



# SENTIMENT ANALYSIS OF MAJOR MUTUAL FUND RELATED NEWS ARTICLES IN INDIA AMID THE COVID-19 OUTBREAK, TO OBTAIN INVESTOR SENTIMENT IN MUTUAL FUNDS & TO FORECAST ASSETS UNDER MANAGEMENT (AUM), A MUTUAL FUND MARKET INDICATOR

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## ABSTRACT

*The outbreak of the COVID-19 Pandemic caused widespread panic among people around the world. Many countries enforced a fierce lockdown to curb the spread of the virus. But the lockdown had other plans for Businesses as many of them were forced to shut shop leading to highly volatile market conditions and Bearish Economic Conditions in most countries. But was this, the perception of the Investors as well? This Paper aims to find out the sentiment of Investors on Mutual Funds in the Indian Market with Assets Under Management (AUM), a predominant performance gradient for Mutual Funds, as a proxy to analyse the impact of news articles related to the Mutual Fund Industry amid the COVID-19 Outbreak. The paper also goes on to establish a significant mathematical relationship between Sentiment Scores & AUM and to using Regression to generate a Forecasting model that could be used to forecast future AUM given a sentiment score.*

**Key words:** Assets Under Management (AUM), COVID, Mutual Funds, Sentiment Analysis, VADER

**Cite this Article:** Amit Sundaram, Sentiment Analysis of Major Mutual Fund Related News Articles in India Amid the COVID-19 Outbreak, to Obtain Investor Sentiment in Mutual Funds & to Forecast Assets Under Management (AUM), a Mutual Fund Market Indicator, *International Journal of Management*, 11(11), 2020, pp 117-127.

<http://www.iaeme.com/IJM/issues.asp?JType=IJM&VType=11&IType=11>

## 1. INTRODUCTION

From its emergence in the 1990's in various newspapers, journals, Economic & Business Publications, Behavioural Finance has grown into becoming one of the most, if not the most, important field of study for scores of researchers and academicians in understanding what drives the sentiment of investors in order to invest in various financial instruments such as Stocks, Bonds, Mutual Funds etc. Behavioural Finance is at the heart of understanding the sociological and psychological issues that influence investors in making a decision to invest in a particular financial instrument at a given point of time or not, based on a large number of factors such as heuristics, manias, panics, loss aversion, overconfidence, overreaction, market inefficiency etc.

The accepted theories in Finance which have been in usage for a long time are known as traditional or Standard Finance. The roots of standard Finance are conceptualized around two foundations namely 'The Modern Portfolio Theory' & 'Efficient Market Hypothesis'.

Modern Portfolio Theory or commonly referred to as MPT was pioneered by (*Markowitz, H. 1952*) published in the Journal of Finance. It basically talks about how investors who are averse to risk can build portfolios based on an identified level of market risk to maximize expected returns or minimize investor risk based on an identified level of expected return.

The other important foundational theory in traditional Finance is called the Efficient Market theory or referred to as the EMT pioneered by (*Fama, 1970*) published in the Journal of Finance. The premise of this Hypothesis/ theory is that the prices of shares reflect any and all information in the market and that alpha generation of returns are possible. The theory addresses the fact that since trading of stocks in exchanges always take place at their fair market value, even proper timing and expert stock selection should not make investors beat the market and the only way for an investor to obtain high returns is by purchasing investments that are riskier.

But, these two accepted foundational theories of Finance for Investors do not capture the entire dynamics of investing and none more so than the irrationality of the Investors. This is where Behavioural Finance comes to the forefront

Analysis of Investor Sentiment is an area of research in the field of Behavioural Finance. It is not an exact science but we can obtain the pulse of an asset or a particular market and this would also help us understand the inclination of an investor to invest in a particular financial instrument/ product.

This paper primarily deals in gauging investor sentiments and perception to invest in mutual funds in the Pre-Covid and in the Covid Era. The perception of Investors is captured through Sentiment Analysis by analysing sentiment volatility through news articles obtained about mutual funds.

Analysis of sentiments in the domain of Finance is done by various researchers such as (*Smailović, J., Grčar, M., Lavrač, N., & Žnidaršič, M., 2014*); (*Azar, P. D., 2009*). etc. This paper is unique in which it talks about the change in Investor sentiment to invest in Mutual Funds going from the Pre- Covid Era to the Covid Era in the Indian Mutual Fund Market. This paper predominantly brings into limelight the usage of sentiments derived through newswires about mutual funds from Economic Times and Livemint Covid-19 timeline of major mutual fund news articles announcement as a proxy. This is then used to analyse the impact it had on Assets Under Management for a Mutual Fund House.

## 2. LITERATURE REVIEW

The traditional or standard theories of Finance such as the Modern Portfolio Theory (*Markowitz, 1952*) & Efficient Market Theory (*Fama, 1970*) discount the fact that human

beings make irrational decisions and how it exists in a startling and an unexpected scale (Sutherland, S., 1992). These theories, in essence, neglected the sentiments of the public at large and are unable to explain market volatility during highly unforeseen circumstances such as the COVID-19 Pandemic. Many time series study has brought this to light as well. The paper on how the efficiency of the financial system is connected to human behaviour (Shiller, R. J., 1999) in which he talks about how human behaviour from anthropology, sociology and psychology have helped in motivating recent empirical research on Financial Market Behaviour. He states that the Efficient Market Hypothesis is based on notions that are primitive like people accurately maximize the expected utility, behave rationally and are able to process all available information. He also goes on to explain the various anomalies of the Efficient Market Theory (Shiller, R. J. 2003). Other Researchers who speak about Behavioural Finance and irrationality in decision making by Investors include (Ricciardi, V., & Simon, H. K., 2000); (Forbes, W., 2009); (Shleifer, A., 2000); (Montier, J., & Strategy, G. E., 2002).

Sentiment Analysis is an area of study in the field of Natural Language Processing (NLP). Sentiment analysis is essentially the algorithmic approach to treat sentiments, opinions & text subjectivity (Medhat, W., Hassan, A., & Korashy, H., 2014). Sentiment Analysis uses various computer Algorithms, computer methodologies and Artificial Intelligence, also known as AI to retrieve information from information systems which is subjected to Natural Language processing to obtain and analyse sentiment (Feldman, R., 2013).

Sentiment Analysis which is also interchangeably used as 'Opinion Mining' has branched itself from Computer Sciences to various other fields of study such as Social Sciences, Psychology and Management Education. The ever-increasing importance of analysing sentiments has coincided with the rapid increase of social media platforms and its usage by people in order post their reviews and opinions in blogs, discussion forums, Facebook, Twitter and various other platforms. These reviews and opinions amount to such a large volume of data that is opinionated and is recorded digitally for analysis (Liu, B., 2012).

The techniques used to perform the task of opinion mining can broadly be classified under three main approaches. (Garg, S., & Verma, N., 2018)

### ***Machine Learning (ML) Approach***

This approach primarily deals in training computer systems in a way that it is able to make a decision by itself given a dataset. (Saleh MR, Martín-Valdivia MT, Montejo-Ráez A, Ureña-López LA, 2011); (Habernal I, Ptáček T, Steinberger J, 2015); (Pang B, Lee L, Vaithyanathan S, 2002).

The Machine Learning Approach is in-turn classified into 3 sub techniques namely Supervised ML, Unsupervised ML and Reinforcement ML. In the Supervised ML approach, the machine or computer system is trained using data that is labelled. A labelled dataset is one which contains both the raw data and its results. Thus, the labelled dataset is split into test dataset and training dataset. The training dataset is used in order to train the network. Once this is done, the test set acts as a completely new dataset which is used to predict the accuracy. Unsupervised ML uses neither labelled nor classified dataset. This is in-turn fed to the machine in order to obtain a hidden pattern from unlabelled, non classified dataset. Reinforced learning basically means learning from experience. In this approach, the computer system or machine automatically identifies the behaviour that is most ideal based on the context in order to maximize performance.

### ***Lexicon Based Approach***

In language, the purpose of a lexicon is to act as a connection between a language and the knowledge that is expressed in it. The Lexicon Based Approach in Sentiment Analysis primarily involves calculation of document orientation using the semantic orientation of phrases or specific words in a document. (Turney, 2002). The Lexicon Based approach is further classified under two sub-headings i.e. the Dictionary based Approach & Corpus Based Approach. The Dictionary Based Approach is a method in which a set of words that are opinionated and whose polarity is known is gathered. This word set is then grown using word database systems in order to obtain synonyms and antonyms. The words that are newly found is added back and the iteration is repeated again. The iterations are repeated until no new words are obtained (Taboada M, Brooke J, Tofiloski M, Voll K, Stede M, 2011); (Kanayama and Nasukawa, 2006); The Corpus based approach uses a collection of text from a specific domain. This text is then induced with a semantic lexicon that is specific to that domain.

### ***Hybrid Based Approach***

This is an approach thought of by researchers to obtain maximum efficiency through the combination of both the Lexicon Based Approach & the Machine Learning Approach.

### ***Sentiment Analysis used in the domain of Behavioural Finance***

There has also been research to identify sentiments and opinions from financial articles which may be in the form of news articles, blogs, discussion forums, microblogs etc. Research has been conducted to analyse the tone of the authors in various news articles related to finance to correlate measurable movements in stock price and go on to predict the magnitude of change in price movements (Schumaker, R. P., Zhang, Y., Huang, C. N., & Chen, H., 2012).

The identification of the polarity of sentiments that are obtained in financial news (Devitt, A., & Ahmad, K., 2007), tells us that financial text data is not just facts that are unadulterated. They carry with them a series of emotions that could make you cry or laugh and this could make you buy swaps or options in one company and can make you short sell your stocks in another company.

A number of studies have shown how factual data and the aspects of a news articles that intrigue emotion affect the markets in a very significant manner. This would in-turn go on to tell how an investor perceives the market and the impact that this would have on him to invest in various financial instruments and products such as stocks, bonds, mutual funds, commodities etc.

Results conducted from other experiments show how various resources of finance have profoundly different effects to the investments made by various investors. (M. Day and C. Lee, 2016).

With the rise social media platforms and ever-increasing growth of the number of active users each day, it is no surprise that there is a large volume of opinionated blogs, posts, comments on platforms like Twitter, Facebook, Quora etc. One such paper uses this concept to make a financial analysis in the retail sector with comments that have been extracted from Twitter and shows how news articles obtained from social media platforms and blogs also act as an invaluable resource to understand financial dynamics. (Souza, T. T. P., Kolchyna, O., Treleven, P. C., & Aste, T., 2015).

### 3. METHODS AND MATERIAL

#### 3.1. The Evaluation Corpus

This paper essentially deals with the impact of major news related to mutual funds, a few months before the COVID-19 Pandemic made its first appearance in news articles in India to the time when the Pandemic became a full-fledged situation in the country causing widespread panic in the country and the subsequent months after its onset where the Government of India & various State Governments imposed lockdowns to reduce the spread of the virus and eventually flatten the curve of people infected with the virus.

The paper analyses newswire articles specifically related to the Indian Mutual Fund Industry obtained from 'The Economic Times' and 'Mint' news media Companies as a proxy to obtain and analyse how these news articles play a role in affecting one of the most critical parameters of performance of a Mutual Fund House known as the 'Assets Under Management' data also known as AUM. The effect of the tone and opinion, these mutual fund news articles had on investors' sentiment to invest in mutual funds and how it affected AUM [of all mutual fund houses in India put together] is analysed in this paper. The Timeline Considered in the paper is from June of 2019 to July of 2020.

#### 3.2. Indicator used to measure the performance gradient of Mutual Funds – AUM

To assess the impact of announcements made in the Mutual Fund Industry, an Indicator known as 'Assets Under Management' or AUM is taken into consideration. The values of the total Assets Under management of the entire Indian Mutual Fund Industry is obtained from Association of Mutual Funds India or popularly known as AMFI ([www.amfi.com](http://www.amfi.com)). The AUM value obtained is on the last date of each month.

### 4. EXPERIMENTAL MODEL

#### 4.1. VADER Sentiment Analysis Model

(Valence Aware Dictionary and Sentiment Reasoner) also known as VADER is a rule-based lexicon tool used for the analysis of texts in order to detect the polarity of a given sentence, clause, paragraph or a document in general and also to identify emotion strength/ intensity in the particular text that is used. (Hutto & Gilbert, 2014).

The intensity of emotion obtained from a particular text, also known as sentiment scores in a text is mapped against lexical features in the VADER which relies on an inbuilt dictionary. The VADER model in our analysis is programmed in such a way as to obtain sentiment scores between -1 (highly negative) to +1 (highly positive) as seen later in the results section of the paper. The sentiment scores for a particular text is obtained by adding the strength of each word in the text used.

The VADER model is attuned to perform exceptionally well on social media texts as seen on Twitter (Elbagir, S., & Yang, J., 2019), Facebook and various other blogs. The advantage of the VADER model is that it does not require any structured or label data rather it uses valence-based, human curated and generalizable gold standard lexicon in order to analyse sentiment intensity. It is also generally fast enough and does not compromise on the speed and maintains a high standard of performance with regular data streaming online. The MODEL also outperforms various other standard models and benchmarks such as Support Vector Machine (SVM), Linguistic Inquiry and Word Count (LIWC), the General Inquirer etc. In the analysis, Python VADER sentiment class which is publicly available is used.

One Important point to keep in mind that the VADER model uses its methods and process of going through the corpus is it uses a Wisdom of the Crowd approach (WoTC) in order to estimate the valence of sentiments for each of the lexical features present in its Dictionary

(Surowiecki, J., 2005). In his paper, Surowiecki describes how the aggregation of the cognitive abilities of large groups of human beings such as problem decision making, problem solving, innovating & predicting is far superior to individual thinking. This is used by the VADER model in order to obtain collective valence sentiments to the lexical features present in its dictionary.

This Model has been used to obtain scores in various other scenarios such as teaching evaluations (Newman, H., & Joyner, D., 2018), Languages apart from English such as Bengali (Amin, A., Hossain, I., Akther, A., & Alam, K. M., 2019)

## 5. METHODOLOGY

News articles related to the Mutual Fund Industry in India is obtained from two well renowned news agencies namely 'The Economic Times' and 'Mint'. The timeline of the articles ranges from June of 2019 to July of 2020 which is representative of a few months before the COVID-19 Pandemic made its first appearance in news articles in India to the time when the Pandemic became a full- fledged situation in the country causing widespread panic in the country and the subsequent months after its onset .A total of about 183 significant news articles related to the mutual fund industry, averaging about 13 articles per month, was collected over the mentioned timeframe

These articles then undergo the necessary cleaning in order to make a well- organized Corpus. The Corpus is then fed into the Valence Aware Dictionary and Sentiment Reasoner or VADER model in order analyse the intensity or the strength of the sentiments in the text to give us sentiment scores for each of the months in the timeframe considered.

To assess the impact of the news articles on the Mutual Fund Industry in India, an indicator known as 'Assets Under Management' or AUM, one of the key market indicators to understand the performance of the Mutual Funds, is used as a proxy. The values of AUM collected each month is the summation of the Assets under Management of all registered mutual funds in India which is obtained from the Association of Mutual Funds India (AMFI).

Once the sentiment scores are obtained for each of the months in the timeframe, A Simple Linear Regression is conducted with sentiment scores and AUM values as variables to ascertain a relationship between them and also to come up with a predictive model which is further explained in the next section.

### 5.1. Regression

At its core, Regression Analysis helps in finding out the relationship of a single dependent variable also known as the 'outcome' variable with one or more independent variables also referred to as 'covariates' or 'predictors'. It helps us to sort out and ascertain mathematically, which of the covariates in the given data set have a significant impact on the outcome variable. (Sykes, A. O., 1993).

There are predominantly two types of regression models.

### 5.2. Linear Regression Model

In this, regression analysis is done in order to assess if there is a relationship that is significant between two variables in a dataset. One being the covariate/ predictor variable and the other one being the outcome.

### 5.3. Multiple Regression Model

This model is used to analyse if there is a mathematically significant relationship between sets of variables.

In this paper a Linear Regression Model is used with Sentiment score as the independent/predictor variable (x-variable) and Assets Under Management is the dependent/ outcome variable (y-variable).

## 6. RESULTS & ANALYSES

The Corpus generated upon collection of news articles related to the Mutual Fund Industry was fed into VADER model to obtain sentiment scores

**Table 1** The results of the VADER Model are as follows

Month	Sentiment	AUM
Jul-2020	0.6808	2711894.09
Jun-2020	-0.9217	2425040.37
May-2020	-0.7845	2454757.57
Apr-2020	-0.7903	2393485.71
Mar-2020	-0.8634	2226202.88
Feb-2020	0.743	2722937.39
Jan-2020	0.3182	2785803.67
Dec-2019	0.6652	2654074.76
Nov-2019	0.8316	2704699.41
Oct-2019	0.7845	2632824.43
Sep-2019	-0.8316	2450786.76
Aug-2019	0.7003	2547593.76
Jul-2019	0.8484	2453626.38
Jun-2019	-0.9154	2425040.37

The sentiment scores range from -1 (strong negative) to +1 (strong positive). The impact of these sentiment scores can be seen on the Indicator used i.e. AUM. In general, an increase in the sentiment score from one month to the next generally showed an increase in Assets Under Management barring few months as exceptions. The fall in AUM from February 2020 to March 2020 was a drastic 22.31% which is a sudden outlier in the table.



**Figure 1** Sentiment Scores over Time

*Results and Analyses of the Linear Regression Model used to ascertain a mathematically significant relationship with Sentiment score as the independent/ predictor variable (x-variable) and Assets Under Management is the dependent/ outcome variable (y-variable).*

**Table 2** Regression statistics

Regression Statistics	
Multiple R	0.758949614
R Square	0.576004517
Adjusted R Square	0.54067156
Standard Error	109804.3204
Observations	14

The correlation value is 0.76 indicates that the sentiment score and AUM are positively related. Next, we look at the value of R squared. This stat provides a measure of how well the model fits into the actual data. It gives us a measure of the linear relationship between the independent variable, in this case the *sentiment score* and the dependent variable, *AUM*. The adjusted R squared accounts for the increase in variables. Since the model has one predictor, R squared is a good indicator. In this case, R squared is 0.576. That is, 57.6% of the variance in AUM can be explained by the sentiment score(predictor).

**Table 3** ANOVA

	Degrees of freedom	F stat	p value
Regression	1	16.30218829	0.00164658
Residual	12		
Total	13		

$$F(1,12) = 16.302, p=0.001$$

The F stat is a strong indicator to identify if there is a relationship between the independent variable & the dependent variable. The further away the F stat is from 1, the better the model. The F stat, in this case is 16.302 which is significantly more than 1 relative to the size of our data and the p value is 0.001 which is below 0.05 (95% confidence level) which makes the model significant. This signifies that the independent variable – *sentiment* – is a good predictor of the dependent variable – *AUM*.

**Table 4** Coefficients table

	Coefficients	Standard Error	t Stat	P-value
Intercept	2536980.697	29373.33536	86.37019	3.87E-18
Sentiment	152736.641	37828.60122	4.037597	0.001647

The equation of the model is:  $y = 152736.641x + 2536980.697$

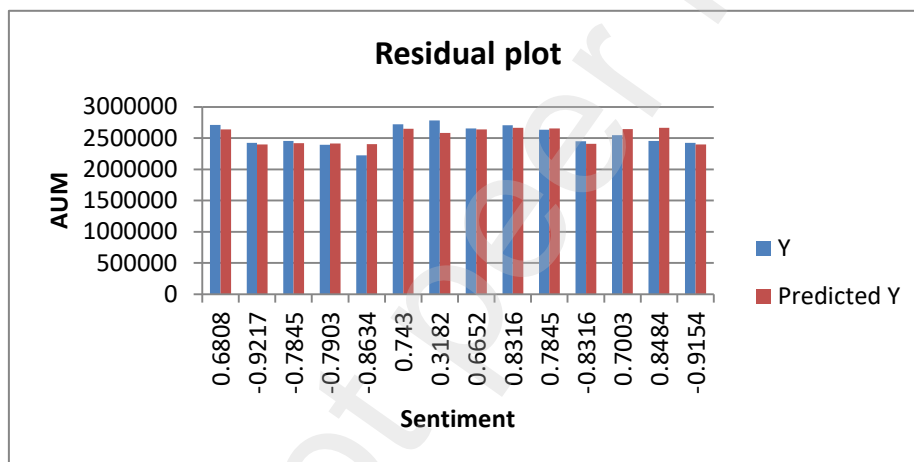
*Assets under management = 152736.641 \* Sentiment score + 2536980.697*

The closer the p score is to zero, it is more unlikely that the relationship between the independent variable and the dependent variable is due to randomness. An accepted cut off point is 0.05. In this case, the p score associated with “sentiment” is 0.0016. Therefore, the null hypothesis of the coefficient being zero can be rejected and it can be concluded that there exists a relationship between the independent variable (sentiment score) and the dependent variable (Asset under management).



**Table 5** Residual Analysis

Observation	Predicted Y	Residuals
1	2640963.802	70930.29
2	2396203.335	28837.04
3	2417158.802	37598.77
4	2416272.93	-22787.2
5	2405107.881	-178905
6	2650464.021	72473.37
7	2585581.496	200222.2
8	2638581.111	15493.65
9	2663996.488	40702.93
10	2656802.592	-23978.2
11	2409964.907	40821.85
12	2643942.167	-96348.4
13	2666562.463	-212936
14	2397165.576	27874.8

**Figure 2** Residual Plot

Upon conducting basic residual analysis, it can be seen that there are no striking outliers among the residuals. The distribution is fairly normal. This gives us another indication that this model is a good fit with the data.

Hence, based on the analysis of the results done above, we can see that there exists a mathematically significant relationship between AUM (outcome variable) and sentiment score (predictor variable) and the equation *Assets under management* =  $152736.641 * \text{Sentiment score} + 2536980.697$  can be used to predict values of AUM given a sentiment score.

## 7. DISCUSSION & CONCLUSION

The sentiment scores generated using the VADER Sentiment Analysis Model from mutual fund related news articles & the prevailing market volatility at the time-frame considered gives us a rather fair picture of the sentimental roller coaster an Investor might have gone through from June of 2019 to July of 2020 (time-frame considered for the analysis). Many countries & Especially India imposed a set of fierce and timely lockdown(s) in order to inhibit the spread of the virus. The nation was put under a lockdown in four phases, the first of which started on the 25<sup>th</sup> of March 2020 and the last one ending on the 31<sup>st</sup> of May, easing a few days in between for people to store up on essentials. But this painted a completely different

picture for Companies, Businesses & the Indian Economy in general as all commercial and private establishments were forced to shut-down. An upwards of 53% of businesses in India were projected to be significantly affected. The fall in Investor sentiment impacted Industries, Government & plans of Privatization. There was also a complete disruption of Global Trade & Supply Chain activities.

The downward sloping Economy due to COVID-19 did not seem to spare the mutual fund industry as well with many funds falling short of their respective benchmarks in the bear market. During the four phases of the lockdown starting from March of 2020 and ending on the last day of May 2020 saw a significant reduction in Assets Under Management (as seen in the Table 1). The fall in AUM from February 2020 to March 2020 was a drastic 22.31%. This directly correlates with strong negative sentiment scores (as seen in table 1) obtained through the sentiment Analysis of News Articles. The three months, also saw a huge volume of outflows due to redemptions by investors in many Equity, Debt and several other schemes owing to fear in the minds of the Investors created due to the pandemic and businesses shutting shop overnight. This was also coupled by problems in debt funds due to liquidity concerns. Franklin Templeton who have a longstanding history of giving positive returns closed down six of its debt funds because of problems in liquidity which was a major blow to the mutual Fund market & to Investor Sentiments.

But as the lockdown was lifted, several fiscal stimulus measures were implemented by the Government in June which uplifted Investor Sentiments as a result of which sentiment scores increased, moving to the positive in the month of July. Thus, the sentiment scores over the months considered highly correlated with AUM values and helped in obtaining a linear model relating the two variables. What news lies ahead for the investors is yet to be seen in further months as people get more attuned to dealing with the pandemic.

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