



Unveiling Investor Sentiment: A Behavioural Finance Perspective In Understanding It's Market Implications

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Abstract: The increasing occurrence of abnormal phenomena in financial markets has challenged the assumptions of traditional finance, leading to the emergence of behavioural finance. This field, developed in the 1970s and 1980s, focuses on investor behaviour and explains market anomalies through the lens of sociology, incorporating psychology and behaviour into financial analysis (Baker & Wurgler, 2006). This shift in perspective has spurred extensive research into investor behaviour and sentiment. Several studies have focused on measuring and quantifying investor sentiment. Composite sentiment indexes, such as that developed by Baker and Wurgler (2007), utilize principal component analysis (PCA) to combine multiple sentiment indicators into a single index, capturing the collective sentiment of investors. In this paper, PCA is employed to construct an investor sentiment composite index using Indian stock market data, providing a nuanced understanding of investor sentiment in India. Secondly, the dynamic relationship between Investor Sentiment and Market Return is tested using multivariate time-series regression model. The model does succeed in reflecting the explanatory power of Investor Sentiment in predicting stock market return. Recognizing this phenomenon empowers investors to gain deeper insights into the market, enabling them to navigate their investment decisions more effectively. Moreover, this understanding opens avenues for additional research into refining methods of measuring investor sentiment, ultimately enhancing its utility in guiding investor behaviour.

Keywords - Investor sentiment, behavioural finance, market return, principal component, regression

I. Introduction

Since Fama put forward the efficient market hypothesis in 1970, the classical financial theory has developed rapidly. This hypothesis believes that the investors in the market are rational and the price of assets can fully reflect their basic value. However, more and more abnormal phenomena in the financial market have brought about a great impact on the classical financial theory, which has prompted financial scientists to further consider the basic assumptions of traditional finance. Behavioural finance, developed in the 1970s and 1980s, takes investor behaviour as the research object and explains the abnormal phenomenon of financial market from the perspective of sociology based on investor psychology and behaviour [Baker & Wurgler 2006]. This has also prompted a large number of scholars to study investor behaviour and investor sentiment.

Black (1986) first introduced the concept of “noise trader” and pointed out that the existence of noise traders improved the liquidity of the market but reduced the effectiveness of the market. Delong et al. (1990) proposed a noise trader model (DSSW), which for the first time considered the influence of investor sentiment in the asset pricing model. Lee et al. put forward investor emotion hypothesis (LST) and explained the value of the closed fund with investor’s emotion. DSSW model and LST model lay a theoretical foundation for the later research on the relationship between investor sentiment and stock market. And then many researchers discussed the formation and quantification of investor sentiment.

In view of relevant literature research at home and abroad, there are generally two ways to measure investor sentiment. One is the direct method. It is compiled by surveying investors’ views on future market trends. It includes Investors’ Intelligence (II) Index, American Association of Individual Investors Index (AAII), Friendship Index, and “CCTV Watch Index.” The other is the indirect method. It constructs an investor sentiment index by selecting market data related to investor sentiment. It includes Advance Decline Line (ADL), Arms Index (ARMS), New High-New Low Index (HI/LO), Closed-End Fund Discount, and Consumer Confidence Index (CCI). In recent studies, the composite index of sentiment has been used to stand for single emotional indicators, such as that of Baker and Wurgler (2007). They used principal component analysis (PCA) to construct an investor sentiment composite index from six single sentiment indexes. The central idea of principal component analysis (PCA) is to reduce the dimensionality of a data set consisting of a large number of interrelated variables, while retaining as much as possible the variation present in the data set (Jolliffe 2002). For the related theories and applications of principal component analysis, please refer to literature. In this paper, principal component analysis is used to construct the investor sentiment composite index based on Indian stock market data. The index, constructed in this way, better captures the sentiment of individual investors in India. The rest of this article is as follows. Section 2 gives the review of literature. Section 3 constructs the investor sentiment index using the time series data on SPSS. Section 4 gives the multivariate time series model along with the result. Finally, in Section 5 the conclusion is given. Recently, many researchers have considered the relationship between investor sentiment and stock market returns and volatility from an empirical perspective.

Objective of the Study

- To construct the composite investor sentiment Index based on Indian Stock Market data
- To test if this Index can successfully be used to measure its influence on Stock Market Returns.

Data Collection and Methodology

- Model has been taken from Baker and Wurglar (2007) to calculate the Investor Sentiment Index.
- A time-series data analysis has been done on SPSS using factor analysis to compute Investor Sentiment Index,
- A multi-variate time-series regression model has been proposed and tested at the level of firms listed in Bombay Stock Exchange and the results have been summed up.
- The S&P BSE Sensex data for the period 2012 to 2022 has been used.
- Data for daily closing price for the period January, 2012 to December 2022 forms our base data.
- A parsimonious Investor Sentiment Index have been calculated using four underlying proxies of sentiment – Relative Strength Index, Psychological Line Index, Trading Volume and Adjusted Turnover Rate.
- The S&P BSE Sensex data for the period 2012 to 2022 has been used.

II. Literature Review

Hu and Wang (2012) studied the influence of investor sentiment on asset value. Ni et al. (2015) studied the nonlinear effect of investor sentiment on the monthly stock market return using the panel quantile regression model. The study found that investor sentiment had a significant effect on the stock market's monthly returns. Lutz (2016) used a dynamic model to construct a new indicator to measure investor sentiment and found that it was asymmetric. Chen (2017) constructed a measure that directly reflects investors' attention toward the global benchmark indices and studied the relationship between this measure and investor sentiment. Debata et al. (2017) examined the impact of local and foreign investor sentiment on emerging stock market liquidity. A positive effect of investor sentiment on liquidity was found. Ryu et al. (2017) examined how investor sentiment and trading behavior affect asset returns. They found that high investor sentiment induced higher stock market returns. Takanori (2018) investigated the relationships among an exchange merger, investor sentiment, and liquidity by analyzing data from the 2013 merger of the Tokyo Stock Exchange and Osaka Securities Exchange. They found that the investor sentiment effect occurs more strongly in small stocks. Ding et al. (2019) obtained a multirisk asset model by extending the DSSW model and verified the cross-sectional impact of investor sentiment on stock returns by using this model. Under this model, investor sentiment is divided into short-run and long-run components, and it is predicted that long-run components are negatively correlated with cross-sectional returns, while short-run components are positively correlated with cross-sectional returns.

Chen et al. (2019) studied the trend following trading behavior on the Chinese stock market and used the network model to describe the interpersonal relationship. It proved the inefficiency of timing arbitrage in China's stock market. The above research works consider the market as a whole. Chen et al. (2010 & 2014) constructed an investor composite emotional index with principal component analysis. They used this composite sentiment index as a threshold variable to divide the stock market. TAR model was used to divide the Hong Kong stock market and the Chinese mainland stock market into three states, respectively. Linear AR model was established for the stock market return in each state, and its predictive ability was discussed. However, the TAR model can only study univariates. Chiraz and Soumaya (2016) investigated the effect of exposure to aggregate volatility risk on stock returns in both high-sentiment and low-sentiment regimes by using both cross-sectional and time series analysis. They found that exposure to aggregate volatility risk is negatively related to returns when sentiment is low. However, this relation loses its significance when the sentiment is high. Dong et al. (2019) discussed the effects of different mechanism probabilities and investor heterogeneity on the risk contagion effect of the stock market. Wang (2019) examined the role of institutional investor sentiment in determining beta-return relationships, and through empirical analysis showed that the beta-return relationship is asymmetric between the bearish period and the bullish period.

Paraboni et al. (2018) examined the relationship between sentiment and risk in financial markets. Their results are consistent with Prospect Theory, indicating that when liquidity is thought to be low, investors try to reduce the negotiations that positively influence risk. On the other hand, based on the reverse scenario, when sentiments indicate high liquidity, there is an increase in the volume of negotiations, and thus, a decrease in risk. In another study, Zaremba and Konieczka (2017) observed that portfolios which were based on four factors of size (market value), value (book-to-market value), momentum (annual rate of returns excluding dividends for 12 months prior to November 31), and liquidity (average daily turnovers in the past month) had positive stock returns. In Iran, Kardan et al. (2017)'s results indicated an increase in the explanatory degree of CAPM by adding sentiment indices. Similarly, Khajavi and Fa'al Qayyum (2016) reported that earnings announcement had influenced skewness and returns. Accordingly, when earnings are not announced, the relationship between skewness and returns is negative and significant, but by earnings announcement, the relationship loses its significance. In addition, Hejazi et al. (2015) examined the impacts of market, liquidity, and momentum on major stock price changes. The results showed a significant relationship between the variables under study and major stock price changes.

III. Computation of Investor Sentiment Index (S_{RMRF})

There is substantial literature available on the determination of investor sentiment. Our study uses the model by Baker and Wurglar (2006). A parsimonious Investor Sentiment Index have been calculated using four underlying proxies of sentiment – Relative Strength Index, Psychological Line Index, Trading Volume and Adjusted Turnover Rate.

Relative Strength Index (RSI): This popular market indicator reflects if the market is oversold or overbought. Kim and Ha (2010) uses this index as one of the sentiment indicator and forms a composite investor sentiment index. Chen, Chong and Duan (2010) also uses the relative strength index as a proxy for sentiment to construct the composite investor sentiment index. The Relative Strength Index is computed as follows:

$$RSI_t = 100 * RS_t / (1 + RS_t)$$

$$RS_t = \frac{\sum_{t=1}^6 \max(P_t - P_{t-1}, 0)}{\sum_{t=1}^6 \max(P_{t-1} - P_t, 0)}$$

Where P_t is the closing price of stock or portfolio at time t , and P_{t-1} is the closing price of stock or portfolio at time $t-1$. A relative strength index of below 50 means that losses are greater than gains. When the relative strength index is above 50, it generally means that the gains are greater than losses. The market is overbought with an RSI of 80 and the market is oversold with an RSI of 20.

Psychological Line Index (PSY): Kim and Ha (2010) uses this index to construct a composite investor sentiment index. Yang and Gao (2014) uses the PSY as an indicator of sentiment to look beyond the obvious sentiment of the market and identify undertones for a trend change. The psychological line index (PSY) is as follows:

$$PSY_t = \frac{T^u}{T} * 100$$

Where T^u is the number of days during the year that the sensex price has increased compared to the previous day; and T is the trading period. Market is overbought with PSY of 75 and the market is oversold with a PSY of 25.

Trading Volume (VOL): Both Baker and Stein (2004) and Liao et al. (2011) uses individual trading volume as a sentiment indicator. The trading volume is used as one of the sentiment proxy accordingly.

Adjusted Turnover Rate (ATR): Baker and Stein (2004) suggests that turnover rate can serve as an indicator of sentiment. Also, Yang and Zhang (2014) uses the adjusted turnover rate as an investor sentiment index. The ATR is as follows:

$$ATR = \frac{R_t}{|R_t|} * \frac{VOL_t}{\text{shares o/s at time } t} * 100$$

Given below is the summary statistics of the four variables:

Descriptive Statistics					
	N	Minimum	Maximum	Mean	Std. Deviation
RSI	2721	5.375323667	95.71628130	55.36045662	19.35267931
PSY	2721	.000000000	100.0000000	53.86500061	21.89610578
ATR	2721	-130.772647	156.4768885	4.709527358	63.20837062
TRADING VOL N	2721	7.539913934	156.4768885	61.14158071	16.66789293
Valid N (listwise)	2721				

The mean value of RSI is 55.36 and 53.86 indicating that gains are greater than losses. An ATR of 4 indicates a bullish market trend. Each variable is likely to include a sentiment component, and we use PCA to isolate the common component and formulate an investor sentiment index. This leads to a parsimonious investor sentiment index (S):

$$S_t = .707ATR_t + .892RSI_t + .886PSY_t$$

Factor Analysis for Investor Sentiment Index

Pre-requisites of factor analysis – KMO and Bartlett's Test

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.622
Bartlett's Test of Sphericity	Approx. Chi-Square	2990.090
	df	6
	Sig.	.000

KMO measure of sampling adequacy is 0.622. KMO is a statistical measure to determine if the data is suitable for us to apply Factor Analysis. It measures the sampling adequacy of the 4 factors that have been used. Thumb Rule says that a value greater than 0.8 is a big thumbs up i.e. the data is very good to perform factor analysis. Our value of .622 indicates that our data is adequate/good to perform factor analysis. Bartlett Test of Sphericity tests the null hypothesis that the variables are not correlated / orthogonal. Significance level of less than 0.05 means that there is substantial correlation in the data and we can go ahead with factor analysis. In our case the significance level is .000, which is clearly less than 0.05. Therefore, the null hypothesis can be rejected.

Total Variance Explained								
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings	
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance
1	2.092	52.307	52.307	2.092	52.307	52.307	2.081	52.029
2	1.011	25.275	77.583	1.011	25.275	77.583	1.022	25.554
3	.657	16.433	94.016					
4	.239	5.984	100.000					

Extraction Method: Principal Component Analysis.

Around 77.5% of the variance of these factors are being explained by the first two components. Total percentage of variance explained is 77%. So this result is also good as minimum 70% needs to be considered.

Rotated Component Matrix ^a		
	Component	
	1	2
ATR	.707	.168
TRADING VOL N		.983
RSI	.892	-.134
PSY	.886	
Extraction Method: Principal Component Analysis.		
Rotation Method: Varimax with Kaiser Normalization.		
a. Rotation converged in 3 iterations.		

Component Transformation Matrix		
	Component	
	1	2
1	.995	-.102
2	.102	.995
Extraction Method: Principal Component Analysis.		
Rotation Method: Varimax with Kaiser Normalization.		

Here, our 4 variables are grouped between these 2 components. The values are called Eigen values. Eigen values of more than 0.5 needs to be considered.

Each variable is likely to include a sentiment component, and we use Principal Component Analysis to isolate the common component. This leads to a parsimonious investor sentiment index (S):

$$S_t = .707ATR_t + .892RSI_t + .886PSY_t$$

(Taking the Eigen values of the 3 factors above, the Investor Sentiment Index have been constructed)

One might object to the above equation as a measure of investor sentiment on the grounds that the principle component analysis cannot distinguish between a common sentiment component and a common market excess return component. We therefore construct an investor sentiment index that explicitly removes the market excess return variation from the parsimonious investor sentiment index based on the principle component analysis. To remove the common dependence of the parsimonious investor sentiment index on the market factor, we perform the following regression:

$$S_t = b_0 + b_1RMRF_t + E_{pt}$$

The residual of this equation may be the market investor sentiment index.

Coefficients ^a					
Model		Unstandardized Coefficients		Standardized Coefficients	Sig.
		B	Std. Error	Beta	
1	(Constant)	95.836	1.266		.000
	RMRF	-102.033	85.430	-.023	.232
a. Dependent Variable: Smrf					

$$S_t = 95.836 - 102.033RMRF_t + 34.6$$

The final Investor Sentiment Index (S_{RMRF}) was computed after deducting the market excess return component from the parsimonious investor sentiment index.

IV. Multivariate Time Series Model

The following model is used to test if Investor Sentiment Index (S_{RMRF}) has an impact on stock returns.

$$R_{mt} - R_{ft} = \alpha + \beta_1 RMRF_t + \beta_2 S_{RMRF,t} + E_t$$

Model Summary ^b										
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	.490 ^a	.240	.239	.0067743198	.240	428.545	2	2718	.000	1.353

a. Predictors: (Constant), Smrf, RMRF
b. Dependent Variable: R

Findings and Result

- The variables Investor Sentiment Index can explain 23% of the total variation in the Market excess return.
- We can conclude by saying that Investor Sentiment Index has some impact on excess returns of S&P BSE Sensex. Also, there are more factors in addition to the above variables, which can explain the market excess return.

V. Conclusion

the market-based composite investor sentiment index of Baker and Wurgler 2006 is one of the most used sentiment index. In this paper, we use Baker-Wurglar (2006) model to compute the Investor Sentiment Index and to study the dynamic relationship between investor sentiment and stock market returns in Indian Stock Market from January 2012 to December 2022. The research results found a 24 percent explanatory power of Investor Sentiment Index computed from the model of Baker and Wurglar 2006. In India, generally speaking, the overall quality of investors is not high. Investors tend to be affected by some noise. And then they can influence stock market returns and volatility. Stock market returns and volatility, in turn, affect investor sentiment. The above conclusion can help investors better understand their own characteristics of investment risk and return and provide some help for relevant regulatory authorities to grasp investor sentiment and market risk in a more specific way. It is conducive to the relevant departments to make better policy decisions.

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