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MOMENTUM EFFECT, VALUE EFFECT, RISK PREMIUM AND PREDICTABILITY OF STOCK RETURNS – A STUDY ON INDIAN MARKET

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ABSTRACT

Efficient market hypothesis (EMH), one of the central pillars of modern financial theories, often fails to explain the 'financial anomalies'. One fatal challenge of EMH probably comes from the theoretical assumption of 'rational man'. According to EMH, the fully rational investor may change his demand for financial assets on the basis of available information. According to EMH, at any given point of time, the stock price should reflect all the available information, and predictability of stock returns should be impossible. However, the literature shows ample evidence of abnormal returns related to firm and market specific attributes. In financial literature, these variations are often termed as 'financial anomalies'. Within the framework of behavioural finance, there are research results that contain evidence on predictability of future stock market returns based on financial anomalies (Stanivuk *et al.*, 2012). Value effect and momentum effect are the two prominent financial anomalies (Ho, 2012). This paper explores the predictability of Indian stock market returns using multiple discriminant analysis. Our result shows that the risk premium, momentum and value effect may have significant power for predicting the Indian stock market returns. The validity test of the model also corroborates the impact of financial anomalies over predictability of stock returns.

Contribution/ Originality: This study contributes in the existing literature, by exploring the predictability of Indian stock market on the basis of risk premium, value effect and momentum effect. This study is one of very few studies which have investigated the predictability of Indian stock market from the context of financial anomalies.

1. INTRODUCTION

Predictability of stock returns from the perspective of financial anomalies is an interesting topic to explore for financial researchers. This paper explores the predictability of Indian stock market on the basis of risk premium, value effect and momentum effect. Despite of the existance of papers that explain the predictability of stock returns on the basis of investor sentiment proxies (Baker and Wurgler, 2000; Brown and Cliff, 2004; Bandopadhyay and Jones, 2006) there are very few work that explains the predictability of Indian stock market from the context of asset pricing models, and financial anomalies. In this paper, we considered risk premium (Sharpe, 1964; Lintner, 1965) value effect (Chan *et al.*, 1991) and momentum effect (Jegadeesh and Titman, 1993) for exploring the predictability of Indian stock market.

Our study is based on Indian security market data. We considered the Fama and French (1992) three factor model along with the momentum factor as developed by Carhart (1997). We applied the four factor Carhart model on Indian stock market data to see if they are really useful in predicting the Indian stock market. The result of our empirical study shows enough predictability power of the momentum effect (WML), value effect (HML) and risk premium (r_m-r_f). As we did not find much significant correlation between size effect (SMB) and the market return, therefore the predictability of size effect is not considered in this paper.

Our primary question is, whether the risk premium, size effect and the value effect are really capable of predicting the future market returns. The validation of the model also corroborates the impact of financial anomalies on future stock market returns.

2. LITERATURE REVIEW AND MOTIVATION

Behavioral finance has emerged as a fresh approach to address the anomalies of traditional finance theory. Behavioral finance theories does not consider the assumption of rational participants. Empirical results show that the efficient market hypothesis often may not be able to explain the financial phenomena e.g. firm characteristics such as size effect and value/growth stocks, Long –run reversals, short-term momentum etc.

The original capital asset pricing model (CAPM), as proposed by Sharpe (1964); Lintner (1965) and Mossin (1966) assumes that investors are rational creature and the relationship between asset betas, and expected return changes in a linear fashion. Fama and French (1992) challenged this view by demonstrating that beta is unrelated to asset return. A behavioral explanation of this phenomenon is the role played by 'noise traders' in the market. 'Noise' trading or unsophisticated trading often takes place due to optimistic or pessimistic beliefs or sentiments by unsophisticated traders (Black, 1986). According to Antoniou *et al.* (2015) noise traders' activities affect the high beta stocks more at the time of optimism.

Value effect was first noted by Basu (1977) who observed that firms having high earning/price ratio (E/P) earn higher return than estimated by CAPM. Similarly, later on researchers discovered that stocks with high Book value / market value (B/M), Cash flow / price (C/P) also earns abnormally high return compared to those having lower E/P, B/M, and C/P (Banz, 1981; Lakonishok *et al.*, 1994; Fama and French, 1998).

One behavioral explanation for value effect is linked to investor irrationality, which leads to abnormal earning by high B/M portfolios. According to Lakonishok *et al.* (1994).

investors make error in expecting future earnings on growth and value stocks. They become overoptimistic about the past good performers, and also over pessimistic about the past poor performers. This leads to over pricing of growth stocks and under pricing of value stocks. The views expressed by Lakonishok *et al.* (1994) also supported by empirical evidence (La Porta *et al.*, 1997; Skinner and Sloan, 2002).

Another important financial anomaly called momentum effect is first noticed by Jegadeesh and Titman (1993). They found stocks that generated high return over the past three to twelve months (winners) outperform the stocks that generated low returns (losers) over the next three to twelve months.

Momentum effect found ample empirical support both at industry level as well as in international markets (Rouwenhorst, 1998; Moskowitz and Grinblatt, 1999; Griffin *et al.*, 2003; Griffin *et al.*, 2005). The behavioural explanation of momentum effect is based upon investor psychology and market inefficiency (Barberis *et al.*, 1998; Daniel *et al.*, 1998; Hong and Stein, 1999). 'Conservatism bias', 'representative heuristic', and 'self-attribution bias' are considered responsible for momentum effect (Barberis *et al.*, 1998; Daniel *et al.*, 1998).

Momentum profits are attributed to the bounded rationality of investors, who use partial information when updating their information (Hong and Stein, 1999). An argument is momentum profits arise only under optimism, and are driven principally by strong momentum in losing stocks (Antoniou *et al.*, 2013).

Fama and French (1993) proposed a three factor model to capture the average returns associated with US markets.

$$R_i(t) - R_f(t) = \alpha_i + b_i\,(R_{mt} - R_{ft}) + s_i\,SMB(t) + h_i\,HML(t) + e_i(t) \quad \text{---------------------} \ (1)$$

In this regression equation, $R_i(t)$ is the return on asset i for month t, and $R_f(t)$ is the risk free rate. SMB(t) explains the size effect on stock returns, and is the difference between the returns on diversified portfolios of small stocks and big stocks. HML(t) represents the value effect. It is the difference between returns on diversified portfolios high book-to-market (value) stocks and low book-to-market (growth) stocks.

Carhart (1997) further added momentum effect to equation (1),

$$R_i(t) - R_f(t) = \alpha_i + b_i\,(R_{mt} - R_{ft}) + s_i\,SMB(t) + h_i\,HML(t) + w_i\,WML(t) + e_i(t) \quad \text{----------} \ (2)$$

In equation (2), the difference of past returns between winners' portfolio and the losers' portfolio for month t is termed as WML. WML represents the momentum effect of stocks returns.

Fama and French (1992) and Carhart (1997) proposed the model on the basis of US market data. Fama and French (2012) also examined the size, value, and momentum effect in international markets.

Pandey and Sehgal (2016) examined the size effect in Indian market. Their study shows evidence of strong size effect in Indian stock market. Sehgal and Jain (2011) also tasted the momentum patterns in Indian market. Their finding shows momentum profits in Indian context for prior return portfolios are stronger for 6-6 compared to 12-12 strategies. Sehgal and Tripathi (2007) also identified significant value effect in Indian market.

Though there are studies in India that demonstrates existence of size, value and momentum effect in Indian market, there are few studies that explores on the issue of predictability on the basis of asset pricing models. Our paper adds to the existing literature by exploring the predictability of Indian stock markets by using the asset pricing model.

So, the literature provides ample evidence that value effect and momentum effect results from the behavioural anomaly of investors. Our motivation behind this paper is to explore if the value effect and momentum effect may be used for predicting the future stock market returns.

Despite the existing literature documents that investor sentiment exhibits certain degree of predictability of stock returns, few studies address the issues with respect to the Indian stock market return. This paper attempts to shed light on how financial anomalies can help to enhance our understanding of stock price behaviour when it plays various roles in the asset pricing models from the perspective of Indian market.

The purpose of this paper is to propose new directions of the roles of investor sentiment that researchers could adopt in the analysis of the explanatory power of value effect and momentum effect for stock price behaviour.

3. RESEARCH OBJECTIVE AND METHODOLOGY

The objective of this paper is to assess the predictability of stock returns in relation to the investor sentiment. To achieve this objective, we investigated the role investor sentiment may play in asset pricing. The paper aims to examine the ability of momentum and value premium in predicting the stock market returns. As discussed earlier, in literature, there is ample evidence that investor sentiment captures the momentum and value premium.

In this paper, we considered the WML, HML, and market premium as independent variable and examines the efficacy of investor sentiment as predictors of stock market returns. This paper seeks to understand the effect of investor sentiment on the predictability of stock returns. As discussed earlier, WML, HML, and market premium possesses a behavioral explanation to explore.

To achieve the abovementioned objective, we started with Capital asset pricing model (CAPM), and then added two extensions to it. The first one is the momentum factor as documented by Jegadeesh and Titman (1993) and the second one is the value permium.

The momentum factor is represented by winners-versus-loser (WML) portfolio. And the value premium is represented by high-minus-low (HML) portfolio. We considered the Nifty 50 as a proxy for market portfolio.

3.1. Sample Composition

The secondary data of Nifty used in this analysis has been collected from the website of National Stock Exchange of India (NSE) (www.nseindia.com). The data for SMB, HML, WML, and Risk Premium is sourced from *Data library for Indian market* maintained by Indian Institute of Management, Ahmedabad (http://www.iimahd.ernet.in/~iffm/Indian-Fama-French-Momentum/four-factors-India-90s-onwards-IIM-WP-Version.pdf) The monthly data is being collected for the period starting from January, 2004 to February 2014. The data for March 2014 to December 2015 is used for validation of model.

As the sample size is high (>40), therefore the normality test is not a pre-requisite for applying parametric tests (Elliott and Woodward, 2007). Therefore, normality test is not mandatory in this case. However, the Q-Q plots of the variables are shown in annexure 1.

3.2. Period of the Study

The sample period starts from January, 2004 to February 2014 for classification purposes. Also the data from March 2014 to December, 2015 is used for validation of the model.

3.3. Variables Specification

In the proposed model, we considered the winner minus loser (WML), high minus low (HML), and market risk premium (RP) as independent variables.The impact of investor sentiment on momentum effect and value effect is well discussed in literature. In this paper, we will test the effect of investor sentiment on stock returns in Indian market. In the present study, we tried to understand, if the investor sentiment really influences the stock return in Indian market. Before choosing the variables and applying Discreminant Analysis, we first need to classify the nifty return as 'impacted' and 'not impacted'. While there is no definitive method for defining a market return as 'impacted' or 'not impacted' here we have used a method that is simple and objective: if the return of nifty over a given month rose above the average market return, it is considered as 'impacted' by investor sentiment, and otherwise it is classified as 'not impacted' by investor sentiment. Here we have taken monthly Nifty (Index of National Stock Exchange) return as proxy for market return. To obtain the return at the end of each month, we have used the ending price of last trading day for each month. We considered Nifty return as market return proxy, as it represents around 65% of total market capitalization as of May, 2016. NSE is also the largest trading platform for stocks in India.

The return has been calculated by the following formula

$$\text{Return of Stock} = \frac{P_t - P_{t-1}}{P_{t-1}} \text{ X } 100.$$

Where,

Pt = Price at the T month

Pt-1 = Price at the T -1 month

$$\text{Market return} = \frac{Nifty\,(t) - Nifty\,(t-1)}{Nifty\,(t-1)} \text{ X } 100$$

Similarly Nifty (t) = Nifty at the t month and Nifty (t-1) = Nifty at the (t-1) month.

We considered the monthly data for the period starting from December 2003 to February 2014. As discussed earlier we have taken dependent variable as 'impact' or 'no-impact' and five independent variables.

Table-1. Dependent variable

Impact on Nifty Return	
Impact	Return above average Market return i.e Nifty
No Impact	Return below average Market return i.e Nifty

Table-2. Dependent Variable Encoding

Original Value	Internal Value
Impact	1
No Impact	0

Table-3. Independent variables

Name of the Variables	**Description of the variables**
HML	High minus low
WML	Winner minus Loser
Risk_Prem	Risk Premium

4. EMPIRICAL TESTING

First, we constructed the correlation matrix as shown in table (4). As may be observed from table 4, the significance of correlation between SMB and nifty return is 0.570. which implies there is hardly any relationship between SMB portfolio return and Nifty return. So, we decided to exclude SMB from discriminant function and include only risk premium (r_m-r_f), HML and WML.

Table-4. Correlation Matrix

		Nifty_Ret	**SMB**	**HML**	**WML**	**Risk_prem**
Nifty_Ret	Pearson Correlation	1	-0.054	-.315(**)	.350(**)	-.879(**)
	Sig. (2-tailed)		0.570	0.001	0.000	0.000
	N	115	115	115	115	115
SMB	Pearson Correlation	-0.054	1	.469(**)	-0.041	.195(*)
	Sig. (2-tailed)	0.570		0.000	0.667	0.037
	N	115	115	115	115	115
HML	Pearson Correlation	-.315(**)	.469(**)	1	-0.119	.408(**)
	Sig. (2-tailed)	0.001	0.000		0.206	0.000
	N	115	115	115	115	115
WML	Pearson Correlation	.350(**)	-0.041	-0.119	1	-.434(**)
	Sig. (2-tailed)	0.000	0.667	0.206		0.000
	N	115	115	115	115	115
Risk_prem	Pearson Correlation	-.879(**)	.195(*)	.408(**)	-.434(**)	1
	Sig. (2-tailed)	0.000	0.037	0.000	0.000	
	N	115	115	115	115	115

From Table 5, we get the discriminant equation (3) as

$$Z = -0.118+0.138*Risk\_Prem+0.047*HML- 0.007*WML \text{ -----------------(3)}$$

To calculate the Cutting Score Z for unequal size of two groups we use the formula

$Z = (no^{-}Z_0 + n_1^{-}Z_1)/2$ Where Z_0 = Group Centroids for 'No impact' and Z_1 = Group Centroids for 'Impact'

Here n_0 = 71 , n_1 = 44 and Z_0 = 0.598, Z_1 = – 0.965. Substituting the values in the equation, we get cutting score of -0.005

Now from the Discriminant equation as above, if put the values of the variables Risk premium, HML and WML, we will get a score. If the score is more than -0.001, it will be classified as IMPACT otherwise NO IMPACT.

Table-5. Canonical Discriminant Function Coefficients(Using SPSS)

	Function
HML	0.047
WML	0.007
Risk_prem	0.138
Constant	-0.118

Unstandardized coefficients

The coefficients displayed in this table are the coefficients of the canonical variable. The coefficients are used to compute canonical variable scores for each case.

Table-6. Functions at Group Centroids

	Function
Nifty Binary	1
No Impact	0.598
Impact	-0.965

*Unstandardized canonical discriminant functions evaluated at group means.

4.1. Classification Accuracy

The classification table helps to assess the performance of the model by cross tabulating the observed response categories with the predicted response categories.

Table-7. Classification Results(Using SPSS)

Classification Results(a)

			Predicted Group Membership		
		Nifty Binary	**0**	**1**	**Total**
Original	Count	No Impact	59	12	71
		Impact	5	39	44
	%	No Impact	83.1	16.9	100.0
		Impact	11.4	88.6	100.0
a. 85.2% of original grouped cases correctly classified.					

The Table 7 shows the comparison of the observed and the predicted performance of the Nifty return and to the extent that it can be correctly predicted. This table measures the degree of success of the classification for this sample. The number and percentage of cases correctly classified and misclassified are displayed. From the above Table 7 it is demonstrated that the companies, which does not get impacted by investors' behaviour. have 83.1% correct classification rate, while companies that got impacted by investors' behaviour have 11.4% correct prediction rate. Overall correct classification was observed in 85.2% of original grouped cases.

4.2. Tests of Goodness of Fit

The ranks and natural logarithms of determinants printed are those of the group covariance matrics.

Table -8. Log Determinants(Using SPSS)

Log Determinants

Nifty_Binary	Rank	Log Determinant
No Impact	3	10.575
Impact	3	10.665
Pooled within-groups	3	10.669

In the multi-group model, log determinant values provide an indication of which groups covariance matrices diverge most. For each group, its log determinant is the product of the eigen values of its within group covariance matrix. The rank is the row or column rank which is the maximum number of linearly independent rows or columns. From Table 8, it is clear that all three variables are linearly independent and all three variables are important for measuring the performance of the index. The present study also estimated the Box's M statistic, which provides useful information about the calibration of the model. Box's M statistic tests the null hypothesis of equal population covariance matrices.

The significance of Box's M statistic is based on an F transformation. The hypothesis of equal covariance matrices is rejected if the significance level is small (less than say 0.10). The hypothesis of equal covariance matrices is not rejected if the significance level is large (more than say 0.10). The test can be significant when within-group sample sizes are large or when the assumption of multivariate normality is violated. Here the value of significant level is very large i.e. 0.373 which implies it is highly accepted. So we can conclude that there is no significant difference between covariance matrices of two populations. So we can classify the two populations by DA.

Table -9. Box's Statistics Test Results

Test Results

Box's M		**6.676**
F	Approx.	1.078
	df1	6
	df2	55,229.995
	Sig.	0.373

*Tests null hypothesis of equal population covariance matrices.

Table-10. Structure Matrix (Using SPSS)

Structure Matrix

	Function
	1
Risk_prem	0.964
HML	0.502
WML	-0.363

*Pooled within-groups correlations between discriminating variables and standardized canonical discriminant functions Variables ordered by absolute size of correlation within function.

The structure matrix contains within-group correlations of each predictor variable with the canonical function. This matrix provides another way to study the usefulness of each variable in the discriminant function. Risk premium has the highest correlation with the discriminant scores, followed by percentage increase in HML, and WML.

4.3. Validation of the Model

Model validation requires checking the model against independent data to see how well it predicts. Typically, the steps of model fitting start with collecting an independent data set and validating the results on it. To validate our model, we have taken 21 test samples as given in the annexure III. The validation result is given in the Table 10.

Table-11. Classification Results

		Prediction		**Total**
		Impact	**No Impact**	
Actual	**Impact**	**9**	**2**	**11**
	No Impact	**2**	**8**	**10**
		81.81%	**80%**	**21**
80.95% of original grouped cases correctly classified.				

The Table 11 shows the comparison of the observed and the predicted performance of the evaluation data set and to the extent that it can be correctly predicted. The 81.81% of the times impact on Nifty return were classified correctly while 80% of the times no impact on Nifty return were predicted correctly. The overall prediction rate is 80.95%. So we can conclude that our model equation can reasonable predict the performance of Nifty by using three predictor ratios.

5. SCOPE FOR FUTURE RESEARCH AND CONCLUSION

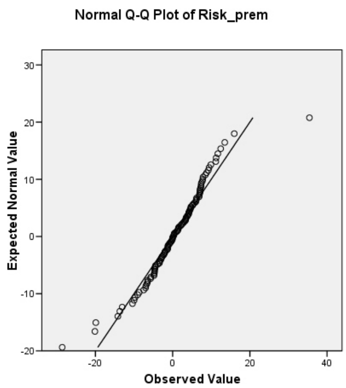
The study employs the multiple discriminant analysis models, to determine whether the sentiment of investors significantly affect the performance of the stock returns

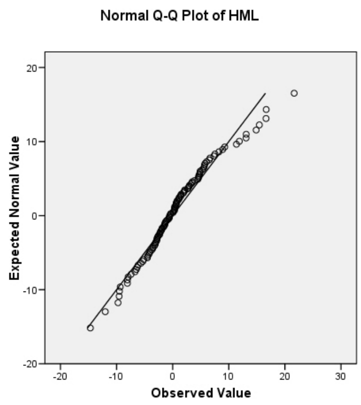
We used three proxies finally to represent the investor sentiments. These proxies are Risk premium, High minus low (HML) and Winner minus loser (WML). The study reveals significant impact of investor sentiment on stock returns. The model shows that the three proxies can classify upto 85.2% into two categories 'impact' and 'no impact'. The model is also validated by using monthly data from March, 2014 to December, 2015. The overall prediction rate is 80.95% in case of validation period. This indicates that our model is reasonably good in predicting the future stock market returns by using the investor sentiment proxies.

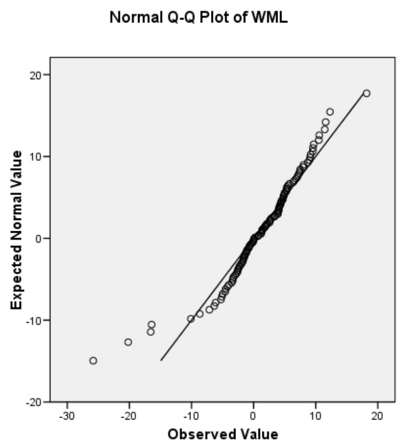
We identified two important areas for future scope of research. One important point to note here is that the model is structured after deleting the outliars. Therefore, in extreme situations of euphoria or depression, it may be challenging to apply the model most suitably. A further development of this model may be required for capturing the predictability factor at the time of extreme scenarios.

Secondly, we covered the entire period of February, 2004 to January, 2014 in this period. This is a long period that went through both optimistic phase as well as pessimistic phase. A future research may be taken up to explore, if the predictability of momentum effect, value effect, and risk premium varies with prevailing optimism and pessimism in the market.

Annexure-I







Annexure-II. Sample Data Set (116 Observations)

Month	Risk_Prem	HML	WML	Nifty	Nifty_Ret	Nifty_RetBinary
200312	19.05120044	11.74731	-2.60308	2139.93		
200401	-5.658387764	-9.34468	5.27027	2062.42	0.036221	1
200402	-1.259000985	-7.93819	2.585612	2052.4	0.004858	1
200403	-0.041122209	-5.17401	7.982136	2020.25	0.015665	1
200404	3.433906011	6.650796	1.245006	2048.22	-0.01384	0
200409	7.709809881	7.336307	-4.21523	2020.62	0.013475	1
200410	1.279246178	4.62564	4.988939	2069.39	-0.02414	0
200411	9.896722188	15.44902	1.827413	2268.99	-0.09645	0
200412	9.247121509	8.249964	1.87281	2418.88	-0.06606	0
200501	-1.993262619	-1.63239	4.39615	2393.76	0.010385	1
200502	3.844331065	6.037351	4.01612	2447.94	-0.02263	0
200503	-3.411059082	0.314559	5.557902	2369.69	0.031966	1
200504	-4.678075783	5.508978	-1.71103	2214.96	0.065295	1
200505	8.435881594	13.07745	-1.50125	2433.73	-0.09877	0
200506	3.369301629	1.431353	-0.97732	2599.93	-0.06829	0
200507	6.921827866	8.900859	9.521326	2711.24	-0.04281	0
200508	6.072395349	21.64431	8.994249	2801.99	-0.03347	0
200509	5.622392125	-14.6792	-3.36966	3066.15	-0.09428	0
200510	-9.981096925	-8.0784	-6.33627	2795.89	0.088143	1
200511	11.26517381	-3.00652	4.384687	3127.8	-0.11871	0
200512	6.14434945	-5.32001	4.166527	3353.37	-0.07212	0
200601	6.176885323	0.318021	8.030291	3549.92	-0.05861	0
200602	2.095883818	-4.14746	-0.46853	3639.43	-0.02521	0
200603	9.445545186	-4.45819	7.16075	4028.82	-0.10699	0
200604	6.961848509	7.546438	4.971222	4155.54	-0.03145	0
200605	-14.18822699	0.312349	-0.05668	3642.31	0.123505	1

200606	-4.718756797	-9.48618	6.570333	3721.71	-0.0218	0
200607	-0.824822822	-1.54574	-2.29739	3745.46	-0.00638	0
200608	8.814090459	4.674531	-4.53126	4073.55	-0.0876	0
200609	5.99737031	-2.58423	5.34209	4288.97	-0.05288	0
200610	4.18712711	0.56038	6.390882	4476.5	-0.04372	0
200611	4.741706122	-1.09861	-3.32966	4729.13	-0.05643	0
200612	0.363988489	13.10443	3.399343	4758.45	-0.0062	0
200701	3.002935889	11.87851	-1.87799	4899.39	-0.02962	0
200702	-8.653237639	-3.25327	-2.55517	4504.73	0.080553	1
200703	-0.069616519	-1.99339	-0.7247	4605.89	-0.02246	0
200704	6.877461388	-0.5807	0.225539	4934.46	-0.07134	0
200705	5.148924996	0.356322	1.663965	5185.95	-0.05097	0
200706	1.743298769	3.230293	-0.78482	5223.82	-0.0073	0
200707	4.691409513	1.96421	-1.435	5483.25	-0.04966	0
200708	-1.380811833	16.6705	0.027155	5411.29	0.013124	1
200709	13.48829416	14.87359	3.956491	6094.11	-0.12618	0
200801	-20.13190877	-2.84969	1.185848	6245.45	-0.02483	0
200802	-0.935052836	-4.50007	-2.98656	6356.92	-0.01785	0
200803	-13.06570607	-8.06556	-4.9839	5762.88	0.093448	1
200804	11.69764203	5.63356	0.708803	6289.07	-0.09131	0
200805	-7.010602395	0.825354	-3.98828	5937.81	0.055852	1
200806	-19.89981968	-4.26879	-2.58969	4929.98	0.169731	1
200807	7.215044987	2.151253	2.122408	5297.47	-0.07454	0
200808	0.148913937	-3.55362	-2.77073	5337.28	-0.00751	0
200809	-13.67368806	-6.15106	4.029424	4807.2	0.099317	1
200810	-28.59684511	-1.41488	7.329911	3539.57	0.263694	1
200811	-6.94915423	-0.67334	11.60046	3379.53	0.045215	1
200812	11.1800236	0.380473	-16.5652	3635.87	-0.07585	0
200901	-4.840050098	0.1105	12.29892	3538.57	0.026761	1
200902	-4.784089043	0.597062	4.816556	3403.33	0.038219	1
200903	7.370561977	-6.47966	-7.11922	3720.51	-0.0932	0
200904	15.96390879	2.765784	-16.4228	3480.75	0.064443	1
200905	35.43233947	4.838734	-25.8241	4448.95	-0.27816	0
200906	-2.632174353	-3.9843	2.578913	4375.5	0.01651	1
200907	7.876201597	0.064642	-0.07695	4636.45	-0.05964	0
200908	2.306624505	11.35739	-5.25882	4732.35	-0.02068	0
200909	7.378475904	2.994355	2.161749	4958.95	-0.04788	0
200910	-6.681428376	-3.7415	10.56274	4711.7	0.049859	1
200911	7.430555465	1.885419	5.774941	4941.75	-0.04883	0
200912	4.479858283	4.579933	-0.62593	5178.4	-0.04789	0
201001	-3.390150576	-0.5962	1.417594	4882.05	0.057228	1
201002	-1.224281969	1.056227	3.858059	4922.3	-0.00824	0
201003	3.785098857	3.424411	1.342831	5282	-0.07308	0
201004	1.468775805	2.680367	2.633886	5278	0.000757	1
201005	-3.890289421	-6.31948	-2.47617	5066.55	0.040063	1
201006	4.331692551	-3.0872	-1.63198	5269.05	-0.03997	0
201007	1.419114619	4.482085	5.288242	5367.6	-0.0187	0
201008	0.303834985	3.488453	4.143739	5408.7	-0.00766	0
201009	7.804940179	2.928615	-0.29244	6018.3	-0.11271	0
201010	-0.187792891	5.651148	3.37052	6017.7	9.97E-05	1
201011	-5.716919406	-9.73634	5.360069	5751.95	0.044161	1
201012	2.516976689	1.428324	-6.11173	6134.5	-0.06651	0
201101	-10.40447196	-1.9267	4.811695	5512.15	0.101451	1
201102	-4.513735547	-12.0195	2.761942	5303.55	0.037844	1
201103	7.109843831	6.509008	1.31593	5654.25	-0.06613	0
201104	0.408010068	0.777512	0.805566	5749.5	-0.01685	0
201105	-3.341716794	-0.54076	4.313941	5476.1	0.047552	1
201106	-0.512674719	-2.77452	4.726908	5471.25	0.000886	1
201107	-2.191470796	1.505264	3.918115	5482	-0.00196	0
201108	-9.059387126	-7.41094	10.49578	4839.6	0.117184	1

201109	-2.35125062	-2.33933	-1.08748	4943.25	-0.02142	0
201110	4.11682992	-1.36321	-1.15675	5360.7	-0.08445	0
201111	-9.725929742	-0.90672	9.554955	4710.05	0.121374	1
201112	-6.42038165	-2.33771	7.516806	4624.3	0.018206	1
201201	12.45614557	5.765315	-20.1996	5204.7	-0.12551	0
201202	4.167073414	-0.35845	-2.24835	5429.3	-0.04315	0
201203	-2.951309397	-2.2183	9.089304	5295.55	0.024635	1
201204	-1.232863991	-0.41175	2.925124	5190.6	0.019819	1
201205	-6.50819436	-1.88441	7.045711	4920.4	0.052056	1
201206	5.2653384	-1.24542	-3.52984	5278.9	-0.07286	0
201207	-1.787628689	1.160866	4.719254	5099.85	0.033918	1
201208	-0.382108577	-1.36283	7.429752	5258.5	-0.03111	0
201209	7.111338886	0.629309	-8.66671	5703.3	-0.08459	0
201210	-2.035432967	-2.69317	4.065245	5664.3	0.006838	1
201211	3.475401398	9.273402	-5.12432	5879.85	-0.03805	0
201212	1.068703843	0.652215	0.074747	5908.35	-0.00485	0
201301	0.699156525	-2.81072	-1.20987	6074.65	-0.02815	0
201302	-7.513593177	-9.54694	8.707083	5850.3	0.036932	1
201303	-2.811515581	-5.67386	11.45508	5682.55	0.028674	1
201304	3.316965097	16.63648	-1.99271	5871.45	-0.03324	0
201305	-0.02142657	-2.15367	6.818463	5985.95	-0.0195	0
201306	-4.572904121	2.117858	18.19907	5842.2	0.024015	1
201307	-3.033884192	4.883628	9.180279	5886.2	-0.00753	0
201308	-4.470324408	-3.11985	-10.1004	5471.8	0.070402	1
201309	4.618587075	3.912544	-1.40827	5833.2	-0.06605	0
201310	7.096491222	1.146991	-4.55864	6144.9	-0.05344	0
201311	-1.204701547	4.800859	-3.26407	6176.1	-0.00508	0
201312	2.806798658	5.243662	-1.69688	6313.8	-0.0223	0
201401	-4.686150267	-6.71917	9.667885	6089.5	0.035525	1
201402	1.505185301	-3.51062	4.48657	6276.95	-0.03078	0
				Average	-0.01176	0

Annexure-III- Validation Data Set (21 Observation)

Month	HML	WML	Rm-Rf	Nifty	Nifty Ret	Nifty Binary	Model Value	Model Binary	
201403	3.420329	-9.71963	7.136766	6695.9					
201404	9.870077	-4.03236	0.423661	6782.75	1.297062	1	0.376132338	1	Match
201405	12.63898	-15.6519	11.52618	7229.95	6.593196	1	1.957081326	1	Match
201406	7.853882	3.179349	6.615012	7508.8	3.856873	1	1.1862596	1	Match
201407	-9.25885	-2.206	-0.70688	7790.45	3.750932	1	-0.66615762	0	No Match
201408	-4.76137	2.01949	2.017242	7954.35	2.103858	1	-0.04926855	0	No Match
201409	1.776142	3.78611	0.654095	7968.85	0.18229	0	0.082246556	1	No Match
201410	0.474683	4.145719	2.780563	8169.2	2.514165	1	0.317047803	1	Match
201411	-0.52368	5.418325	2.090624	8588.25	5.129633	1	0.183821658	1	Match
201412	-3.00988	2.148539	-2.17779	8200.7	-4.51256	0	-0.54495994	0	Match
201501	-0.06407	4.709791	4.375959	8808.9	7.41644	1	0.515839385	1	Match
201502	-2.74868	-0.12825	0.402858	8844.6	0.405272	0	-0.19249109	0	Match
201503	-8.15642	4.764915	-3.51066	8341.4	-5.68935	0	-0.95246835	0	Match
201504	4.030583	-1.43558	-3.16123	8305.25	-0.43338	0	-0.37486172	0	Match
201505	-5.0424	3.40346	2.780754	8433.65	1.54601	1	0.052575423	1	Match
201506	-8.04626	1.723738	-1.70382	8381.1	-0.6231	0	-0.71923503	0	Match
201507	2.624559	8.531871	2.728491	8532.85	1.810622	1	0.44160905	1	Match
201508	-9.54413	3.84613	-6.83584	8001.95	-6.22184	0	-1.48299678	0	Match
201509	2.082525	2.229631	-1.02798	7868.5	-1.66772	0	-0.14637555	0	Match
201510	4.218913	-5.59235	1.187992	8065.8	2.507466	1	0.205085317	1	Match
201511	2.728746	-0.26062	-0.95813	7942.7	-1.5262	0	-0.12379545	0	Match
201512	1.387976	3.044291	0.616989	7861.05	-1.02799	0	0.053689363	1	No Match
				Average	0.829128		0.005656082		

N	**21**
Matched	**17**
Not Matched	**4**

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