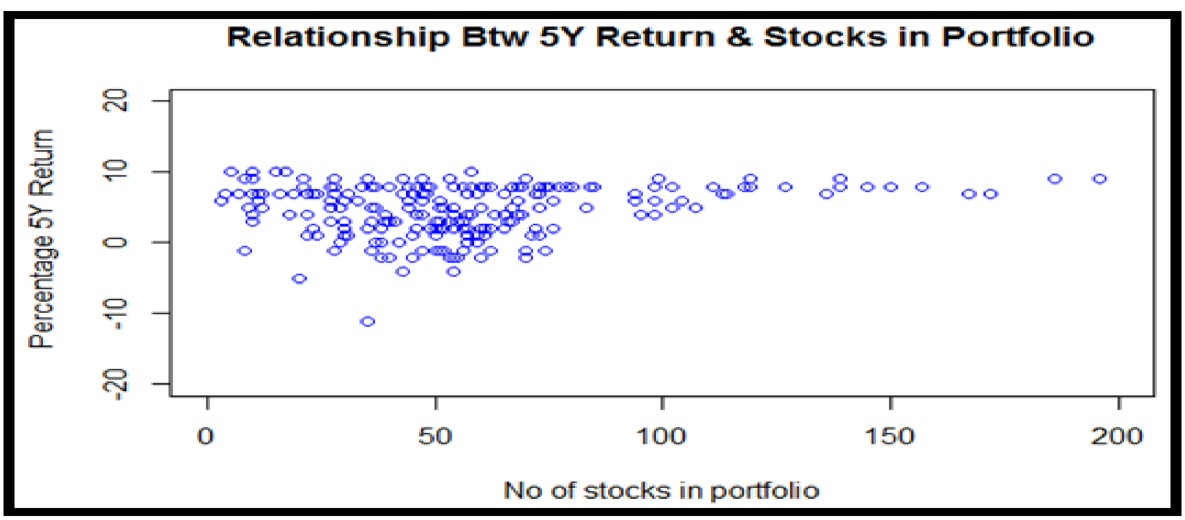


Figure 36: Scatter Plot of Annualized 5Y Return v/s Number of stocks in Portfolio

➢ Correlation Plot and Correlation Matrix were drawn to understand the correlation of response variable – Annualized 5Y Return with individual explanatory / independent variable

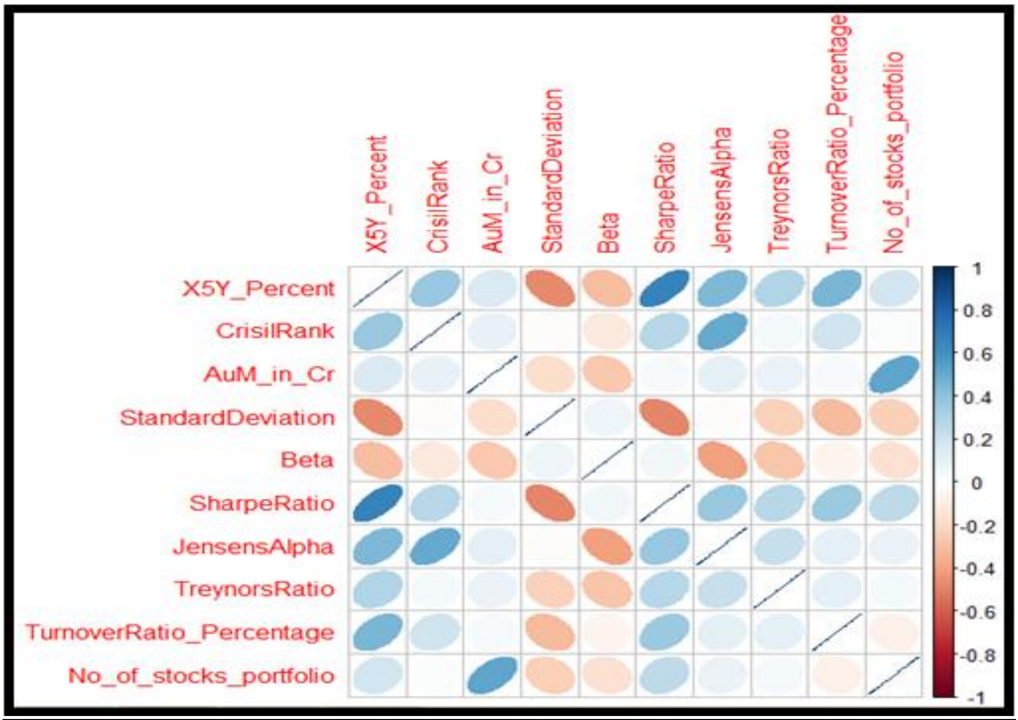


Figure 37: Correlation Plot 5Y – Response v/s Explanatory variables

```
> cor(historic_5year[, c(1:10)])
```

	X5Y_Percent	CrisilRank	AuM_in_Cr	StandardDeviation	Beta	SharpeRatio
X5Y_Percent	1.0000000	0.37859261	0.15331504	-0.47978313	-0.30913329	0.66165392
CrisilRank	0.3785926	1.00000000	0.09708943	-0.01923882	-0.11439060	0.27331235
AuM_in_Cr	0.1533150	0.09708943	1.00000000	-0.17953578	-0.26984890	0.03819755
StandardDeviation	-0.4797831	-0.01923882	-0.17953578	1.00000000	0.06329553	-0.48757622
Beta	-0.3091333	-0.11439060	-0.26984890	0.06329553	1.00000000	0.05457431
SharpeRatio	0.6616539	0.27331235	0.03819755	-0.48757622	0.05457431	1.00000000
JensensAlpha	0.4491360	0.50659559	0.10162812	-0.01345779	-0.40326585	0.37145335
TreynorsRatio	0.2954443	0.04330193	0.08477281	-0.22879641	-0.27150579	0.27102015
TurnoverRatio_Percentage	0.4570342	0.19021977	0.03761012	-0.31930298	-0.05996374	0.36519252
No_of_stocks_portfolio	0.1808389	0.01235628	0.52978046	-0.23206628	-0.15196191	0.25299421

	JensensAlpha	TreynorsRatio	TurnoverRatio_Percentage	No_of_stocks_portfolio
X5Y_Percent	0.44913599	0.29544431	0.45703421	0.18083895
CrisilRank	0.50659559	0.04330193	0.19021977	0.01235628
AuM_in_Cr	0.10162812	0.08477281	0.03761012	0.52978046
StandardDeviation	-0.01345779	-0.22879641	-0.31930298	-0.23206628
Beta	-0.40326585	-0.27150579	-0.05996374	-0.15196191
SharpeRatio	0.37145335	0.27102015	0.36519252	0.25299421
JensensAlpha	1.00000000	0.22343148	0.10343390	0.08432423
TreynorsRatio	0.22343148	1.00000000	0.10657455	0.04895566
TurnoverRatio_Percentage	0.10343390	0.10657455	1.00000000	-0.07869040
No_of_stocks_portfolio	0.08432423	0.04895566	-0.07869040	1.00000000

Figure 38: Correlation Matrix 5Y – Response v/s Explanatory variables

From the Correlation Plot and Correlation Matrix of Long Term, it was observed that the explanatory variables Sharpe Ratio., Turnover Ratio., Jensen's Alpha., Crisil Rank. and Treynor's Ratio. had good positive correlation with 5Y Annualized Returns while the variables Standard Deviation and Beta were negatively correlated

6.6.2 DATA MODELLING FOR FEATURE IMPORTANCE – PART A

Linear Regression model was chosen using AIC in stepwise algorithm - a method of fitting regression models in which selection of predictive variables is carried out automatically and in each step a variable will be considered for addition or subtraction from the choice of explanatory variables based on some criteria. AIC is used to estimate the quality of each model with respect to other models and hence helps to select the best model

- **Short Term – Investment Period 1Y**

  From the analysis conducted in previous section, it was observed that the explanatory variables Sharpe Ratio., Turnover Ratio., Jensen's Alpha. and Treynor's. Ratio had good positive correlation with 1Y Annualized Returns while the variables Standard Deviation and Beta were negatively correlated.

```
> stpModel=step(lm(data=historic_1year, X1Y_Percent~.), trace=0, steps=1000)
> stpSummary <- summary(stpModel)
> stpSummary

Call:
lm(formula = X1Y_Percent ~ StandardDeviation + Beta + SharpeRatio +
    TurnoverRatio_Percentage, data = historic_1year)

Residuals:
     Min       1Q   Median       3Q      Max
-28.0506  -5.6152  -0.6558   5.1024  23.8084

Coefficients:
                          Estimate Std. Error t value Pr(>|t|)
(Intercept)               2.037949   1.515055   1.345     0.18
StandardDeviation        -0.339051   0.068085  -4.980 1.31e-06 ***
Beta                    -11.741283   1.360578  -8.630 1.38e-15 ***
SharpeRatio              12.401144   1.128072  10.993  < 2e-16 ***
TurnoverRatio_Percentage  0.009449   0.001549   6.102 4.82e-09 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 8.632 on 215 degrees of freedom
Multiple R-squared:  0.6949,    Adjusted R-squared:  0.6892
F-statistic: 122.4 on 4 and 215 DF,  p-value: < 2.2e-16
```

Figure 38: Applying stepwise algorithm on Short Term – 1Y Data

Initial Linear Regression model suggested by Stepwise Algorithm:-

X1Y_Percent ~ StandardDeviation + Beta + SharpeRatio + TurnoverRatio_Percentage

Two models were created and the best model was chosen by addition / subtraction of explanatory variables

a) <u>Model 1</u> : Considered all explanatory variables i.e Crisil Rank, AuM, Standard Deviation., Beta., Sharpe Ratio., Jensen's Alpha., Treynor's Ratio., Turnover Ratio and No of stocks in portfolio

```
> Model1 <- X1Y_Percent ~ CrisilRank+AuM_in_Cr+StandardDeviation+Beta
                          +SharpeRatio+JensensAlpha+TreynorsRatio
                          +TurnoverRatio_Percentage+No_of_stocks_portfolio
> fit1 <- lm(Model1, data = historic_1year)
> summary(fit1)

Call:
lm(formula = Model1, data = historic_1year)

Residuals:
     Min       1Q   Median       3Q      Max
-27.1407  -5.5469  -0.5656   5.0281  23.4792

Coefficients:
                          Estimate Std. Error t value Pr(>|t|)
(Intercept)              1.535e+00  2.764e+00   0.555    0.579
CrisilRank               5.163e-01  6.400e-01   0.807    0.421
AuM_in_Cr               -9.096e-05  7.666e-05  -1.186    0.237
StandardDeviation       -3.438e-01  7.280e-02  -4.723 4.25e-06 ***
Beta                    -1.264e+01  1.680e+00  -7.528 1.50e-12 ***
SharpeRatio              1.255e+01  1.405e+00   8.930  < 2e-16 ***
JensensAlpha            -2.052e-01  2.444e-01  -0.839    0.402
TreynorsRatio            3.004e-01  1.052e+00   0.286    0.775
TurnoverRatio_Percentage 9.237e-03  1.630e-03   5.665 4.79e-08 ***
No_of_stocks_portfolio   2.888e-03  2.228e-02   0.130    0.897
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 8.681 on 210 degrees of freedom
Multiple R-squared:  0.6986,	Adjusted R-squared:  0.6857
F-statistic: 54.08 on 9 and 210 DF,  p-value: < 2.2e-16
```

Figure 39: Model 1 for Short Term – 1Y Data

After fitting the above model to Short Term Dataset, it was observed that the best fit model excluded **Crisil Rank, Jensen's Alpha., Treynor's Ratio. and No of stocks in portfolio**. Therefore in next model ran the regression after excluded these explanatory variables.

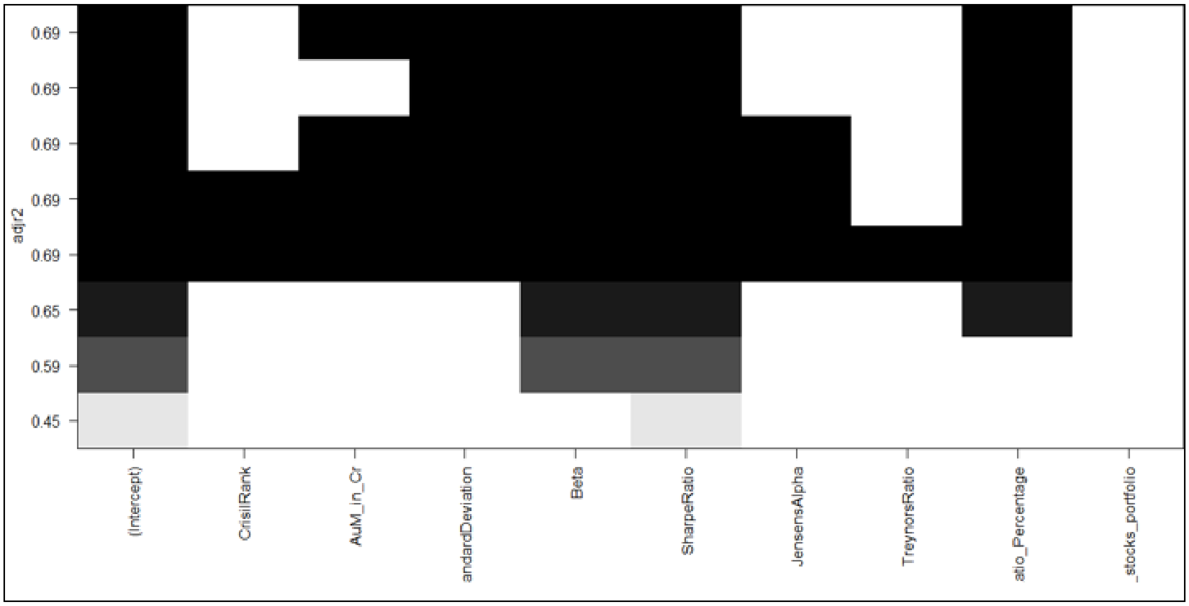


Figure 40 : Fitting Model 1 on Short Term – 1Y dataset

b) Model 2 : Excluded explanatory variables Crisil Rank., Jensen's Alpha., Treynor's. Ratio and No of stocks in portfolio

```
> Model2 <- X1Y_Percent ~ AuM_in_Cr+StandardDeviation+Beta+SharpeRatio+TurnoverRatio_Percentage
> fit2 <- lm(Model2, data = historic_1year)
> summary(fit2)

Call:
lm(formula = Model2, data = historic_1year)

Residuals:
     Min       1Q   Median       3Q      Max
-28.2923  -5.4289  -0.5973   4.9006  23.6913

Coefficients:
                          Estimate Std. Error t value Pr(>|t|)
(Intercept)              3.070e+00  1.718e+00   1.787   0.0754 .
AuM_in_Cr               -8.175e-05  6.450e-05  -1.267   0.2064
StandardDeviation       -3.535e-01  6.894e-02  -5.128 6.55e-07 ***
Beta                    -1.221e+01  1.407e+00  -8.674 1.06e-15 ***
SharpeRatio              1.237e+01  1.127e+00  10.973  < 2e-16 ***
TurnoverRatio_Percentage  9.399e-03  1.547e-03   6.076 5.57e-09 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 8.62 on 214 degrees of freedom
Multiple R-squared:  0.6971,    Adjusted R-squared:  0.6901
F-statistic: 98.52 on 5 and 214 DF,  p-value: < 2.2e-16
```

Figure 41: Model 2 for Short Term – 1Y Data

So for Short Term, it can conclude that :-

i. p-Value is less than 0.05 which means we are rejecting the NULL Hypothesis at 95% Confidence interval
ii. Adjusted R-square value is more for Model 2 instead of model 1 so Model 2 is better
iii. AIC Value is less than Model 1, so Model 2 is better
iv. Top 5 variables in order of significance that determine the performance of Mutual Fund Scheme in Short Term are :- Sharpe Ratio (1), Beta (2), Turnover Ratio(3), Standard Deviation (4) and AuM (5)

```
> summary(fit1)$adj.r.squared
[1] 0.6856543
> summary(fit2)$adj.r.squared
[1] 0.6900556
> AIC(fit1)
[1] 1586.999
> AIC(fit2)
[1] 1580.048
```

```
varImp(fit2, scale = FALSE)
```

	Overall
AuM_in_Cr	1.267350
StandardDeviation	5.127738
Beta	8.673632
SharpeRatio	10.973327
TurnoverRatio_Percentage	6.075899

Figure 42: Important Features for Mutual Fund Performance in Short Term

- **Medium Term – Investment Period 3Y**

From the analysis conducted in previous section, it was observed that the explanatory variables Sharpe Ratio., Turnover Ratio., Jensen's Alpha., Crisil Rank. and Treynor's Ratio. had good positive correlation with 3Y Annualized Returns while the variables Standard Deviation and Beta were negatively correlated

```
> stpModel=step(lm(data=historic_3year, X3Y_Percent~.), trace=0, steps=1000
> stpSummary <- summary(stpModel)
> stpSummary

Call:
lm(formula = X3Y_Percent ~ CrisilRank + StandardDeviation + Beta +
    SharpeRatio + TurnoverRatio_Percentage, data = historic_3year)

Residuals:
    Min      1Q  Median      3Q     Max
-18.297  -1.940   0.268   2.473   8.734

Coefficients:
                           Estimate Std. Error t value Pr(>|t|)
(Intercept)               2.4323930  0.9745499   2.496 0.013318 *
CrisilRank                0.7519473  0.2605229   2.886 0.004297 **
StandardDeviation        -0.0893806  0.0316806  -2.821 0.005233 **
Beta                     -4.5673169  0.6304015  -7.245 7.72e-12 ***
SharpeRatio               5.8404347  0.5391911  10.832  < 2e-16 ***
TurnoverRatio_Percentage  0.0025541  0.0007151   3.571 0.000438 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 3.958 on 214 degrees of freedom
Multiple R-squared:  0.6465,    Adjusted R-squared:  0.6382
F-statistic: 78.27 on 5 and 214 DF,  p-value: < 2.2e-16
```

Figure 43: Applying stepwise algorithm on Medium Term – 3Y Data

Initial Linear Regression model suggested by Stepwise Algorithm:-

```
X3Y_Percent ~ CrisilRank + StandardDeviation + Beta +
                SharpeRatio + TurnoverRatio_Percentage
```

Two models were created and the best model was chosen by addition / subtraction of explanatory variables

a) Model 1 : Considered all explanatory variables i.e Crisil Rank, AuM, Standard Deviation, Beta., Sharpe Ratio., Jensen's Alpha., Treynor's Ratio., Turnover Ratio. and No of stocks in portfolio

```
> Model1 <- X3Y_Percent ~ CrisilRank+AuM_in_Cr+StandardDeviation+Beta
                          +SharpeRatio+JensensAlpha+TreynorsRatio+
                          TurnoverRatio_Percentage+No_of_stocks_portfolio
> fit1 <- lm(Model1, data = historic_3year)
> summary(fit1)

Call:
lm(formula = Model1, data = historic_3year)

Residuals:
     Min       1Q   Median       3Q      Max
-18.5174  -1.9650   0.2565   2.4840   8.0181

Coefficients:
                           Estimate Std. Error t value Pr(>|t|)
(Intercept)               3.183e+00  1.264e+00   2.519  0.01250 *
CrisilRank                6.707e-01  2.925e-01   2.293  0.02285 *
AuM_in_Cr                 4.691e-05  3.505e-05   1.339  0.18216
StandardDeviation        -8.984e-02  3.328e-02  -2.700  0.00750 **
Beta                     -4.416e+00  7.678e-01  -5.751  3.1e-08 ***
SharpeRatio               6.044e+00  6.424e-01   9.408  < 2e-16 ***
JensensAlpha              2.447e-02  1.117e-01   0.219  0.82682
TreynorsRatio             8.204e-02  4.807e-01   0.171  0.86466
TurnoverRatio_Percentage  2.316e-03  7.453e-04   3.107  0.00215 **
No_of_stocks_portfolio   -1.543e-02  1.018e-02  -1.515  0.13117
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 3.968 on 210 degrees of freedom
Multiple R-squared:  0.6513,    Adjusted R-squared:  0.6364
F-statistic: 43.58 on 9 and 210 DF,  p-value: < 2.2e-16
```

Figure 44: Model 1 for Medium Term – 3Y Data

After fitting the above model to Medium Term Dataset, it was observed that best fit model excluded **AuM, Jensen's Alpha**., **Treynor's**. **Ratio and No of stocks in portfolio**. In next model ran the regression after excluded these explanatory variables.

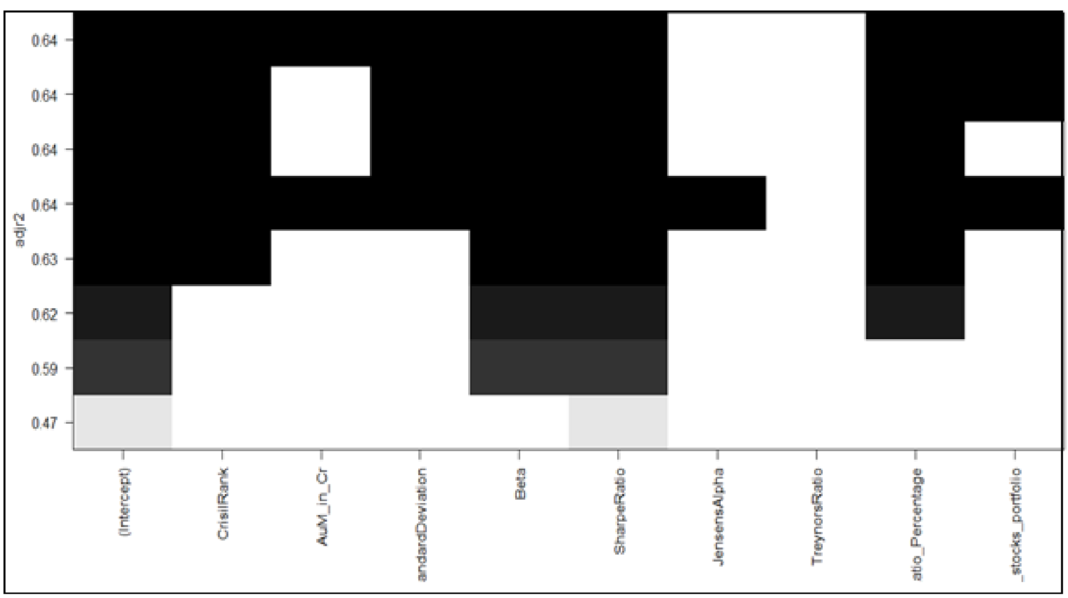


Figure 45: Fitting Model 1 on Medium Term – 3Y dataset

b) Model 2 : Excluded explanatory variables AuM., Jensen's Alpha., Treynor's. Ratio and No of stocks in portfolio

```
> Model2 <- X3Y_Percent ~ CrisilRank+Beta+StandardDeviation+SharpeRatio+
                          TurnoverRatio_Percentage
> fit2 <- lm(Model2, data = historic_3year)
> summary(fit2)

Call:
lm(formula = Model2, data = historic_3year)

Residuals:
    Min      1Q  Median      3Q     Max
-18.297  -1.940   0.268   2.473   8.734

Coefficients:
                          Estimate Std. Error t value Pr(>|t|)
(Intercept)              2.4323930  0.9745499   2.496 0.013318 *
CrisilRank               0.7519473  0.2605229   2.886 0.004297 **
Beta                    -4.5673169  0.6304015  -7.245 7.72e-12 ***
StandardDeviation       -0.0893806  0.0316806  -2.821 0.005233 **
SharpeRatio              5.8404347  0.5391911  10.832  < 2e-16 ***
TurnoverRatio_Percentage 0.0025541  0.0007151   3.571 0.000438 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 3.958 on 214 degrees of freedom
Multiple R-squared:  0.6465,    Adjusted R-squared:  0.6382
F-statistic: 78.27 on 5 and 214 DF,  p-value: < 2.2e-16
```

Figure 46: Model 2 for Medium Term – 3Y Data

So for Medium Term, it can be concluded that :-

i. p-Value is less than 0.05 which means we are rejecting the NULL Hypothesis at 95% Confidence interval
ii. Adjusted R-square value is more for Model 2 instead of model 1 so Model 2 is better
iii. AIC Value is less than Model 1, so Model 2 is better
iv. Top 5 variables in order of significance that determine the performance of Mutual Fund Scheme in Medium Term are :- Sharpe Ratio (1), Beta (2), Turnover Ratio(3), Crisil Rank(4) and Standard Deviation(5)

```
> summary(fit1)$adj.r.squared
[1] 0.6363652
> summary(fit2)$adj.r.squared
[1] 0.6382209
> AIC(fit1)
[1] 1242.57
> AIC(fit2)
[1] 1237.596
```

	Overall
CrisilRank	2.886301
Beta	7.245093
StandardDeviation	2.821302
SharpeRatio	10.831845
TurnoverRatio_Percentage	3.571426

Figure 47: Important Features for Mutual Fund Performance in Medium Term

- **Long Term – Investment Period 5Y**

From the analysis conducted in previous section, it was observed that the explanatory variables Sharpe Ratio., Turnover Ratio., Jensen's Alpha., Crisil Rank. and Treynor's. Ratio had good positive correlation with 5Y Annualized Returns while the variables Standard Deviation and Beta were negatively correlated

```
> stpModel=step(lm(data=historic_5year, X5Y_Percent~.), trace=0, steps=1000)
> stpSummary <- summary(stpModel)
> stpSummary

Call:
lm(formula = X5Y_Percent ~ CrisilRank + StandardDeviation + Beta +
    SharpeRatio + JensensAlpha + TurnoverRatio_Percentage, data = historic_5year)

Residuals:
     Min       1Q   Median       3Q      Max
-12.7693  -1.1620  -0.1039   1.4976   4.2059

Coefficients:
                          Estimate Std. Error t value Pr(>|t|)
(Intercept)              5.0948201  0.5608528   9.084  < 2e-16 ***
CrisilRank               0.4780682  0.1588519   3.010 0.002932 **
StandardDeviation       -0.0648468  0.0178928  -3.624 0.000363 ***
Beta                    -2.1721966  0.3960551  -5.485 1.17e-07 ***
SharpeRatio              2.6250183  0.3280701   8.001 7.82e-14 ***
JensensAlpha             0.0851705  0.0610315   1.396 0.164313
TurnoverRatio_Percentage 0.0015891  0.0003953   4.020 8.07e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 2.177 on 213 degrees of freedom
Multiple R-squared:  0.6414,    Adjusted R-squared:  0.6313
F-statistic: 63.49 on 6 and 213 DF,  p-value: < 2.2e-16
```

Figure 48: Applying stepwise algorithm on Long Term – 5Y Data

Initial Linear Regression model suggested by Stepwise Algorithm:-

```
X5Y_Percent ~ CrisilRank + StandardDeviation + Beta +
                   SharpeRatio + JensensAlpha +
                   TurnoverRatio_Percentage
```

Two models were created and the best model was chosen by addition / subtraction of explanatory variables

a) Model 1 : Considered all explanatory variables i.e Crisil Rank, AuM, Standard Deviation, Beta., Sharpe Ratio., Jensen's Alpha., Treynor's Ratio., Turnover Ratio. and No of stocks in portfolio

```
> Model1 <- X5Y_Percent ~ CrisilRank+AuM_in_Cr+StandardDeviation+Beta
                          +SharpeRatio+JensensAlpha+TreynorsRatio+
                          TurnoverRatio_Percentage+No_of_stocks_portfolio
> fit1 <- lm(Model1, data = historic_5year)
> summary(fit1)

Call:
lm(formula = Model1, data = historic_5year)

Residuals:
     Min       1Q   Median       3Q      Max 
-12.7569  -1.1753  -0.1012   1.4718   4.1524 

Coefficients:
                           Estimate Std. Error t value Pr(>|t|)    
(Intercept)               5.116e+00  6.975e-01   7.335 4.74e-12 ***
CrisilRank                4.789e-01  1.615e-01   2.965 0.003373 ** 
AuM_in_Cr                 4.667e-06  1.935e-05   0.241 0.809616    
StandardDeviation        -6.409e-02  1.837e-02  -3.489 0.000591 ***
Beta                     -2.133e+00  4.238e-01  -5.033 1.03e-06 ***
SharpeRatio               2.632e+00  3.546e-01   7.422 2.82e-12 ***
JensensAlpha              8.257e-02  6.167e-02   1.339 0.182082    
TreynorsRatio             1.097e-01  2.654e-01   0.413 0.679721    
TurnoverRatio_Percentage  1.563e-03  4.114e-04   3.799 0.000190 ***
No_of_stocks_portfolio   -1.692e-03  5.621e-03  -0.301 0.763727    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 2.191 on 210 degrees of freedom
Multiple R-squared:  0.6419,    Adjusted R-squared:  0.6265 
F-statistic: 41.82 on 9 and 210 DF,  p-value: < 2.2e-16
```

Figure 49: Model 1 for Long Term – 5Y Data

After fitting the above model to Long Term Dataset, it was observed that best fit model excluded **AuM, Jenson's Alpha, Treynor's Ratio and No of stocks in portfolio**. In next model ran the regression after excluded these explanatory variables

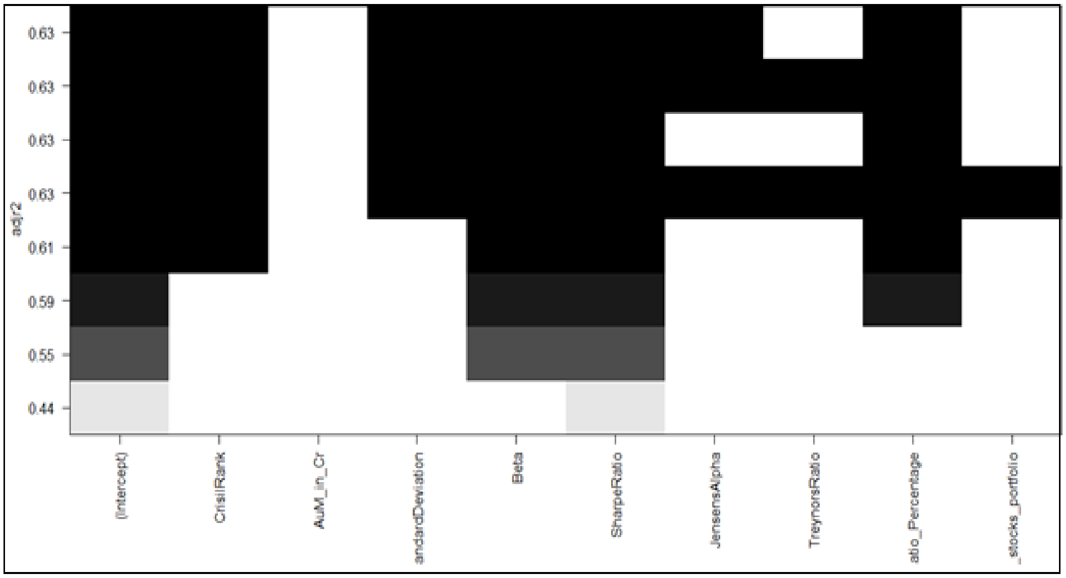


Figure 50: Fitting Model 1 on Long Term – 5Y dataset

b) <u>Model 2</u>: Excluded explanatory variables AuM, Jenson's Alpha, Treynor's Ratio and No of stocks in portfolio

```
> Model2 <- X5Y_Percent ~ CrisilRank+StandardDeviation
                          +Beta+SharpeRatio+TurnoverRatio_Percentage
> fit2 <- lm(Model2, data = historic_5year)
> summary(fit2)

Call:
lm(formula = Model2, data = historic_5year)

Residuals:
     Min       1Q   Median       3Q      Max
-12.5227  -1.2110  -0.0904   1.5290   4.2047

Coefficients:
                          Estimate Std. Error t value Pr(>|t|)
(Intercept)              4.8640060  0.5370953   9.056  < 2e-16 ***
CrisilRank               0.5738382  0.1435797   3.997 8.84e-05 ***
StandardDeviation       -0.0591524  0.0174599  -3.388 0.000838 ***
Beta                    -2.4394872  0.3474277  -7.022 2.87e-11 ***
SharpeRatio              2.8209644  0.2971598   9.493  < 2e-16 ***
TurnoverRatio_Percentage 0.0015332  0.0003941   3.890 0.000134 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 2.181 on 214 degrees of freedom
Multiple R-squared:  0.6381,    Adjusted R-squared:  0.6296
F-statistic: 75.46 on 5 and 214 DF,  p-value: < 2.2e-16
```

Figure 51: Model 2 for Long Term – 5Y Data

So for Long Term, it can be concluded that :-

i. p-Value is less than 0.05 which means we are rejecting the NULL Hypothesis at 95% Confidence interval

ii. Adjusted R-square value is more for Model 2 instead of model 1 so Model 2 is better

iii. AIC Value is less than Model 1, so Model 2 is better

iv. Top 6 variables in order of significance that determine the performance of Mutual Fund Scheme in Long Term are :- Sharpe Ratio (1), Beta (2), Turnover Ratio(3), Standard Deviation(4), Crisil Rank(5) and Jensen's Alpha(6)

```
> summary(fit1)$adj.r.squared
[1] 0.6265382
> summary(fit2)$adj.r.squared
[1] 0.6312728
> AIC(fit1)
[1] 981.1275
> AIC(fit2)
[1] 975.4413
```

	Overall
CrisilRank	3.009522
StandardDeviation	3.624177
Beta	5.484582
SharpeRatio	8.001396
JensensAlpha	1.395518
TurnoverRatio_Percentage	4.020080

Figure 52: Important Features for Mutual Fund Performance in Long Term

6.6.3 Predicting Top Performing Mutual Fund schemes for Short, Medium and Long Term Investment – PART B

Mutual Fund Schemes were classified as either a Good Investment or a Bad Investment using Logistic Regression approach. . I have split the respective datasets for short, medium and long term into training set as well as test set with a split ratio of 0.70 i.e 70% data will be attributed to train data while 30% will be attributed to test data. For a scheme to be considered as a Good investment, it must satisfy the provided assumptions in Section 7.6 (Data Analysis)

- **Predicting Good Investments for Short Term**

```
> dataset_1year$Good<-ifelse((dataset_1year$StandardDeviation<13.274)&(dataset_1year$Beta>0
+                    & dataset_1year$Beta<=1)&(dataset_1year$X1Y_Percent>=6)&(dataset_1year$SharpeRatio>1)
+                    &(dataset_1year$JensensAlpha>0),1,0)

> table(dataset_1year$Good)

  0   1
210  10
```

Got 10 schemes from 220 schemes as Good Investments in Short Term after applying above classification logic

Figure 53: Classification of Mutual Fund Scheme for Short Term Investment

```
> train<-dataset_1year[sampling_hypo1year,]
> test<-dataset_1year[-sampling_hypo1year,]
> dim(train)
[1] 154    9
> dim (test)
[1] 66   9
```

Figure 54: Split dataset into Train and Test to apply Short Term model

```
> hypo1result<-glm(Good ~ StandardDeviation + Beta + X1Y_Percent
                          + SharpeRatio + JensensAlpha
                                ,data = train,family = binomial)
```

Figure 55: General Linear Model on Short Term – Train dataset

```
> summary(hypo1result)

Call:
glm(formula = Good ~ StandardDeviation + Beta + X1Y_Percent +
    SharpeRatio + JensensAlpha, family = binomial, data = train)

Deviance Residuals:
   Min       1Q   Median       3Q      Max
-2.077    0.000    0.000    0.000    1.808

Coefficients:
                  Estimate Std. Error z value Pr(>|z|)
(Intercept)        -19.680      9.373  -2.099   0.0358 *
StandardDeviation   -6.425      4.859  -1.322   0.1861
Beta               -14.390     10.983  -1.310   0.1901
X1Y_Percent          3.060      1.739   1.759   0.0785 .
SharpeRatio          8.200      4.600   1.783   0.0747 .
JensensAlpha        -2.791      2.741  -1.019   0.3084
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 68.579  on 153  degrees of freedom
Residual deviance: 14.515  on 148  degrees of freedom
AIC: 26.515

Number of Fisher Scoring iterations: 16
```

Figure 56: Summarizing Model – Short Term

Optimal cutoff function was used to improve 0 and 1 prediction and reduce misclassification error. Got 0.12 as the Optimal cutoff and 0.011 as the misclassification error

```
predicted <- plogis(predict(hypo1result, test))
optcutoff <- optimalCutoff(test$Good, predicted)[1]
misClassError(test$Good,predicted,threshold = optcutoff)
plotROC(test$Good,predicted)
```

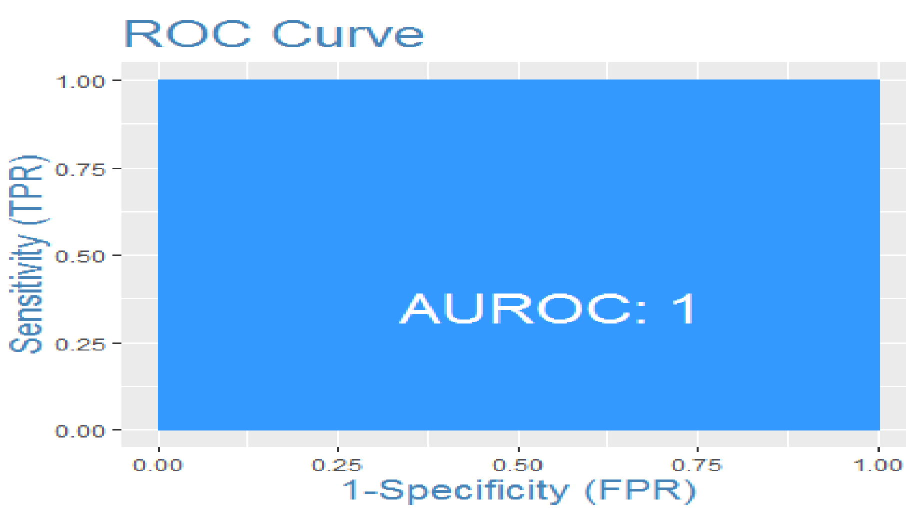


Figure 57: Assess performance of Model – Short Term

- **Predicting Good Investments for Medium Term**

```
> dataset_3year$Good<-ifelse((dataset_3year$StandardDeviation<13.274)&(dataset_3year$Beta>0 & dataset_3year$Beta<=1)
+                  &(dataset_3year$X3Y_Percent>7)&(dataset_3year$SharpeRatio>1)&(dataset_3year$JensensAlpha>0),1,0)
> table(dataset_3year$Good)

  0   1
210  10
```

Got 10 schemes from 220 schemes as Good Investments in Medium Term after applying above classification logic

Figure 58: Classification of Mutual Fund Scheme for Medium Term Investment

```
> summary(hypo3result)

Call:
glm(formula = Good ~ StandardDeviation + Beta + X3Y_Percent +
    SharpeRatio + JensensAlpha, family = binomial, data = train)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-0.89376  -0.00735   0.00000   0.00000   2.62076

Coefficients:
                  Estimate Std. Error z value Pr(>|z|)
(Intercept)       -33.2270    18.6873  -1.778   0.0754 .
StandardDeviation  -0.7210     0.4923  -1.465   0.1430
Beta               -4.2625     7.3581  -0.579   0.5624
X3Y_Percent         4.0204     2.6583   1.512   0.1304
SharpeRatio         2.9723     2.3226   1.280   0.2006
JensensAlpha        0.5605     2.2786   0.246   0.8057
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 50.705  on 153  degrees of freedom
Residual deviance: 11.833  on 148  degrees of freedom
AIC: 23.833

Number of Fisher Scoring iterations: 13
```

Figure 59: Summarizing Model – Medium Term

Optimal cutoff function was used to improve 0 and 1 prediction and reduce misclassification error. Got 0.98 as the Optimal cutoff and 0.03 as the misclassification error

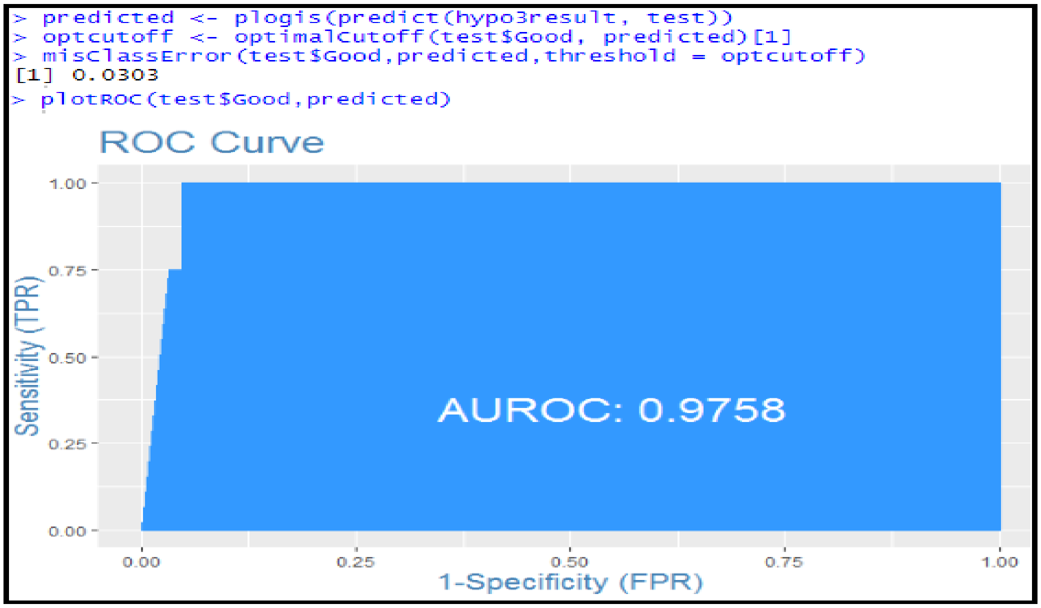


Figure 60: Assess performance of Model – Medium Term

- **Predicting Good Investments for Long Term**

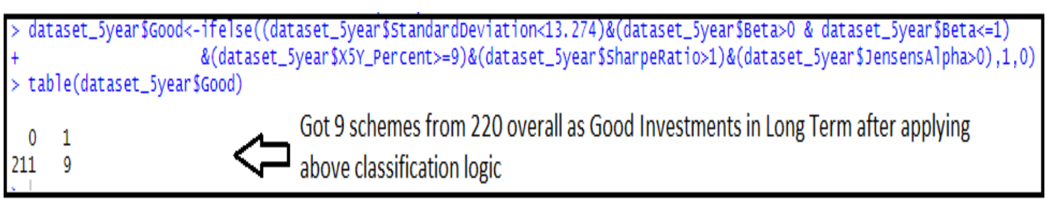


Figure 61: Classification of Mutual Fund Scheme for Medium Term Investment

```
> summary(hypo5result)

Call:
glm(formula = Good ~ StandardDeviation + Beta + X5Y_Percent +
    SharpeRatio + JensensAlpha, family = binomial, data = train)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-1.85683  -0.03531  -0.00003   0.00000   1.91975

Coefficients:
                  Estimate Std. Error z value Pr(>|z|)
(Intercept)       -30.8918    15.7259  -1.964   0.0495 *
StandardDeviation  -0.2455     1.2141  -0.202   0.8397
Beta               -8.5885     8.1972  -1.048   0.2948
X5Y_Percent         3.6003     2.1362   1.685   0.0919 .
SharpeRatio         4.5288     4.4255   1.023   0.3061
JensensAlpha       -1.9783     2.3350  -0.847   0.3969
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 37.100  on 153  degrees of freedom
Residual deviance: 12.001  on 148  degrees of freedom
AIC: 24.001

Number of Fisher Scoring iterations: 14
```

Figure 62: Summarizing Model – Long Term

Optimal cutoff function was used to improve 0 and 1 prediction and reduce misclassification error. Got 0.016 as the Optimal cutoff and 0.03 as the misclassification error

```
> predicted <- plogis(predict(hypo5result, test))
> optcutoff <- optimalCutoff(test$Good, predicted)[1]
> misClassError(test$Good,predicted,threshold = optcutoff)
[1] 0.0303
> plotROC(test$Good,predicted)
```

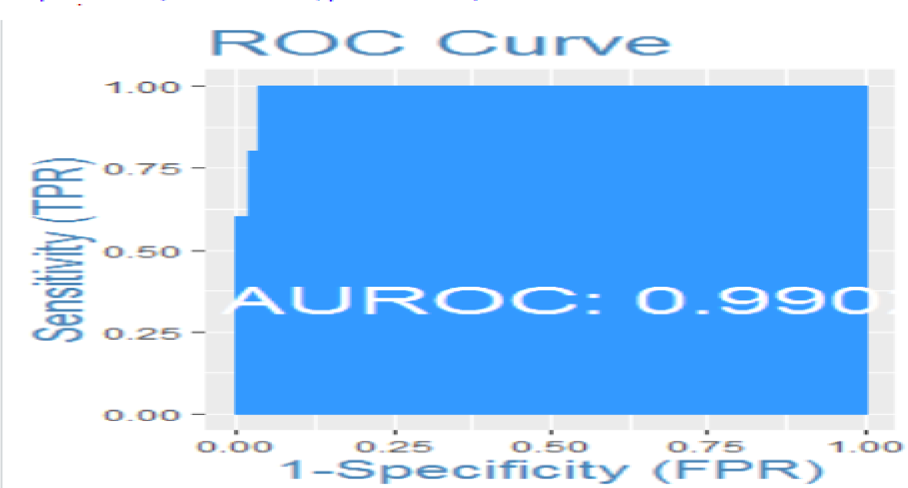


Figure 63: Assess performance of Model – Long Term

TOP MUTUAL FUND SCHEMES FOR LONG TERM INVESTMENT

SchemeName	X5Y_Percent	StandardDeviation	Beta	SharpeRatio	JensensAlpha	TreynorsRatio	TurnoverRatio_Percentage	Good
Aditya Birla Sun Life Corporate Bond Fund	9.0	1.79	0.02	1.89	3.42	2.19	471	1
Axis Banking & PSU Debt Fund	9.0	2.26	0.02	1.63	3.71	1.84	105	1
DSP Government Securities Fund	10.1	4.21	0.72	1.06	0.79	0.06	3768	1
HDFC Corporate Bond Fund	9.0	2.34	0.02	1.45	3.41	2.22	126	1
ICICI Prudential All Seasons Bond Fund	9.0	2.66	0.02	1.28	3.42	1.75	350	1
Kotak Banking and PSU Debt Fund	9.0	2.21	0.87	1.49	0.32	0.04	596	1
SBI Dynamic Bond Fund	9.0	3.36	0.90	1.14	0.56	0.04	1054	1
SBI Magnum Gilt Fund	10.1	3.95	0.01	1.06	4.09	2.86	983	1
SBI Magnum Income Fund	9.0	2.95	0.79	1.03	0.17	0.04	214	1

TOP MUTUAL FUND SCHEMES FOR MEDIUM TERM INVESTMENT

SchemeName	X3Y_Percent	StandardDeviation	Beta	SharpeRatio	JensensAlpha	TreynorsRatio	TurnoverRatio_Percentage	Good
Aditya Birla Sun Life Corporate Bond Fund	8.0	1.79	0.02	1.89	3.42	2.19	471	1
Axis Banking & PSU Debt Fund	9.0	2.26	0.02	1.63	3.71	1.84	105	1
DSP Government Securities Fund	10.1	4.21	0.72	1.06	0.79	0.06	3768	1
HDFC Corporate Bond Fund	9.0	2.34	0.02	1.45	3.41	2.22	126	1
ICICI Prudential All Seasons Bond Fund	8.0	2.66	0.02	1.28	3.42	1.75	350	1
ICICI Prudential Credit Risk Fund	8.0	1.66	0.34	1.62	1.46	0.08	56	1
Kotak Banking and PSU Debt Fund	8.0	2.21	0.87	1.49	0.32	0.04	596	1
SBI Dynamic Bond Fund	9.0	3.36	0.90	1.14	0.56	0.04	1054	1
SBI Magnum Gilt Fund	9.0	3.95	0.01	1.06	4.09	2.86	983	1
SBI Magnum Income Fund	8.0	2.95	0.79	1.03	0.17	0.04	214	1

TOP MUTUAL FUND SCHEMES FOR SHORT TERM INVESTMENT

SchemeName	X1Y_Percent	StandardDeviation	Beta	SharpeRatio	JensensAlpha	TreynorsRatio	TurnoverRatio_Percentage	Good
Aditya Birla Sun Life Corporate Bond Fund	11.0	1.79	0.02	1.89	3.42	2.19	471	1
Axis Banking & PSU Debt Fund	11.0	2.26	0.02	1.63	3.71	1.84	105	1
DSP Government Securities Fund	17.0	4.21	0.72	1.06	0.79	0.06	3768	1
HDFC Corporate Bond Fund	11.0	2.34	0.02	1.45	3.41	2.22	126	1
ICICI Prudential All Seasons Bond Fund	12.0	2.66	0.02	1.28	3.42	1.75	350	1
ICICI Prudential Credit Risk Fund	9.0	1.66	0.34	1.62	1.46	0.08	56	1
Kotak Banking and PSU Debt Fund	11.0	2.21	0.87	1.49	0.32	0.04	596	1
SBI Dynamic Bond Fund	16.0	3.36	0.90	1.14	0.56	0.04	1054	1
SBI Magnum Gilt Fund	17.0	3.95	0.01	1.06	4.09	2.86	983	1
SBI Magnum Income Fund	14.0	2.95	0.79	1.03	0.17	0.04	214	1

Figure 64: Top Performing Mutual Fund Schemes for investment

7. FINDINGS AND RECOMMENDATION

Some of the findings and recommendations from the study and analysis are:-

- Sharpe Ratio, Turnover Ratio., Jensen's. Alpha and Treynor's. Ratio had good positive correlation with 1Y Annualized Returns while the variables Standard Deviation and Beta were negatively correlated
- Sharpe Ratio, Turnover Ratio., Jensen's Alpha., Crisil Rank and Treynor's. Ratio had good positive correlation with 3Y Annualized Returns while the variables Standard Deviation and Beta were negatively correlated
- Sharpe Ratio, Turnover Ratio., Jensen's Alpha., Crisil Rank and Treynor's. Ratio had good positive correlation with 5Y Annualized Returns while the variables Standard Deviation and Beta were negatively correlated
- Top 5 variables in order of significance that determine the performance of Mutual Fund Scheme in Short Term are :- Sharpe Ratio (1), Beta (2), Turnover Ratio(3), Standard Deviation (4) and AuM (5)
- Top 5 variables in order of significance that determine the performance of Mutual Fund Scheme in Medium Term are :- Sharpe Ratio (1), Beta (2), Turnover Ratio(3), Crisil Rank(4) and Standard Deviation(5)
- Top 5 variables in order of significance that determine the performance of Mutual Fund Scheme in Long Term are :- Sharpe Ratio (1), Beta (2), Turnover Ratio(3), Standard Deviation(4), Crisil Rank(5)
- DSP Government Securities Fund, SBI Magnum Gilt Fund, Aditya Birla Sun Life Corporate Bond Fund, SBI Dynamic Bond Fund, HDFC Corporate Bond Fund are some of the good investment options if looking for Short, Medium and Long Term Investment

8. CONCLUSION

Mutual fund industry currently is one and among the greatest favored investment choices throughout world and plays an important part in the financial growth of a nation. They are among the greatest vastly rising products in monetary services marketplace and are appropriate for entire kinds of people/investors from danger/risk opposing to danger/risk bearer. The performance of any scheme largely rests on capital marketplace performance. If the marketplace performance is decent, it will fetch decent returns and vice –versa.

Banks and financial services institutions play a very important role in those wider societal interactions today and analytics is therefore forcing them to rethink their roles to stay relevant in this emerging paradigm. Hence, implementation of analytics to particular business issues has begun to deliver/create value for conventional asset managers. Asset Managers are nowadays seeking applications for Big-Data analytics having scope higher than investment management. The Mktg and Sales teams are trying to utilize investor plus distribution data and additional information to improve customer acquisitions, customer retaining, and conversion rates and improve capital raising. Having seen the potential of this technology and the challenges, it is clear that the opportunity is there for companies but validation of applicable use cases and business along with technical viability must be validated before implementing big data analytics.

Though, the Indian Mutual Fund industry is currently in a nascent stage if compared globally, but is attracting huge volumes of investor cash flows by utlizing several marketing strategies, despite the existing low levels of penetration. Hence it is suggested that organizations focus on areas such as Strategic Positioning, Technology Transformation, Value For Money and Battle for Talent if they are to succeed in rapidly changing environment.

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