Impact of Consumer Sentiment on Defensive and Aggressive Stock Returns: Indian Evidence

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ABSTRACT

This paper aims to study predictive ability of consumer sentiment of individual stocks. We consider two proxies for sentiment. One is explicit (Index of Consumer Sentiment [ICS]), second is implicit (Broad Market Indicator, S&PBSE500) and we pick 50 stocks randomly from S&PBSE500 index. We collect monthly data of all the variables. We group stocks into defensive and aggressive based on their beta value. We posit that sentiment indicators have contemporaneous co-movements and significant predictive ability of defensive and aggressive stocks. Results show contemporaneous co-movement exists between implicit sentiment indicator and stocks; contrarily no such relation exists between explicit sentiment indicator and stocks. We find causation from ICS to S&PBSE500. Both the sentiment indicators have causal relation with aggressive stocks but not with defensive stocks. Result show that only ICS has short-term predictive power of aggressive stocks. We find significant negative relation between consumer sentiment and aggressive stock returns in the following month. This implies high consumer optimism in current month results in price shrink of aggressive stocks in following month. We conclude that implicit sentiment indicator has no predictive ability of stocks and explicit sentiment indicator is able to predict only small number of aggressive stocks. We suggest investors not to follow sentiment indicators blindly because these indicators predictive ability is very limited that too with select aggressive stocks. We find aggressive stocks have high volatility and gain investor attention during optimistic and pessimistic market conditions.

Keywords: Retail Investor, Investor Sentiment, Stock Returns, Noise Trade, Predictive Analytics
JEL Classifications: G40, G41, G14, G17

1. INTRODUCTION

Equity stocks investors can be categorized into rational, arbitrageurs, and noise traders. Rational investors expect nominal return that is in excess of risk that they bear. They make investment decision depending on stock return, risk, and their risk appetite. Arbitrageurs search for undervalued or overvalued stocks in the market and buy or sell accordingly. Noise traders trade on noise in the market. Their investment decision depends on optimism and pessimism about the market movements. When market is optimistic, they pump funds into the market to make quick money. Moreover, when market takes down turn, they are the first to quit the market and create panic. In anticipation of abnormal returns,

noise traders behave irrationally. Noise traders pay much attention to sentiment rather than fundamentals. Sentiment whether positive or negative may influence by many factors at firm level, macro level or global level.

There are multiple methods to measure investor sentiment. The sentiment measure may be explicit or implicit. In explicit sentiment measures, agencies collect sentiment data from consumers/ investors through surveys and obtain investors' opinion on market conditions. Implicit sentiment measures represent investor sentiment in the form of volume, volatility, advances/declines and overnight prices etc. Extant research use both explicit and implicit sentiment measures to explain market movements and returns.

Explicit sentiment measure like University of Michigan's Index of Consumer Sentiment (ICS) is used to predict short-term and long-term market returns. Many of the existing studies link sentiment index to market indices. In this paper, we move one-step ahead and try to link sentiment index with individual stocks. In addition, we try to predict one period ahead return of individual stocks using sentiment index. We believe that influence of consumer sentiment is not uniform across stocks. Measuring and predicting market movements and returns are of less helpful to investors. Investors will benefit only when they know exact impact and predictive power of sentiment index on each stock. Considering this point, we aim to study influence and short-term predictive power of sentiment index at firm level. In addition, we group stocks into defensive and aggressive stocks to measure the impact of sentiment indices at aggregate level. Defensive stocks have beta value ≤1 and moves slowly or in tandem with the market. Aggressive stocks have high beta value and move faster than the market. We posit that sentiment significantly influences aggressive stocks and may not have any significant effect on defensive stocks.

This paper attempts to investigate contemporaneous co-movements, casual relation, and predictive power of sentiment indices of equity stock returns. We make an empirical study relating ICS (explicit sentiment indicator), broad market index (implicit sentiment indicator) and defensive and aggressive stocks. This paper has both theoretical and practical implications. Extant research primarily concentrates on sentiment indicator and aggregate market returns ignoring the fact that understanding the impact of sentiment on individual stocks is pivotal. We posit that when sentiment is positive many investors jump into the market and invest in stocks without thorough analysis. Institutional and big investors invest with meticulous analysis and in promising stocks. However, retail investors invest in any stock that is within their investment reach assuming that all stocks grow phenomenally. Initially this optimism may yield returns to few investors, resulting in more investors entering the market. At some point in time market price of the stock become unexplainable by its fundamentals and takes reverse turn. In such situation, individual investors react sharply and try to get rid of the stock. This creates panic and stock prices shrink steeper. The same may not be true with the market, because market index compose of highly liquid and blue chip stocks.

Furthermore, we argue that market contains both defensive and aggressive stocks and their reaction to sentiment may not be similar. In this paper, we examine these two theoretical issues. Coming to practical application of the findings of this paper are multifold. First, it clarifies whether investors can use sentiment indices to predict stock prices. Second, if there is any predict power of sentiment indices is it similar for all stocks listed in the market. Third, this paper helps individual investors to be vigilant about market sentiments. Rest of the paper is present in six sections. Section 2 synthesizes the existing literature and identifies the gaps. Section 3 specifies objectives and hypotheses. Section 4 presents objectives and methodology. Section 5 presents results and discussion. Section 6 focuses on the findings of the paper. Finally, concluding remarks and future directions are presented in section 7.

2. LITERATURE REVIEW

In this section, we present definitions of sentiment, theories behind it, and extant literature relating sentiment to stock returns. First, we present few of the definitions of investor sentiment. Investor sentiment has multiple facets, as investor sentiment is the noise in stock markets (Black, 1986); it refers to investor propensity to speculate about stocks (Baker and Stein, 2004). For Kahneman, Daniel et al. (1991) sentiment is investors' expectations about asset returns that are not justified by fundamentals. Zweig (1973) looks it as investors biased expectations on security value; and according to Baker and Stein (2004) it is investors' misevaluation of an asset. Second, attention theory helps to explain how investor sentiment affects stock prices and markets. Merton (1987) suggests that firms, which attract less investor attention, have to give higher returns to compensate imperfect diversifications. Barber and Odean (2008), with attention theory explains that attention creates buying pressure of uninformed retail investors emphasizing that individual investors are net buyers of attention-grabbing stocks in short run. Aouadi et al. (2013) find that the correlation between investor attention and trading volume is high and attention significantly affects stock markets. Third, empirical analysis of Lee et al. (2002) find that irrational traders will overreact to news and their trading behaviors create waves of optimism/pessimism that generate overpricing/underpricing.

There is vast research that documents significant relationship between investor sentiment and market returns (Baker et al. (2012); Lux (2011); Sayim and Rahman (2015)). In contrast, Schmeling (2009) finds that sentiment negatively forecasts aggregative stock market returns. Fourth, the contemporaneous correlation between consumer sentiment and stock market returns is an interesting issue to research for both academicians and practitioners. Several empirical papers find evidence for positive contemporaneous correlation between consumer sentiment and stock markets (Lux, 2011; Baker et al. 2012). These papers hypothesize that stock markets may display positive contemporaneous correlations with consumer sentiment. That is, higher level of investor sentiment observed today will be connected with high levels of stock returns during the same day. Nevertheless, few other studies report that this connection is not as strong (Jansen and Nahuis, 2013; Kling and Gao, 2008). Finally, the predictability of stock returns is an important topic for research in behavioral finance.

Several studies have investigated the predictability of stock market returns using various investor sentiment measures as explanatory variables (Baker et al. 2012; Huang et al. 2014; Lux, 2011). These papers find that investor sentiment increases the predictability of aggregate stock market returns. Han and Li (2017) show that investor sentiment forecasts positive market returns in short run. Brown and Cliff (2004) find that investor sentiment has a negligible impact on subsequent weekly and monthly market returns. In contrast, Huang et al. (2014) find that investor sentiment is a contrarian predictor of monthly stock returns.

Majority of extant research connect investor sentiment to market returns, and research is conducted in individualist developed countries. Furthermore, research outcomes are mixed, in support of both the arguments i.e., sentiment positively affects, and sentiment

negatively affects. In this paper, we take a different stand and relate investor sentiment to individual stocks, defensive stocks, and aggressive stocks in an emerging market. Further, we link different sentiment indicators to stock returns and examine both contemporaneous correlation and predictive ability.

3. OBJECTIVES AND HYPOTHESES

Principle objective of this paper is to study the predictive power of explicit and implicit sentiment indicators of individual stocks. To attain this objective we set few related objectives to examine. First, we examine contemporaneous co-movement between sentiment indices and stock returns, second, we measure causal relationship between sentiment indices and stocks, three, we examine whether causal relationship is similar or different in case of defensive stocks and aggressive stocks. In this paper, we hypothesize that explicit sentiment index cause implicit sentiment index. Next, both explicit and implicit sentiment indices influence aggressive and defensive stocks. Finally, sentiment indices would be able to predict following month stock returns.

4. DATA AND METHODOLOGY

In India ICS is jointly produced by Bombay Stock Exchange (BSE), Centre for Monitoring Indian Economy (CMIE) and University of Michigan since January 2016. Worldwide University of Michigan's ICS is a popular measure of explicit consumer sentiment. However, in India it is available only from January 2016. ICS is produced on a monthly basis with data collected from 158,628 households picked from 316 towns and 2,844 village spread across the country.

We randomly chose 50 stocks from the list of S&PBSE500 stocks. We find five stocks with incomplete data and those stocks are

replaced with five other stocks. For these 50 stocks, 3-year monthly average close price is collected for the period January 2016 to February 2019 from BSE. Graphical presentation of close prices indicate that few stock have stock splits during this period. These splits are adjusted before calculating the log returns. These stocks represent 33 sectors, close prices of these stocks as of February, 2019 range between INR 23 and INR 56,736 with average close price of INR 2438. Forty stocks have close price <INR 1000, two stocks have close price around INR 20,000, and one stock has close price of INR 56,736. We calculate 3-year beta and group the stocks into defensive and aggressive categories. Aggressive stocks are those with beta value >1, and defensive stocks are those with beta value ≤1. We find 28 stocks as aggressive and 22 as defensive. Eight of the 10 stocks with close price >INR 1,000 are defensive stocks.

We use monthly data of ICS, S&PBSE500, and 50 randomly selected from S&PBSE500 from January 2016 to February 2019. Table 1 summarizes study variables, their measures, as well as their sources. We use ICS monthly data from its inception as a measure of explicit consumer sentiment measure. Similarly, for the same period we use market movements of S&PBSE500 index as a measure of implicit investor sentiment measure. One limitation that this paper finds is the availability of ICS data only for 3-year period. After accessing data until February 2019, we plan to include until latest month. However, our efforts gone in vain due to closure of related webpages in both BSE and CMIE websites. We guess they stopped producing ICS in India.

5. RESULTS AND DISCUSSION

5.1. Unit Root Tests

As a preliminary step, we calculate beta coefficients of 50 stocks considered in this paper. Depending on beta value of each stock, we group them into defensive or aggressive stocks. Stocks those with beta value ≤1 are defensive stocks and those stocks that with beta value >1 are aggressive stocks. We apply two unit root tests (ADF and PP), auto correlation (AC) and partial auto correlation (PAC) and Q-Statistics for endogenous and explanatory variables to measure stationarity and auto correlation in series. ADF and

Table 1: Variables and equations used in the study

Variables		Measure	Source
Endogenous	Stock return	$\ln (p_t/p_{t-1})*100$	BSE India
Explanatory	ICS	$\ln (p_t/p_{t-1})*100$	BSE India
	S&PBSE500	$\ln (p_t/p_{t-1})*100$	

Table 2: Stationary test results

Variables	ADF	PP	AC	PAC	Q-Stat	Prob.
ICS	−5.921***	−6.672***	−0.031	−0.031	0.037	0.848
S&PBSE500	−5.305***	−6.733***	−0.093	−0.093	0.337	0.562
Defensive	−6.675***	−6.637***	−0.083	−0.083	0.269	0.604
Aggressive	−5.900***	−5.893***	0.031	0.031	0.037	0.848

***Represent the significant level of null hypothesis rejected at 1% level

Table 3: Results of descriptive statistics

ICS		S&PBSE500		Defensive		Aggressive	
Mean	0.05	Mean	0.99	Mean	0.70	Mean	0.52
Standard deviation	2.28	Standard deviation	4.24	Standard deviation	3.62	Standard deviation	7.23
Kurtosis	2.70	Kurtosis	0.25	Kurtosis	0.18	Kurtosis	0.47
Skewness	−0.51	Skewness	−0.49	Skewness	−0.46	Skewness	−0.81
Minimum	−6.74	Minimum	−9.25	Minimum	−8.38	Minimum	−19.07
Maximum	6.33	Maximum	10.11	Maximum	7.77	Maximum	12.61
Sum	1.75	Sum	35.52	Sum	25.21	Sum	18.61

PP tests hypothesize that unit root is present in the series and AC and PAC checks for auto correlation in series. Results are present in Table 2. We reject the null hypothesis of presence of unit root. All series find to be stationary. To get a micro level understanding of presence of unit root in each of the 50 stocks, we carried out similar tests. We find all the 50 stocks to be stationary. Due to space constraint, the results do not depict here.

5.2. Descriptive Statistics

Table 3 presents summary statistics of endogenous and explanatory variables. Results indicate that market index yielded higher returns than defensive and aggressive stocks. Aggressive stocks report low return and high risk. Skewness and Kurtosis values are within limits indicating normal distribution of series.

5.3. Correlation Analysis

To observe how much each endogenous series changes with explanatory variables we calculate the co-movement among variables. The correlation coefficient that measures the co-movement is present in Table 4. We find significant positive correlation between implicit sentiment index and endogenous variables. There is negative and insignificant correlation between explicit sentiment indicator and endogenous variables. We find preliminary evidence for the argument that explicit sentiment index has no co-movement with endogenous variables.

5.4. Causality between Endogenous and Explanatory Variables

As correlation is not same as causation, to help the direction of causation between endogenous and explanatory variables we calculate sequence of granger causality tests with one lag. Results present in Table 5. We find that at 10% level of significance ICS granger cause S&PBSE500, and S&PBSE500 granger cause aggressive stocks. Similarly, at 5% level of significance ICS granger cause aggressive stocks. Results of causality tests indicate both explicit sentiment and implicit sentiment have significant causation of aggressive stocks.

5.5. Contemporaneous Co-movements

To get an in-depth understanding of correlation between explanatory variables and individual stocks we run sequence of correlations between variables. When we run the contemporaneous co-movements between BSE500 and individual stocks, we observe that 44 stocks have contemporaneous co-movement with BSE500. However, six stock listed in Table 6 do not have any such co-movement. All these six stocks are defensive stocks. Their r^2 values range between 0.02 and 0.10 with P > 0.05. In addition, we find that none of the stocks has contemporaneous co-movement with ICS.

5.6. Short-term Predictability

To predict short-term influence of explanatory variables of endogenous variables we use equation 1. The implicit sentiment indicator (BSE500) fails to predict short-term price movements of individual stocks. Results of one period ahead prediction of stock prices using BSE500 for all the sample stocks have P > 0.05. On the other hand, the explicit sentiment indicator (ICS) is able to predict five stocks at 5 % level and another three stocks at 10% level. All these eight stocks are aggressive stocks. Influence of

sentiment is negative and statistically significant as shown in Table 7.

$$r_{t+1} = \beta_0 + \beta.Sent_t + \epsilon_t \qquad (1)$$

We observe that all the stocks those have negative relation with sentiment indicator are aggressive stocks. All those stocks have high beta value and standard deviation. Results are present in Table 8. High beta and volatility in those stocks clearly indicate that during the times of optimism and pessimism these stocks gain investor attention and react aggressively. When compared to market returns those stocks report higher return, volatility and beta.

6. FINDINGS

In this paper, we find aggressive stocks yield higher return with associated high risk compared to defensive stocks. When we measure contemporaneous co-movement between sentiment indicators and endogenous variables results are mixed. There is a significant positive correlation between implicit sentiment indicator (S&PBSE500) and endogenous variables. On the other hand explicit sentiment indicator (ICS) negatively correlate with endogenous variables, furthermore, these associations are weak. We hypothesize that ICS granger cause S&PBSE500, defensive stocks and aggressive stocks, and S&PBSE500 granger cause defensive stocks and aggressive stocks. Results prove our hypotheses correct with regard to causation between ICS and S&PBSE500, and ICS and aggressive stocks. We also find S&PBSE500 granger cause aggressive stocks. The paper does not find and any causation between sentiment indicators and defensive stocks.

Table 4: Cross order correlation results

	ICS	S&PBSE500	Defensive	Aggressive
ICS	1.00			
S&PBSE500	0.01	1.00		
Defensive	−0.01	0.91	1.00	
Aggressive	−0.11	0.90	0.88	1.00

Table 5: Granger causality test results

Null hypothesis	F-statistic	Prob.
BSE_500 does not Granger cause ICS	0.74	0.40
ICS does not Granger cause BSE_500	3.08	0.09
DEFENSIVE does not Granger cause BSE_500	0.00	0.99
BSE_500 does not Granger cause DEFENSIVE	0.11	0.74
AGGRESSIVE does not Granger cause BSE_500	2.70	0.11
BSE_500 does not Granger cause AGGRESSIVE	3.64	0.07
DEFENSIVE does not Granger cause ICS	1.73	0.20
ICS does not Granger cause DEFENSIVE	1.16	0.29
AGGRESSIVE does not Granger cause ICS	1.93	0.17
ICS does not Granger Cause AGGRESSIVE	4.24	0.05

Table 6: Stocks with no contemporaneous co-movement with market index

Stock	Coefficient	Std. error	R²	F-statistic	Prob.	Aggrsv/defensive
Cipla	0.43	0.27	0.07	2.55	0.12	Defensive
HCL tech	0.23	0.21	0.04	1.25	0.27	Defensive
IOC	0.72	0.51	0.05	1.97	0.17	Defensive
ITC	0.65	0.34	0.10	3.71	0.06	Defensive
MCX	0.76	0.40	0.10	3.60	0.07	Defensive
Mind tree	0.36	0.44	0.02	0.68	0.42	Defensive

Table 7: Impact of ICS on select aggressive stocks

Stock	Coefficient	Std. error	t-statistic	Prob.	Aggressive/defensive
Bharat financial	−2.53	0.67	−3.78	0.00	Aggressive
Blue star	−1.84	0.66	−2.80	0.01	Aggressive
Whirlpool	−1.52	0.61	−2.48	0.02	Aggressive
Century ply	−1.92	0.87	−2.21	0.03	Aggressive
Shree cement	−1.40	0.61	−2.30	0.03	Aggressive
Gujarat alka	−1.73	0.87	−1.98	0.06	Aggressive
Rain Industries	−2.16	1.22	−1.78	0.08	Aggressive
Sobha	−1.25	0.70	−1.80	0.08	Aggressive

Table 8: Descriptive statistics of aggressive stocks that have impact of sentiment

Descriptive	BSE500	Bharat_Financial	BlueStar	Century_Ply	Shree_Cement	Whirlpool
Mean	0.99	1.62	1.40	0.24	1.13	2.60
Standard deviation	4.24	10.53	9.80	12.01	8.54	8.62
Kurtosis	0.25	−0.07	−0.53	0.26	0.01	3.51
Skewness	−0.49	−0.24	0.02	−0.27	0.03	−1.29
Range	19.36	45.42	38.29	55.73	40.10	44.46
Minimum	−9.25	−23.09	−17.90	−31.22	−19.19	−28.01
Maximum	10.11	22.33	20.39	24.51	20.91	16.45
Beta	1	1.53	1.64	1.51	1.50	1.17

The statistical results of contemporaneous co-movement between market index and individual stocks are significant, except six defensive stocks remaining 44 stocks correlate with market movement. Results are in support of contemporaneous co-movement between ICS and individual stocks. None of the stocks correlates with explicit sentiment indicator. In this paper, we hypothesize that explicit sentiment indicator (ICS) has short-term predictive ability of individual stocks. Results are not encouraging. We find ICS is able to predict only five of 28 aggressive stocks, and has no predictive power of defensive stocks. Hypothesis test results of predictive analysis indicate that ICS is negatively relate to select individual aggressive stocks. This mean in the following month of high consumer sentiment prices of aggressive stocks shrink and in the following month of low consumer sentiment prices of aggressive stocks surge. This result indicates that correction happens quicker in aggressive stocks.

7. CONCLUSION

In this paper, we adapt behavioral finance approach to explain the stock price returns. We posit that sentiment indicators can help predict stock prices in short-term. This paper contributes to the literature by addressing the causal relationship between investor sentiment and individual stock returns in the context of developing economy. We estimate short-term predictive power of sentiment indicators of defensive and aggressive stocks. Our results suggest contemporaneous co-movement between broad market index and stock returns. Closer investigation suggests that causation happens between market indicator and aggressive stocks, but not defensive stocks. Moreover, we document a significant causation between ICS and aggressive stocks. Our findings additionally suggest a significant negative short-term predictive ability of ICS of aggressive stocks. In contrary to our hypothesis there is no significant short-term predictive ability of market index.

Overall, our results suggest that, sentiment indicators are not effective in predicting short-term stock returns in the Indian context. ICS's ability to predict five aggressive stocks indicate presence of noise trade in those stocks. Those five stocks have high beta values and high volatility indicating aggressive buying and selling during times of investor optimism and pessimism. Our findings have important implications for investors who trade on noise. Investors must be aware that sentiment indicators have little or no predictive power of stock returns in short-term. While making investment decisions they need to analyze meticulously each individual stock that they wish to buy or sell and take final call. Blindly going by sentiment indicators may hamper their return expectations. In this paper, our focus is on top 500 stocks listed in Bombay Stock Exchange.

Further research should scrutinize small price stocks that consist of 60% of stocks listed in BSE. Those stocks have market price below INR 100 and attracts large number of retail and institutional investors during bull run or optimistic sentiment period. As ICS is not available now in India, researchers should study those stocks

using other explicit or implicit sentiment indicators. Such study results would be a great help for retail investors who many a times trade on noise.

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