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Binary Logistic Regression Modeling in Predicting Consumer Behavior towards Mutual Fund Investment

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Abstract - **Mutual fund, as a financial investment option, has gained reasonable acceptance in India since its inception. While traditional forms of investment have its own merits, the sheen of mutual fund has also been realized by Indian investors. A huge investor class have scored mutual fund higher than its counterparts on many counts. While the popularity of this new age investment option is on a rise, however, a mixed view is also experienced. The present study explores the behaviour of investors' towards mutual fund. The study is based on the premise of regression analysis and binary logistic regression has been used to develop a model that best represents the consumer behaviour. The best model selection is based on the information criteria of Akike. Also, from the model, the researchers have evaluated the probability of mutual fund purchase by consumers. Finally, the research work shows computation of odds ratio that signifies the extent to which the probability of purchasing mutual fund would change with unit change in the levels of the covariates. This study is descriptive in nature and is based on primary survey with a sample size of 376. The results reveal that high returns are the most preferred determinant of investment behavior followed by the liquidity which is also evident from the odds ratio computation.**
Keywords: **Predictive Modeling, Binary Logistic Regression, Investor Behavior, Mutual Fund**

I. INTRODUCTION

The economic liberalization in India has brought a recent trend for the common and small investors who are willing to participate in the various investment avenues. There are large number of retail investors, with the ability to save and invest in share market, gold, real estate, insurance and post office. The Indian investment industry is witnessing an exponential growth as a result of infrastructural development in manufacturing and services sector, in personal financial assets and rise in foreign participation. In this context of a growing risk appetite, rising disposable income, and increased financial awareness, the study explores the investors' perception of Mutual fund popularity based on 376 primary responses. The study empirically attempts to examine the determinants of investors' perception towards mutual fund investment in Kolkata by using Binomial Logistic Regression Analysis.

Mutual fund is an investment vehicle made up of a pool of funds collected from many investors for the purpose of investing in securities such as stocks, bonds, money market instruments and similar assets. Mutual funds are operated by money managers, who invest the funds capital and attempt to produce capital gains and income for the funds investors. A mutual funds portfolio is structured and maintained to match the investment objectives stated in its prospectus. Just like a share has a price, a mutual fund unit has an NAV. NAV represents the market value of each unit of a fund or the price at which investors can buy or sell units. The NAV is generally calculated on a daily basis, reflecting the combined market value of the shares, bonds and securities (as reduced by allowable expenses and charges) held by a fund on any particular day. Mutual Fund serves as a key financial intermediary to playing a crucial role in converting the investor's saving to capital market, thus establishing a link between saving and capital market. Small Investors are unable to diversify their investment because of their limited funds. But Mutual fund offer ways to diversify risk.

The Mutual fund industry in India came into being in 1963 with the setting up of the Unit Trust of India (UTI) the industry registered a major milestone in 1993 when the private sector comes in the Mutual Fund sector. But every investment has some risk. The average abnormal return in the post-ranking quarter is 39 basis points. The post-ranking abnormal return disappears when funds are evaluated over longer periods. Results suggest that superior performance is a short-lived phenomenon that is observable only when funds are evaluated several times a year. Patnaik (2017) observed that there is a big relief to Mutual Funds agents and distributors that they will not have to pay a tax on services provided by them and the liability in this regard would entirely be on the Fund houses. Literature on Mutual Fund performance is enormous. A few research studies that have influenced the preparation drawing on results obtained in the field portfolio analysis, a new predictor of mutual fund performance one that differs from virtually all those used previously by incorporating the volatility of a funds return. Literature also shows derived a risk- adjusted measure of portfolio performance (Jensen's alpha) that estimates how much a manager's forecasting ability contributes to fund's returns.

Assets managed by mutual funds (MFs) in the country has crossed the Rs 25-lakhcrore milestone at the end of August 2018, with the strong participation of retail investors in the last few years and substantial inflow into liquid funds from Corporate. From Rs 23.1 lakh crore at the end of July 2018, assets under management (AUM) of the 42 fund houses together was Rs 25.2 lakh crore on August 31 2018, data by industry trade body AMFI (2018) showed. According to AMFI CEO N. S. Venkatesh, the positive fluctuations in AUM are because of the industry body's investor awareness campaign and strong participation from retail investors. About a year ago, AMFI, on behalf of the MF industry, had launched an awareness campaign with the tag line 'Mutual funds sahihai', which has now emerged to be popular among Indians. Retail investors have started putting money in mutual funds schemes, especially in those that invested mainly in shares through the systematic investment plan (SIP) route. As of August, inflows through SIPs were nearly Rs 7,700 crore, compared to Rs 4,947 crore in August 2017 and Rs 3,334 crore as of August 2016, AMFI data showed.

Review of literature was done categorically, starting with a structured study on attributes that influence choice of investment options followed by demographic analyses on mutual fund investors etc. Subsequent discussion also provides literature support for methodological framework of logistic regression.

There is a group of literature that discusses the attributes that influence the choice of mutual fund as an investment avenue (e.g. Tax benefit, High returns, capital appreciation, liquidity, diversification, risk factor etc.) to determine the actual act of investment in Mutual Fund. For instance, Sujit and Amrit (1996) stated that the main factor influenced the salaried and business class group to invest in mutual fund is tax benefit. The study was made at a time where Mutual fund had just landed in the market and tax benefit was showcased as a chief feature. Agarwal (2001) suggested that the public provident fund is the most beneficial with the least risk factor investment for all group of people (salaried class, self-employment and retired persons) as well as for both tax payer and non-tax payer.

Tapan and Tripathy (2002) expressed that investors are very much concerned about the safety and minimum return for the amount invested in the mutual fund. Factors like tax rebate under section 80 C and past performance of the company are also taken into consideration by investor before making investment. Chalam (2003) argued that the majority of the investor the first choice of investment is real estate and the second preference to the mutual fund schemes followed by gold and other metals. Singh and Chander (2006) analyzed that investment decisions making done by the majority of investor based on the recommendation done by the professionals and financial advisors. Muttapan (2006) concluded that the factor influencing investment in mutual fund is tax exemption. Ranganathan (2006) studied that for retirement purpose the investors preferred to invest in the pension fund as well as provident fund and they would not prefer to investment in mutual fund for their future needs. Parihar, Sharma and Parihar (2009), pointed out that return followed by liquidity, flexibility, affordability and transparency are the influential factors to make investment in mutual funds by the investor. Krishnamoorti (2009) pointed out that investor educational backgrounds, job, reading habit of news relating to investment are closely associated with the investment decision of investor. Kumar and Vikkraman (2010) studied the factors influenced the investors to invest in equity shares are liquidity, low investment and capital appreciation. Many others have argued that the various investment channels should be kept updated to the investor through print and electronic media. The bank employees believed that insurance is an investment avenue rather than risk coverage instrument. Kumar and Vikkaraman (2010) stated in his article that the investor preferred to invest in gold followed by bank for the safe investment. For the security purpose the investors are preferred to invest in insurance. Anbarasu, Clifford and Annette (2011) expressed that the knowledge of the investor about the investment avenues are low. Pati and Shome (2011) reviewed that the secured avenue of bank deposit schemes are preferred by households rather than unsecured avenues of savings even though it gives high return.

Another set of literature offer description of the demographic profile of mutual fund investors. Mittal and Dhade (2007) stated that service class, business class, housewives, professionals and students prefer to invest in equity/mutual fund, debenture/bonds, real estate/ bullions, post office deposits/derivatives and derivatives/equities respectively. Mittal and Vyas (2008), studied that the demographic information such as age, educational qualification, income and marital status will have significant effect of an investor investment decision. Gupta and Jain (2008) analyzed the main reservations of the investors towards mutual fund are volatility, price manipulation, wrong attitude of brokers, mismanagement of corporate executives. Wang (2011) expressed that variables like awareness, income level and skill plays a vital role which influence youngster to invest in mutual funds. It is also found that the irrespective of educational qualification, job, age, income level investor would like to protect their future by taking an insurance policy.

Yogesh and Charul (2012) analyzed that due to low returns the conventional investment options like Post Office Saving Schemes, Public Provident Funds are not preferred by the investors. However, investment on gold is preferred by female investors. Kaushal and Bhatt (2012) discussed that due to less risk all income group and category of investor prefer to invest in bank deposits as well as post office deposits. Whereas investment in equity shares, mutual funds, insurance, commodities and real estate are preferred by higher income group with higher education. Palanivelu and Chandrakumar (2013) identified the low and middle income group of investor and irrespective of them give preference to invest in insurance and bank deposit. In our study we have refined and considered the responses of the business class, salaried and self-employed professionals inly.

Scholarly contributions related logistic regressions were also reviewed to establish a sound theoretical background on the concept of the analytical method contemplated for this study. Sampath (2002) presented the steps involved in developing a logistic regression model based on student test scores, performance at high schools, and other demographics to predict whether or not a student will eventually enroll if admitted. Yusuff, Mohammed, Ngah and Yahaya (2012) studied the diagnosis of breast cancer from mammograms is complemented by using logistic regression. Sheridan (1993) utilized to predict the retention of 477 master's and 124 doctoral candidates at a large Canadian university. Selected demographic, academic and financial support variables were used as independent variables. The dichotomous dependent variable was whether the student successfully completed the degree. Boamah and Hufstedler (2015) predicted social trust with five demographic variables from a national sample of adult individuals who participated in the General Social Survey (GSS) in 2012. The five predictor variables were respondents' highest degree earned, race, sex, general happiness and the importance of personally assisting people in trouble. The study assesses the impact of the predictors on the likelihood that respondents would report that they have low social trust. Many other studies including that of Khare (2011), Ramadoss (2016) and Vernon and Smith (2011) have used logistic regression to predict certain outcomes.

Much of the research work conducted on MF do not address the view point of consumer's behaviour and prediction of the same is scarcely noticed. The present study makes an attempt to broaden the scholarly contribution in this context using a predictive modelling approach that is best suited for subjective analysis having discrete categories of attributes. Logistic regression model have been widely used (citation) in such circumstances across varied domains. The identified gap has been structured under specific objectives that include identifying attributes as dependent and independent from a detailed literature survey.

It is then followed by model development using binary logistic regression approach from where the importance and significance of the independent variables (attributes) would be ascertained. Finally, the probability of a consumer opting for MF would be calculated and the effect of changes in the attributes on the outcome (consumer behaviour) evaluated from the developed model. The rest of the paper is planned as follows. Section II details the framework of the present study including those of research design, methodology, sampling and data collection. The detailed findings and analysis is captured in section III followed by conclusion in section IV.

II. RESEARCHFRAMEWORK

The framework of the present research has been developed under four pillars of design, method, sampling and data collection. To begin with the design of research is first explained followed by the mathematical model used.

A. Research Design

Out of different study designs, cross sectional and longitudinal study, the former is preferred to the latter as it gives the population characteristics at a particular point in time which is also the aim of the present work. This study is descriptive in nature which can also be used for predictive analytics.

B. Research Methodology

The ensuing study uses Logistic Regression, also called logit regression or logic model, where the dependent variable is categorical (Agresti, 2002). Binomial or binary logistic regression (Anderson, Sweeney& Williams,2014) includes those models where dependent variables can assume only two discreet values '0' and '1' which may represents outcomes such as interested or not interested, pass or fail, accepted or not accepted, win or lose etc. Logistic regression can be multinomial as well where the dependent variable might have more than two outcome categories. The binomial or binary logistic model is primarily used to evaluate or estimate or determine the probability of a binary response or outcome based on one or more independent or predicated variables. Logistic regression in many ways is similar to ordinary regression or multiple regressions where a set of independent variables are used to predict the outcome of the dependent variables. However in logistic regression the relationship is non-linear and may be expressed with multiple explanatory variables (Agresti, 2002)as:

$$E(y) = \frac{e^{\beta_0+\beta_1x_1+\beta_2x_2 \ldots\ldots\ldots\ldots+\beta_nx_n}}{1+e^{\beta_0+\beta_1x_1+\beta_2x_2 \ldots\ldots\ldots\ldots+\beta_nx_n}} \ldots\ldots\ldots\ldots\ldots\ldots (1)$$

β_0 is the intercept and $\beta_1,\beta_2, \ldots\ldots\ldots\ldots\beta_n$ are regression coefficients.

Here E(y) can assume two discreet values '0' and '1' in case of binary or binomial logistic regression which may be written as (for two and three independent variables):

$$\hat{y} = Estimate of p(y=1|x_1,x_2,x_3) = \frac{e^{\beta_0+\beta_1x_1+\beta_2x_2+\beta_3x_3}}{1+e^{\beta_0+\beta_1x_1+\beta_2x_2+\beta_3x_3}}$$

for three independent variables

$$\hat{y} = Estimate of p(y=1|x_1,x_2) = \frac{e^{\beta_0+\beta_1x_1+\beta_2x_2}}{1+e^{\beta_0+\beta_1x_1+\beta_2x_2}}$$

for two independent variables.

The independent variable may either be continuous or categorical but the above form of logistic regression violates the linear assumption of regression. Also the linear regression does not make sensical predication for a binary dependent variable. Thus it is important to convert a binary variable into a continuous one so that it may take any real value (+ve or –ve). In order to achieve that binomial logistic regression first takes the odds of an event happening for different levels of each independent variable and then takes the ratio of those odds. The logarithm of this ratio is referred to as logit (also called log-odds) which is used to create continuous criteria of the dependent variables. The logit transformation is referred to as the link function in logistic regression though the dependent variable of logistic regression is binomial. The logit is a continuous criterion upon which linear regression is performed. The logit function for equation (1) may be represented or calculated as:

$$logit[E(y)] = \ln\left[\frac{E(y)}{1-E(y)}\right] = Ratio of odds$$

The odds ratio for independent variables represents the change in odds for 1 unit change in the independent variables holding all other independent variable constant. The odds ratio also enables us to compare the odds for different events.

$$logit[E(y)] = \ln\left[\frac{\frac{e^{\beta_0+\beta_1x_1+\beta_2x_2 \ldots\ldots +\beta_nx_n}}{1+e^{\beta_0+\beta_1x_1+\beta_2x_2 \ldots\ldots +\beta_nx_n}}}{1-\frac{e^{\beta_0+\beta_1x_1+\beta_2x_2 \ldots\ldots +\beta_nx_n}}{1+e^{\beta_0+\beta_1x_1+\beta_2x_2 \ldots\ldots +\beta_nx_n}}}\right]$$

$$logit[E(y)] = \ln\left[\frac{\frac{e^{\beta_0+\beta_1x_1+\beta_2x_2 \ldots\ldots +\beta_nx_n}}{1+e^{\beta_0+\beta_1x_1+\beta_2x_2 \ldots\ldots +\beta_nx_n}}}{\frac{1}{1+e^{\beta_0+\beta_1x_1+\beta_2x_2 \ldots\ldots +\beta_nx_n}}}\right]$$

$$logit[E(y)] = \ln\left[e^{\beta_0+\beta_1x_1+\beta_2x_2 \ldots\ldots +\beta_nx_n}\right]$$

$$logit[E(y)] = \beta_0 + \beta_1x_1 + \beta_2x_2 \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots + \beta_nx_n$$

Thus, logit of the probability of an event is a simple linear equation. A unique relationship exists between the odds ratio for a variable and its corresponding regression coefficient which is
$\mathrm{OddsRatio\ (OR)} = e^{c\beta_i}$ where 'c' represents the change in independent variables.

The theoretical knowledge base on binary logistic regression has been used to identify the effect of change (variation) in the attributes that affect consumer behaviour towards mutual fund investment.

C. Sampling

In this study, the researchers used judgmental sampling, a non-probability sampling technique. This sampling method is based on the researcher's judgment in drawing elements within the sample. Such sample representation is expected to assist evaluation of the research objectives set. This type of sampling technique is also known as purposive sampling or authoritative sampling.

The process involves nothing but purposely handpicking elements from the population based on the researcher's knowledge and judgment. It represents one of the viable sampling techniques in obtaining information from a very specific group of people. In the present study business class, salaried individuals and self-employed professionals have been considered.

D. Data Collection

Primary data forms the basis of this research and the same have been collected using questionnaire as the survey instrument. Before initiating the full scale survey, a pilot survey was done to identify and eliminate the defects in the questionnaire. The study used a structured questionnaire with a mix of open and close ended questions. Minor changes had to be made in the original questionnaire before the final investigation was initiated. The questionnaire was framed in two parts.

First part deals with demographic profile containing open, close ended questions. Second part of the questionnaire contains Likert scale questions relating to investors' opinion on various attributes related to mutual fund investment. Undisguised face to face interview was conducted. The sample size required was calculated from the expression: N = [{t^2 x p (1 – p)}/m^2] where N: Sample size required, t: confidence level at 95% (standard value of 1.96), m: margin of error at 5% (standard value of 0.05) and p: estimated prevalence of consumer knowledge about mutual funds (70%). N was found to be 323. In the full-scale survey, 500respondents in Kolkata city were included in the study.

A total of 425 filled in questionnaires were received and responses of 376 questionnaires were finally considered for analysis owing to their completeness. Internal consistency estimates of reliability of primary data were conducted and Cronbach's α was found to be 0.62. Lance, Butts and Michels (2006)opines that even an α value < 0.7 but > 0.6 is worth considering as such results are obtained many a times due to different attributes measuring heterogeneous items. In the ensuing study, R 3.4.0 version have been used for analysis.

III. ANALYSIS AND FINDINGS

The analysis was done in a step wise manner. Initially all the 6 attributes were included in building the binary logit model. Step wise reduction of attributes was done and the goodness of model fit compared on the basis of Akaike Information Criteria (AIC). The AIC (Akaike, 1974)selects the best fitted model from a group of models as the one that minimizes AIC and is expressed as $\mathrm{AIC} = \ln \hat{\sigma}^2 + \frac{2}{n}r$ where ln = the natural log; $\hat{\sigma}^2$ = the residual sum of squares divided by the number of observations; n = number of observations and r = the total number of parameters (including the constant term) in the model. Tables I and II represent the five models that have been developed.

The logit model [E(yx_i)] with all 6, 5, 4, 3and 2 criteria may be expressed as:

Logit [E(y6)] = $-0.936 + 0.527x_1 + 0.601x_2 + 0.431x_3 + 0.612x_4 + 0.431x_5 + 0.483x_6$ with AIC = 527.72

Logit [E(y5)] = $-0.253 + 0.106x_2 - 0.095x_3 + 0.107x_4 - 0.074x_5 - 0.023x_6$ with AIC = 527.38

Logit [E(y4)] = $-0.842 + 0.093x_2 + 0.151x_4 - 0.039x_5 + 0.013x_6$ with AIC = 526.25

Logit [E(y3)] = $-1.149 + 0.122x_2 + 0.166x_4 + 0.026x_6$ with AIC = 524.36

Logit [E(y2)] = $-1.044 + 0.116x_2 + 0.155x_4$ with AIC = 522.45

The notation x represents the number of attributes and x_i denote the ith attribute; i = 1 to 6. Here, x_1 represents tax benefit, x_2: high returns, x_3: price, x_4: liquidity, x_5: diversification and x_6: safety. It is noted that the mod (z value) of all attributes are < 1.96 and are significant at 90%. The value of the coefficients refers to the effect of x_i on the log odds that logit [E(y)] = 1. Further the positive sign of the coefficients indicate an increased chance of investment in mutual funds and vice-versa. On these lines, the attributes with negative coefficients have been removed in the step wise model development.

The attribute - price has been removed from model 2 in developing model 3, while the attribute – diversification, has been removed from model 3 while developing model 4. Model 2 further shows that high returns and liquidity are the only two attributes that have positive coefficients. In fact the best model developed, which is Logit [E(y2)] = $-1.044 + 0.116x_2 + 0.155x_4$ with the lowest AIC value, also has these two attributes. In developing this model (model 5), the safety attribute has been removed from model 4 owing to it's extremely low value of coefficient.

TABLE I LOGISTIC REGRESSION MODEL ESTIMATION (MODEL 1, 2 & 3)

Attribute Names	Model 1			Model 2			Model 3		
	Estimate	Std. Error	z value	Estimate	Std.Error	z value	Estimate	Std.Error	z value
Intercept	-9.936	8.853	-1.122	-0.253	1.324	-0.191	-0.842	1.161	-0.725
Tax Benefit	0.527	0.472	1.117						
High Returns	0.601	0.473	1.271	0.106	0.141	0.757	0.093	0.140	0.668
Price	0.431	0.483	0.892	-0.095	0.102	-0.930			
Liquidity	0.612	0.475	1.288	0.107	0.127	0.836	0.151	0.118	1.284
Diversification	0.431	0.474	0.909	-0.074	0.127	-0.584	-0.039	0.121	-0.326
Safety	0.483	0.470	1.028	-0.023	0.102	-0.226	0.013	0.094	0.138
AIC	527.72			527.38			526.25		

Source: Authors Computation

TABLE II LOGISTIC REGRESSION MODEL ESTIMATION (MODEL 4&5)

Attribute Names	Model 4			Model 5		
	Estimate	Std.Error	z value	Estimate	Std. Error	z value
Intercept	-1.149	0.676	-1.701	-1.044	0.575	-1.814
Tax Benefit						
High Returns	0.122	0.110	1.110	0.116	0.108	1.074
Price						
Liquidity	0.166	0.110	1.507	0.155	0.104	1.490
Diversification						
Safety	0.026	0.086	0.298			
AIC	524.36			522.45		

Source: Authors Computation

Using the identified model, the probability of consumers investing in mutual funds has been estimated. All possible combinations of x_1 and x_2 have been considered. It is also clear that with increase in the value of an independent variable (keeping the other constant), i.e. more favoured opinion on the attribute, probability that a consumer would opt for investment in mutual fund have been found to increase. It is also noted that highest probability is found for $x_1 = 5$, $x_2 = 5$ option and the next highest probability is found for $x_1 = 4$, $x_2 = 5$ option owing to the higher coefficient value of x_2 than x_1 and not the reverse option of $x_1 = 5$, $x_2 = 4$.

TABLE III PROBABILITY ESTIMATION USING THE BEST FITTED BINARY LOGISTIC REGRESSION EQUATION

x_1	x_2	β_0	β_1	β_2	$\beta_0 + x_1.\beta_1 + x_2.\beta_2$	$Y = e^{\beta 0 + x1.\beta 1 + x2.\beta 2}$	I + Y	E(y) = Y / (1 + Y)
1	1	-1.044	0.116	0.155	-0.773	0.462	1.462	0.316
1	2	-1.044	0.116	0.155	-0.618	0.539	1.539	0.350
1	3	-1.044	0.116	0.155	-0.463	0.629	1.629	0.386
1	4	-1.044	0.116	0.155	-0.308	0.735	1.735	0.424
1	5	-1.044	0.116	0.155	-0.153	0.858	1.858	0.462
2	1	-1.044	0.116	0.155	-0.657	0.518	1.518	0.341
2	2	-1.044	0.116	0.155	-0.502	0.605	1.605	0.377
2	3	-1.044	0.116	0.155	-0.347	0.707	1.707	0.414
2	4	-1.044	0.116	0.155	-0.192	0.825	1.825	0.452
2	5	-1.044	0.116	0.155	-0.037	0.964	1.964	0.491
3	1	-1.044	0.116	0.155	-0.541	0.582	1.582	0.368
3	2	-1.044	0.116	0.155	-0.386	0.680	1.680	0.405
3	3	-1.044	0.116	0.155	-0.231	0.794	1.794	0.443
3	4	-1.044	0.116	0.155	-0.076	0.927	1.927	0.481
3	5	-1.044	0.116	0.155	0.079	1.082	2.082	0.520
4	1	-1.044	0.116	0.155	-0.425	0.654	1.654	0.395
4	2	-1.044	0.116	0.155	-0.270	0.763	1.763	0.433
4	3	-1.044	0.116	0.155	-0.115	0.891	1.891	0.471
4	4	-1.044	0.116	0.155	0.040	1.041	2.041	0.510
4	5	-1.044	0.116	0.155	0.195	1.215	2.215	0.549
5	1	-1.044	0.116	0.155	-0.309	0.734	1.734	0.423
5	2	-1.044	0.116	0.155	-0.154	0.857	1.857	0.462
5	3	-1.044	0.116	0.155	0.001	1.001	2.001	0.500
5	4	-1.044	0.116	0.155	0.156	1.169	2.169	0.539
5	5	-1.044	0.116	0.155	0.311	1.365	2.365	0.577

Source: Authors Computation

Finally, the odds in favor of consumers buying mutual fund is estimated from the odds ratio computation. It is defined as the odds at $X = x_i + 1$ divided by the odds at $X = x_i$. The odds increase multiplicatively by e^{β} for every unit rise in x. The same have been computed for changes in x_i for both high returns and liquidity. Since the attributes can assume 5 categorical values ranging from 1 to 5, four levels of changes are possible. The computations of odds ratio indicate that for change, rather improvement in high returns in mutual funds would lead to higher probability of consumers opting for it compared to comparable changes in liquidity.

TABLE IV ODDS RATIO COMPUTATION WITH INDEPENDENT VARIABLES (IVS)

c (Change in IV)	β_1	$c\beta_1$	Odds Ratio$_1 = e^{c\beta 1}$	β_2	$c\beta_2$	Odds Ratio$_2 = e^{c\beta 2}$
1	0.116	0.116	1.123	0.155	0.155	1.168
2	0.116	0.232	1.261	0.155	0.31	1.363
3	0.116	0.348	1.416	0.155	0.465	1.592
4	0.116	0.464	1.590	0.155	0.62	1.859

Source: Authors Computation

IV. CONCLUSION

This paper addresses consumer behavior in the mutual fund market using a binomial logistic regression approach where six independent variables were initially considered (Tax benefits, High returns, Price, Liquidity, Diversification and Safety) and the customer act of choosing to invest (or not) as the dependent variable. Analysis was done stepwise to obtain the best fit model. The best fit model showed high returns and liquidity are significant in predicting customer behavior regarding mutual fund investment. Positive sign of regression co-efficient for variable x_2 (x_2: High returns) and x_4 (x_4: Liquidity) suggests direct proportionality between covariates and the dependent variable. Thus, more the options of high returns, more is the possibility of investor opting for mutual fund. Moreover more options for liquidity also improve the chances of mutual fund investment. One might intuitively infer that more liquidity entails less lock-in period for mutual funds, whichis easily liquidated compared to real estate or gold (Disha, 2010).Finally, it is concluded that probability that liquidity increases the chances of investment is more than that of highreturns for aninvestor. Though tax benefit, diversification etc. aresubservient to mutual fund, these variables have emerged to be non-significant. The managerial implication is to strategize campaign, activities and events which will advocate awareness and increase more popularity of mutual fund. Through this research it is also contemplated that mutual fund companies should prioritize more on high returns and liquidity while devising any outreach programs.This study also comes with some limitations. There exists a crippling problem of market uncertainties and risk associated with mutual fund investment (Kathuria & Singhania, 2012). So investors have an innate apprehension regarding investing in mutual fund. The sample size considered in the study was restricted owing to selection of a specific demography of professionals, self-employed and businessmen. Future studies may consider wider variety of investors. Moreover, future studies may also consider attributes other than those considered in the present research work. The present study was conducted in a single city and the same may be expanded to other metropolis and tier II towns.

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