A FUNDAMENTAL ANALYSIS OF PORTFOLIO MANAGEMENT SERVICES

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ABSTRACT:
A portfolio is a bunch of securities for minimizing the risk associated with the investment. To fulfill the objective of risk minimization and to balance the risk against performance, the investors have to make certain decisions. A portfolio management service consists of an investment mix that helps in investment decisions for individuals and organizations. Fundamental analysis is performed to analyze the performance of the company.

In this paper, a fundamental analysis of ten Large Cap Companies is performed for evaluating the performance of the portfolio. The Large Cap Companies that were selected for the process are ICICI Securities Ltd., BSE Ltd., Edelweiss Financial Services Ltd., HDFC Securities Ltd., Aditya Birla Capital Ltd., Sundaram Finance Ltd., Motilal Oswal Securities Ltd., Reliance Securities Ltd., Bajaj Finance Ltd., and India Bulls Ventures Ltd. Companies were analyzed based on their stock price, market price and, P/E ratios. The analysis is based on the comparison of target price and market price to arrive at the best performing company.

This research paper aims to carry out fundamental or equity research of portfolio management services of large-cap companies and also to look out for the opportunities where returns can be maximized in these sectors.

Keywords: ***Portfolio Management Services, Diversification, Stock Price, P/E Ratio***

INTRODUCTION

Equity Research refers to analyzing a company's fundamentals, analyzing its financial statements & scenario building for equity recommendations. It also analyses the market trends & their effects on companies and stocks.

Portfolio management refers to the art and science of making decisions regarding investment mix and matching investments to objectives, asset allocation for individuals and institutions, and balancing risk against performance. The benefit a person can derive from investing in portfolio management services is that a person gets professional assistance concerning less risky securities. Continuous monitoring is done to have proper control. The tax and documentation process is a disadvantage in this sector.

An Index is an indicator or measure of something, and in the context of this paper, it refers to a statistical measure of the change in the securities market. In the case of financial markets, indices consist of a hypothetical portfolio of securities that represents a particular segment.

Fundamental analysis is a method used to determine a company's value by looking at its income statement, balance sheet, and cash flow statement. The analyst tries to measure a company's intrinsic value of future cash flow to net present value. A stock price that trades under a company's intrinsic value, hence it is considered a good investment and vice-versa.

Literature Review:

According to Takano & Gotoh in 2014, they develop an efficient solution algorithm for kernel-based non-linear control policy based on dimensionally reduction technique. It then uses the technique for attaining high-out-of-sample investment performance. 2014 examines the impact of political instability on the composition of the international portfolio under the discrete-time version of Markowitz's MV portfolio selection problem. It studies to what extent international diversification can outperform domestic stock portfolios in presence of instability risk. Levy & Levy, 2014, compare the performance of main optimization methods in literature when parameter estimation errors are accounted for. It then proposes two novel methods: variance-based constrained optimization (VBC) and global variance-based constrained optimization (GVBC) which considers that estimation errors are larger for stocks with larger sample variance. According to Castellano & Cerqueti, 2014 an extension of the MV Markowitz model is done by considering the presence of infrequently traded stocks and their impact on the long-run optimal portfolio and short-term trading strategies. Bernard & Vanduffel, 2014 infer optimal portfolio with state-dependent constraints by considering the dependence between the portfolio and the benchmark. This paper also derives tighter bounds on the Sharpe Ratio (SR) which is useable for fraud detection. Fu et. al., 2014 study optimal asset allocation in a regime-switching market comprising of an option, an underlying stock, and a risk-free bond. The paper considers power and logarithmic utility functions and provides a solution to the portfolio optimization

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problem in incomplete markets. Yunusoglu & Selim, 2013 discusses the design of a fuzzy rule-based expert system (ES) for portfolio managers. The ES considers the investor's risk profile and specific preferences by changing some parameters only. The ES outperforms all risk profiles when compared with a benchmark. Tamizet. al., 2013 incorporate macroeconomic, regional, and country-based factors in addition to factors specific to mutual funds into three variants of goal programming models for selecting a portfolio of mutual funds across ten countries. Cumming et. al., 2013, proposes a modified appraisal value-based private equity (PE) benchmark that shows that this method has statistically lower levels of risk than when listed PE indices are used as a proxy. The listed PE indices are considered insufficient for portfolio optimization as they do not include the entire PE universe and their expected valuations often do not match the actual PE valuation, especially during a crisis. Miguel et. al., 2013 proposes new calibration criteria for shrinkage estimators of moments of asset returns and shrinkage portfolios. It then studies a multivariate non-parametric approach to compute the optimal shrinkage intensity for independent and identically distributed returns. It also carried out a comprehensive empirical investigation of shrinkage estimators for portfolio selection on six empirical datasets. As per Behr et. al., 2013 there is a constrained minimum variance portfolio strategy to achieve portfolios with statistically significant higher Sharpe Ratio (SR). This strategy is built on the shrinkage estimation theory and imposes a data-dependent structure on the empirical variance-covariance matrix estimate by trading off the reduction of sampling error and loss of sample information. This strategy achieves sizeable reductions in out-of-sample variances w.r.t. the other minimum variance portfolio strategies like constrained short selling, factor model, etc. Li & Xu, 2013 propose a compelled multi-objective portfolio selection model with random returns for investors.

A compromise approach-based genetic algorithm is designed. The model can introduce judgment and expert opinion following the attitudes of the investors. Gupta et. al., 2013 proposes a multi-criteria credibility portfolio selection fuzzy model integrated with a real-coded genetic algorithm (RCGA) which maximizes credibility such that the short-term return, long-term return, and liquidity of the portfolio are greater than some given threshold levels. Several constraints, namely, capital budget constraint, cardinality constraint, and diversification constraints are applied for investments in individual assets. Lim et. al., 2013 develops an MV framework of portfolio selection based on DEA cross-efficiency evaluation. The efficiency score and variance of the cross efficiencies of the decision-making units (DMU) are used to represent the DMU's return and risk characteristics. Markowitz's MV formulation is then used to determine the inclusion of the DMU in a portfolio. Hjalmarsson & Manchev, 2012 shows how the weights in an MV optimization problem can be directly estimated as functions of the underlying stock characteristics, such as volume and momentum. It also studies the long-short portfolio choice in international MSCI indices for eighteen developed markets using three different characteristics: book-to-market, dividend-price ratio, and momentum. The paper brings forth the robust performance achieved by parameter zing portfolio weights directly as functions of underlying characteristics, unlike methods where the returns are modeled and estimated in an intermediate step. Kourtiset. al., 2012 focuses on the estimation of the inverse covariance matrix in the context of optimal portfolio choice using a 'shrinkage approach' to the maximum likelihood estimator of the inverse covariance matrix to replace portfolio risk and increase risk-adjusted returns. Chen & Kwon, 2012 proposes a robust selection problem for tracking a market index. The model is a 0-1 integer problem that avoids the computational difficulties of using quadratic tracking error by maximizing pair-wise similarities between assets of the tracking portfolio and its target index. Aranha et. al., 2012 extend the memetic tree-based genetic algorithm with the concept of terrain-based memetic algorithms for tackling the portfolio optimization problem. Huang & Qiao, 2012 introduces risk index as an alternate risk measure and employs uncertainty theory to solve a multi-period portfolio selection problem where the expected and standard deviation values of the uncertain security returns are given by expert evaluations. Chiamet. al., 2009 uses the compensatory property of evolutionary algorithm (EA) and particle swarm optimization (PSO) to show its application in computational finance areas which include real-world problems like portfolio optimization. It uses PSO as a local optimizer for fine-tuning in the evolutionary

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search which improved the convergence ability of the evolutionary search. Huang and Jane, 2009 integrate the moving normal autoregressive exogenous (ARX) prediction model along with grey systems theory and rough set (RS) theory to create an automated stock market forecasting method and portfolio selection technique. (Huang, 2009) coordinates fuzzy C-means (FCM) classification theory, variable precision rough set (VPRS), average autoregressive exogenous (ARX) prediction model, and grey systems theory for stock market forecasting and portfolio selection. Lin and Ko, 2009 introduces the genetic algorithm (GA) based portfolio value at risk (PVaR) forecasting mechanism using the extreme value theory (EVT). The experiments on the seventy-eight companies listed and traded on the Taiwan Stock Exchange show the stability and robustness of this algorithm with success rates higher than the exponential weighted moving average (EWMA) and historical simulation (HS) methods both with 95% and 99% confidence levels.

Research Objectives:

•To fundamentally analyze the large-cap companies in terms of their share price and market capitalization.

• To determine stock valuation and growth drivers from the available options.

•To predict the change in the index of selected companies.

•To compare the portfolio of selected companies

Scope of the study:

The study covers information related to equity funds and portfolio management. This study will help in the formulation of strategies to be developed and implemented in tune with the goals of the investment. It is also helpful in review and monitoring the performance of selected portfolios.

Limitations of the Study:

This study has been conducted purely to understand fundamental analysis for investors. This study is restricted to large cap companies. Continuous updating of stocks is necessary due to daily fluctuation in the price of stocks.

Key players of the research:

ICICI Securities Ltd.; BSE Ltd.; Edelweiss Financial Services Ltd.; HDFC Securities Ltd.; Aditya Birla Capital Ltd.; Sundaram Finance Ltd.; Motilal Oswal Securities Ltd.; Reliance Securities Ltd.; Bajaj Finance Ltd.; India Bulls Ventures Ltd.

Data Analysis & Interpretation:

For conducting fundamental analysis for the stocks in the PMS Sector, only Large Cap organizations are mulled over i.e. stocks with a market capitalization over 5000 crore rupees. Underneath table below demonstrates the loads of 10 organizations having market capitalization over 5000 crore rupees and are additionally recorded under the NSE Index.

Test of Stationarity

Ho: Test is non-stationary

H1: Test is stationary

Null Hypothesis: D(ABSOLUTE_CHANGE) has a unit root

Exogenous: Constant

Lag Length: 0 (Automatic - based on SIC, maxlag=4)

Augmented Dickey -Fuller test statistic		t-Statistic	Prob.*
Test critical values:		-6.373450	0.0000
	1% level	-3.808546	
	5% level	-3.020686	
	10% level	-2.650413	

Table:1.1

Interpretation:

The first assumption is to check the stationarity by using ADF test statistic i.e. Augmented Dickey-Fuller test statistic. The above analysis is tested in E-views software. Test of stationarity refers to a unit root test or tests whether a time series variable is non-stationary and possesses a unit root. The null hypothesis is generally defined as the presence of a unit root and the alternative hypothesis is either stationarity, trend stationarity, or explosive root depending on the test used. The value of P has been depicted in the above analysis & if the value is less than 5%, the hypothesis is rejected. Ho: Series is non-stationary- rejected. Hence, the test is stationary.

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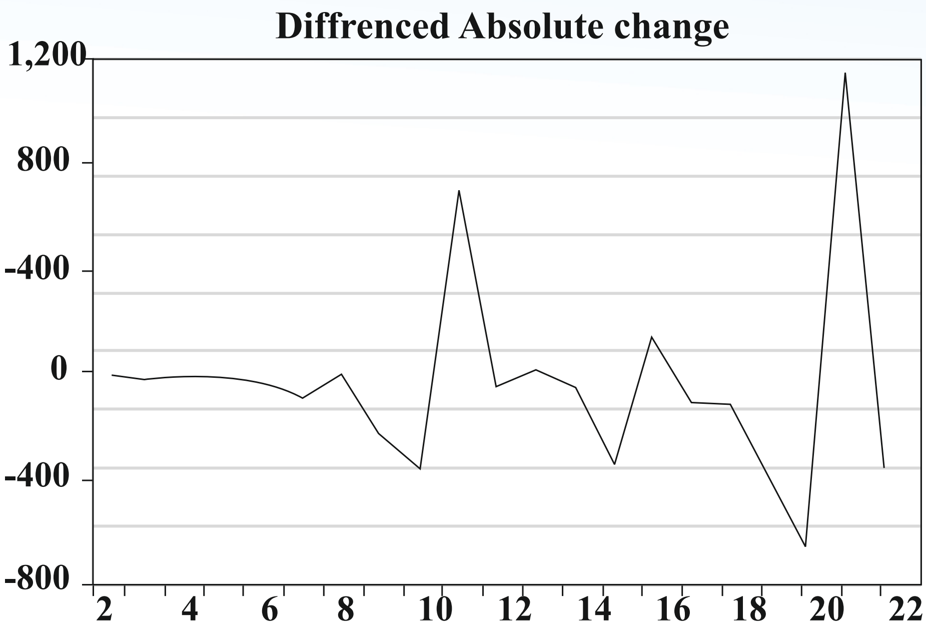

Figure: 1.1

ARIMA

Auto-Regressive Integrated Moving Average
Dependent Variable: ABSOLUTE_CHANGE
Method: Least Squares
Sample (adjusted): 2 22 Included observations: 21 after adjustments
Failure to improve SSR after 12 iterations a MA Backcast: 1

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-2982.574	7866.439	-0.379152	0.7090
AR(1)	0.981244	0.059538	16.48106	0.0000
MA(1)	-0.999585	0.170438	-5.864804	0.0000
R-squared		Mean dependent var		-405.1581
Adjusted R-squared		S.D. dependent var		416.1375
S.E. of regression		Akaike info criterion		14.47271
Sum squared resid		Schwarz criterion		14.62192
		Hannan-Quinn		
Log-likelihood	-148.9634	criteria.		14.50509
F-statistic	8.485149	Durbin-Watson stat		1.683772
Prob(F-statistic)	0.002536			
Inverted AR Roots	.98			
Inverted MA Roots	1.00			

Table:1.2

Interpretation:

The forecasting model is based on the ARIMA model. Here, change= A+B(AR(1))+C(MA(1)), where, AR is autoregression and MA is moving average & AR depends on PAC i.e partial autocorrelation and AC= autocorrelation. In this model, the price is calculated based on the price of previous day, where, A, B, C remains constant.

Determination of Sectoral P/E ratio:

Sectoral P/E ratio is determined by finding the average P/E ratios of the different large-cap companies in the PMS sector & ignoring the ones who have a P/E ratio of more than 100.

Valuation of stocks:

The P/E proportion of each stock is then compared with the sectoral P/E ratio to determine whether the stock is Undervalued or Overvalued. For example, if the P/E ratio of a stock is lesser than the sectoral P/E ratio then that stock is considered an Undervalued stock. On the other hand, if the P/E ratio of a stock is greater than the sectoral P/E ratio then that stock is considered an Overvalued stock.

Determining Long Term Price Target (LTPT):

A long-term price target gives an investor an idea regarding the point until which he should hold the stock and maximize his profit. The long term price target is a product of Sectoral P/E and EPS of the stock.

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Table: 1.3

COMPANY NAME	P/E Ratio	Avg. P	Under/Overvalue d
ICICI Securities Ltd.	18.31	31.84	Under
BSE Ltd.	7.72	31.84	Under
Edelweiss India Pvt. Ltd.	181.69	31.84	Over
HDFC Securities Ltd.	27.41	31.84	Under
Aditya Birla Capital Ltd.	36.26	31.84	Over
Sundaram Finance Ltd.	-	-	-
Motilal Oswal Securities Ltd.	88.11	31.84	Over
Reliance Securities Ltd.	13.21	31.84	Under
Invesco India Ltd.	-	-	-
Indiabulls Ventures Ltd.	170.52	31.84	Over
*Average P has been calculated on the values			
below 100			

Selection of Value Picks:

The valuation process is completed when the growth in the "Undervalued" stocks is sought for by looking for changes in Revenue (Topline) and Profit (Bottom line) per year. If both the values of Revenue and Profit are increasing in the year on year basis, then the company is accepted. If both the values of Revenue and Profit are decreasing in the current year, then the companies are rejected. The accepted companies are selected for "Value Pick"

Table: 1.4

Value Pick			
Under valuedCo.s	**Revenue**	**Profit**	**Selected or not**
ICICI Securities Ltd.	Increasing	Increasing	Yes
BSE Ltd.	Increasing	Increasing	Yes
HDFC Securities Ltd.	Increasing	Increasing	Yes
Reliance Securities Ltd.	Increasing	Increasing	Yes

Selection of Growth Picks:

After the determination of Value Picks, the next step is to analyze the Overvalued stocks and infer the Growth Picks. For determining the Growth Picks, P/E Growth value (PEG value) is calculated for each Overvalued stock by dividing the P/E ratio of each of these stocks by the percentage change in earnings per share Year On Year and the stocks with positive PEG values and less than or equal to 1 are chosen as Growth Picks. The Overvalued stocks with negative PEG values or with PEG values greater than 1 are rejected.

Table: 1.5

Growth Pick		
Over valuedCo.s	PEG Ratio	Selected or not
	More than	
Edelweiss India Pvt. Ltd.	1	No
Aditya Birla Capital Ltd.	Less than 1	Yes
Motilal Oswal Securities Ltd.	Less than 1	Yes
Indiabulls Ventures Ltd.		No
PEG Ratio=PE/EPS growth		

Formula:

- PEG Ratio = $\frac{\text{P/E Ratio}}{\text{EPS growth}}$

- EPS growth = $\frac{(\text{Current EPS} - \text{Last Year's EPS}) * 100}{\text{Last Year's EPS}}$

Ranking procedure for selected stocks:

Various financial ratios that are significant for the PMS sector have been considered for ranking the selected stocks. These ratios include:

a) Liquidity Ratio
 •Current Ratio •Quick Ratio
b) Return on Assets
c) Debt to Equity

Table: 1.6

	Current Ratio	Quick Ratio	Return on assets	Debt on Equity
Motilal Oswal Securities Ltd.	0.9	0.9	0.9	0.3
BSE Ltd.	1.93	1.93	1.93	-
HDFC Securities Ltd.	0.04	17.48	17.48	-
ICICI Securities Ltd.	1.36	1.34	1.34	0.82
Reliance Securities Ltd.	3.34	4.2	8.94	1.31
Aditya Birla Capital Ltd.	0.14	0.14	0.76	0.09

Table: 1.7
Final Ranking-

Rankings based on-	Current Ratio	Quick Ratio	Return on assets	Debt on Equity
1	Reliance Securities Ltd.	HDFC Securities Ltd.	ICICI Securities Ltd.	Aditya Birla Capital Ltd.
2	BSE Ltd.	Reliance Securities Ltd	BSE Ltd.	Motilal Oswal Securities Ltd.
3	ICICI Securities Ltd.	BSE Ltd.	HDFC Securities Ltd.	ICICI Securities Ltd.

Table: 1.8

	Overall Ranking
1.	BSE Ltd. & ICICI Securities Ltd.
2.	HDFC Securities Ltd.
3.	Reliance Securities Ltd.

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Selection of Growth Picks:

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Calculation of Net Asset Value for the portfolio of PMS stocks:

The total amount of Rs. 10 crores has been allocated to the PMS sector which implies that AUM (Asset under Management) for the PMS sector is Rs. 10 crores. Weightage and Amounts have been assigned to the stocks by respective market share prices of those stocks as of 31st July 2018.

Table: 1.9

Rank	Co. name	Price	Allocation of Funds	No. of shares
1	BSE Ltd.	840.15	30,00,000	3,570.79
1	ICICI Securities Ltd.	326.25	30,00,000	9195.4
2	HDFC Securities Ltd.	2073.25	25,00,000	1205.83
3	Reliance Securities Ltd.	960.6	15,00,000	1561.52
	TOTAL		1,00,00,000	

Benchmark= 1219.43 (as on 31.07.2018)
NAV= AUM/No. of units
NAV=Net Asset ValueAUM=Asset Under Management
AUM=10 Cr
1 unit= Rs. 10
NAV= 10Cr / 1Cr = Rs. 10
Net Asset Value (NAV) for the portfolio of the PMS sector is determined by dividing the Assets under Management (AUM) for the PMS sector by the number of units under consideration. We have taken the number of units as 1,00,00,000.
Hence NAV for the portfolio of PMS sector is = 10, 00, 00,000 / 1, 00, 00,000 = 10.
Therefore, NAV for the portfolio of the PMS sector is 10.
The calculation of NAV has been shown based on each day's share price of the stocks. NAV changes based upon the market.

Table:1.10

Rank	Co. name	Price	Allocation of Funds	No. of shares	Value of Fund
1	BSE Ltd.	793.15	30,00,000	3,570.79	2,832,172.09
1	ICICI Securities Ltd.	323	30,00,000	9195.4	2,970,114.20
2	HDFC Securities Ltd.	2179.5	25,00,000	1205.83	2,628,106.49
3	Reliance Securities Ltd.	1186	15,00,000	1561.52	1,851,962.72
	TOTAL		1,00,00,000		10,282,355.49

Index value as on 31.07.2018= 1219.43 % Change in NAV= 2.82%

NAV= 10.28

Interpretation:

From the above analysis, we can see that the comparison between the change in NAV and the change in PMS Index, the index is beating the benchmark hence, this sector is suitable for investing the money and getting higher returns as according to the index. And also that Aditya Birla Capital doesn't stand in any of the ranks if we follow fundamental analysis.

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Conclusion:

Equity research plays a very crucial role to make a wise investment decision. After having accessed risk capacity & tolerance followed by time horizon and intention of investment, the individual portfolio can fetch systematic returns.

It is always better to analyze, and do continuous updation of funds invested because it may happen that some of the stocks which were not there in the existing portfolio have started performing well and can give better returns as time goes on and some stocks may start falling due to market situation,sector performance or company news which makes it necessary to pull out the investment and invest somewhere else.

We also see that Aditya Birla Capital lacks somewhere in Fundamental Analysis due to which it has not gained any top position, so it needs to work more on its strategies to grab a position among top ones.

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