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Recruiting Investors Sentiment in Forecasting Volatility (A Study on American Stock Market)

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Abstract*: The purpose of the study is to examine the volatility fluctuations based on investor sentiment as various studies has been carried out in the past concentrating mostly on the current reaction of investors sentiment depending on historical volatility estimations. Closing data of NYSE index is considered as independent variable in analyzing both the historical volatility and sentiment index as they are valuated from them. Observation of 807 trading days from the period of 2015-2018 from American Stock Exchange is considered for the study. The study also helps to determine the use of dependent (ARMS Index and Historical Volatility) and independent variable (NYSE Closing price data) among themselves and the reliability of the independent variable. The viability of the dependent variable in deriving the values of the independent variable is analyzed and it as found out that both the dependent variables can act as independent variable in examining the other dependent variable.

Keywords: Historical Volatility, ARMS Index, NYSE Index, Stock Market Return

I. INTRODUCTION

The behavioral models of securities markets posit two types of investors: rational arbitrageurs who are sentiment-free and irrational traders who are prone to exogenous sentiment. If such irrational noise traders base their trading decisions on sentiment, then measures of it may have predictive power for asset price behavior. The long (short) straddle based on a positive (negative) change in volatility forecasting including the sentiment level of the 'turnover ratio (TO)' achieves an average monthly return of 15.84%. The point of view adopted in this study does not lie in examining the optimal combination of volatility models or other control variables.

The main purpose of this study is to investigate whether the forecasting and trading performance could be improved if the information content of sentiment was to be considered in the decision process. A growing body of literature presents evidence of irrational behavior in the stock markets. The poor performance of trades has been attributed to bad market timing due to overreaction to past stock market movements (Bauer, Cosemans, & Eichholtz, 2009). Fama, 1965; Friedman, 1953, argued that noise traders are unimportant in the financial asset price formation process because trades made by rational arbitrageurs drive prices close to their fundamental values. On the other hand, market anomalies, for example, the underreaction and overreaction of stock prices, challenge the efficient markets theory. Although sentiment has been applied to portfolio management, fewer studies investigate the relationship between sentiment and market volatility and its application to trading decision support (Brown, 1999; Low, 2004; Verma & Verma, 2007; Wang, Keswani, & Taylor, 2006). Volatility forecasting model that includes investor sentiment is constructed in order to bridge the gap between price variation and the signal of the investors' overreaction. NYSE's equity market has long been an indispensable market for international investors. The high trading percentage of individual traders in the NYSE equity and derivatives markets might also imply that the noise trading or the investor sentiment might be the cause of the price variations. The investor sentiment proxies have proved to be an asset pricing factor for which there exists a causal relationship between sentiment and market return (Baker & Wurgler, 2006, 2007; Brown & Cliff, 2004; Clarke & Statman, 1998; Fisher & Statman, 2000; Han, 2008; Simon & Wiggins, 2001; Solt & Statman, 1988; Wang, 2001). This study is about the gap between daily returns of the NYSE market and daily returns of volatility index of NYSE by recruiting investor sentiment.

II. LITERATURE REVIEW

George W.Brown (1999) says that sentiment is correlated with volatility, especially in-terms of closed ended investment funds, which is created by irrational investors who directly influence the asset prices based on the noise signal that in-turn results in increased volatility, it is also said that the rational investors pave way to the noise traders when the sentiment is strong. Which is determined when the trading volume is not affected regardless of bullish or bearish market controversial to that, Wayne.Y.Lee,etal,(2002) says that, sentiment and volatility are negatively related, which is same in case of relationship between return and volatility. In-turn, we should find a positive relationship between return and sentiment. However, sentiment is not an investors phenomenon in determining the effect of the stocks. Though the impact of noise traders is not permanent on return, except in case of formation of risk in markets. Supporting Wayne, Checkiat Low (2004) says about the relationship between price and volatility as VIX is considered to be the best collective index of sentiment for option market, it is concluded in the perception and contemporaneous market condition, where both asymmetric and semi-dimensional in nature. It is said that the price and volatility of the financial market are not directly correlated,

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another study by Meir Statman (1988) also says that there is no correlation between index and DJLA as the relationship between bearish sentiment index and DJLA is estimated to determine whether sentiment index is useful to the investors in determining the markets. It is found from the study that, the change in one does not affect the other. i.e., change in DJLA does not have any systematic impact on change in sentiment index.

Which concludes that, though there is a relationship between the two, they are just following one another and not one leading the other. Prithviraj, James, David (2006) in their is the extended version of determination of positive relationship between VIX levels on stock market returns(index), in-terms of examining the function of returns in both the level of implied volatility and its innovations and also in forecasting the power of grouped portfolios with implied volatilities future returns and implied volatility or with the VIX independent variable factors such as MKT, SMB,HML and UMD and found that high risk portfolios have strong significance with the VIX variables, which leads to the possibility for inefficiency of market. In terms of volatility levels and innovations it is suggested that there need to be a separate premium for both. Study of Dragos Stefen Opera, Laura Brad (2014), proves that investor sentiment had impact on the stock price and it also says a statement contradictory to Schmeling (2009), that the impact of investors sentiment over the stock market is mitigated by the rational investors in a very short time say less than a month. Mahajan and Singh (2008) observed the relationship between volume and return, and volume and volatility with the help of sensitive index's daily data of Bombay Stock Exchange. Dependable with distribution hypothesis, positive correlation between volume and volatility was observed another supporting study from Pakistan Market by Mubarik and Javid (2009), the findings recommend that there is an impact on current day trade caused by previous day trading volume, and thus implies that previous days returns and volume has descriptive power in illumination the current market returns. Abdalla (2012) study on Saudi Stock Market discuss about the relationship between stock returns and volatility and finds a positive correlation between them, whereas we can also find a contradictory study on same variables by Nawazish and Sara (2012) says on Karachi Stock Exchange. Another study similar to the above by Léon (2008) a study on regional stock market of West African Economic and BRVM, the study helps in discovering a positive at the same time not statistically significant relationship between expected stock return an expected volatility and it is also said in the study that volatility is higher when the market booms than when the market declines.

A. *Volatility and sentimental proxy*

The analysis is conducted on a daily basis and the study period extends from 2015 to 2018, encompassing a total of 807 trading days. The data used in this study are quoted on the New York Stock Exchange (NYSE).

B. *Variables*

I. **Dependent Variable:** Historical Volatility and ARMS Index

II. **Independent Variable**: NYSE Index Value

C. *Hypothesis*

I. **H1**: Historical Volatility helps in determining the future value of NYSE index

II. **H2**: ARMS index helps in determining the future value of NYSE index

III. **H3**: NYSE index helps in determining the historical volatility and ARMS index

IV. **H4**: Historical Volatility helps in determining the sentiment of investors

V. **H5**: ARMS index helps in determining the price range fluctuation of the market

III. MEASURES OF VOLATILITY

A. *Historical volatility*

By referring to Engle and Gallo (2006), we jointly consider the three volatility measures, namely, absolute daily returns (|R|), daily high-low range (HL) and daily realized volatility (RV), as the benchmark forecasting model used in this study and it is simplified as MHV. Both the |R| and the HL are calculated using daily data, and the RV is calculated by summing the corresponding 5 min interval squared returns (e.g., Andersen & Bollerslev, 1998; Barndorff- Nielsen & Shephard, 2002, among others), and the variable is expressed in terms of percentage annual terms. The calculations can be expressed as follows:

$$|Rt| = |\ln (St/St\text{-}1)|$$

$$HLt = (Ht - Lt) / (St\text{-}1 * 14\%)$$

$$RVt = \sqrt{\sum_{i=0}^{n} \left(\ln \frac{St+i}{St+i-1}\right)^{\wedge} 2} * \sqrt{252}$$

where |Rt| is absolute daily returns at time t, HLt is the daily highlow range variation at time t, RVt is the daily realized volatility at time t, St is the closing price on trading date t, St+1 is the closing price on the previous trading day, Ht is the highest price on date t, Lt is the lowest price on date t, St+i is the intra-day index level of the ith interval on trading day t, St+n represents the closing price on day t, i = 0…, n, and n is the number of time intervals in each day.

IV. MEASURING INVESTOR SENTIMENT

A. *Arms index*

ARMS can be interpreted as the ratio of the number of advances to declines standardized by their respective volumes. It is measured as:

$$\frac{(\text{Advancing Volume / Trading Volume of Advancing Issues})}{(\text{Declining Volume / Trading Volume of Reclining Issues})}$$

where #Advt, #Dect, AdvVolt and DecVolt, respectively, denote the number of advancing issues, the number of declining issues, the trading volume of advancing issues, and the trading volume of declining issues. Its creator, Richard Arms, argued that if the average volume in declining (rising) stocks far outweighs the average volume in rising (falling) stocks, then the market is oversold (overbought) and this should be treated as a bullish (bearish) sign.

V. RESULTS

A. *Descriptive Statistics:*

Date: 11/01/18
Time: 11:00
Sample: 1/02/2015 3/16/2018

	ARMS	HV	NYSE
Mean	1.148151	0.089600	0.000205
Median	1.058301	0.058369	0.000345
Maximum	31.94422	0.697855	0.029209
Minimum	0.013840	1.22E-05	-0.043961
Std. Dev.	1.210230	0.092379	0.008107
Skewness	20.84832	2.128163	-0.703683
Kurtosis	522.5867	9.745635	6.584668
Jarque-Bera	9136212.	2139.219	498.6763
Probability	0.000000	0.000000	0.000000
Sum	926.5579	72.30696	0.165052
Sum sq.dev	1180.513	6.878268	0.052970
Observations	807	807	807

Descriptive Statistics

	Mean	Median	Min	Max	Std. Dev	Skewness	Kurtosis
HV	.090	.058	.000	.698	.092	2.132	6.795
ARMS	1.148	1.058	.014	31.944	1.210	20.887	522.828

R Square	.020
Adjusted R Square	.019
Std. Error of the Estimate	1.199
Durbin-Watson	1.941

I. *Interpretation:*

There are totally 807 observations of NYSE index from the period between 2015 to 2018. The mean value is more for ARMS index when compared to Historical Volatility and New York Stock Exchange for the selected time duration and the same goes with median values as well. The standard deviation of NYSE index is also more for ARMS index to Historical Volatility. The skewness is negative only for NYSE and values are much more positive for ARMS index when compared to Historical Volatility. The Kurtosis value is greater than zero for all. This implies that the data heavy tailed and there is a random variance. The p-value of JarqueBera Test is less than 0.05, indicates data is normally distributed. We could say as if the probability value is less than 0.05 then the data is significant, i.e. it's a normal data and it can be considered for further process and if its above 0.05 it's vice versa. From the above data we could say that the values for all three ARMS, HV and NYSE are significant as all are less than 0.05. Sum of squared deviations should be low for a better fit. NYSE has a low sum of squared deviations which means it varies from the mean value.

B. *Correlogram*

Date: 11/01/18 Time: 11:01
Sample: 1/02/2015 3/16/2018
Included observations: 807

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.036	0.036	1.0463	0.306
		2	0.016	0.015	1.2613	0.532
		3	-0.021	-0.023	1.6331	0.652
		4	0.035	0.037	2.6548	0.617
		5	-0.002	-0.004	2.6599	0.752
		6	-0.028	-0.030	3.3188	0.768
		7	-0.019	-0.016	3.6239	0.822
		8	-0.006	-0.005	3.6537	0.887
		9	-0.001	-0.001	3.6542	0.933
		10	0.003	0.004	3.6598	0.961
		11	-0.017	-0.016	3.8851	0.973
		12	0.131	0.132	18.020	0.115
		13	-0.003	-0.013	18.025	0.157
		14	0.014	0.008	18.176	0.199
		15	-0.018	-0.012	18.442	0.240
		16	0.009	-0.000	18.510	0.295
		17	0.014	0.016	18.680	0.347
		18	0.016	0.020	18.889	0.399
		19	-0.023	-0.020	19.309	0.437
		20	0.014	0.019	19.478	0.491
		21	-0.028	-0.030	20.126	0.513
		22	-0.009	-0.011	20.195	0.571
		23	-0.039	-0.031	21.472	0.552
		24	0.002	-0.014	21.477	0.610
		25	0.002	0.008	21.480	0.666
		26	0.000	-0.004	21.480	0.717
		27	-0.036	-0.032	22.555	0.709
		28	0.042	0.044	24.001	0.681
		29	-0.003	-0.012	24.009	0.728
		30	0.009	0.000	24.079	0.768
		31	-0.013	-0.003	24.222	0.801
		32	0.041	0.033	25.636	0.779
		33	-0.014	-0.010	25.809	0.809
		34	0.008	0.008	25.863	0.840
		35	0.018	0.030	26.130	0.861
		36	-0.007	-0.010	26.169	0.886

I. *Interpretation:*

A correlogram is a graphical interpretation of autocorrelation coefficients in which r_k is plotted against the $log k$, which is very helpful for visual scrutiny. Here all the days the stocks are performing well and it can be identified by seeing that in all cases the stocks come within the spikes. The probability value should be less than 0.05, then only data is taken to be significant. All the variables ARMS, HV and NYSE are having both significant and non-significant data.

C. *Regression:*

Regression analysis helps in identifying the relationship between dependent and independent variables. In this analysis the Independent variable is the American stock exchange index (NYSE index) and the dependent variable is the historical volatility (HV) and ARMS Index. The analysis is carried on the data set for the time span of 807 working days between the period of 2015 to 2018.

Dependent Variable: NYSE_INDEX
Method: Least Squares
Date: 11/01/18 Time: 11:04
Sample: 1/02/2015 3/16/2018
Included observations: 807

Variable	Coefficient	Std. Error	t-Statistic	Prob.
HV	-0.007359	0.002652	-2.775213	0.0056
ARMS	0.000268	0.000205	1.309825	0.1906

R-squared	0.008934	Mean dependent var	0.000205
Adjusted R-squared	0.007703	S.D. dependent var	0.008107
S.E. of regression	0.008075	Akaike info criterion	-6.797493
Sum squared resid	0.052497	Schwarz criterion	-6.785862
Log likelihood	2744.789	Hannan-Quinn criter.	-6.793027
Durbin-Watson stat	1.990515		

I. *Interpretation:*

From the analysis we could find that the t-statistics value for HV is negative whereas for ARMS it is normal (as the value is positive).

When the probability value is less than 0.05 is considered to be significant, with which from the above data we could say that the data values for Historical Volatility is significant. R-squared value indicates that every independent variable (NYSE index) illuminates 2% of the deviation from the dependent variable Historical Volatility (HV) and ARMS Index. All the three criterions: Akaike Info Criterion (AIC), Schwarz Criterion, Hannan-Quinn Criterion shows negative value. Durbin-Watson stat is used to identify the existence of autocorrelation between residuals. The standards should lie between 0 and 4 where a value approaching the least value is positive and the higher value indicates negative autocorrelation. Here the value is approaching towards **1.99** which means there is a positive autocorrelation between the past and present relationship between independent and dependent variables

D. *Unit Root Test*

Group unit root test: Summary
Series: ARMS, HV, NYSE_INDEX
Date: 11/01/18 Time: 11:01
Sample: 1/02/2015 3/16/2018
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 3
Newey-West automatic bandwidth selection and Bartlett kernel

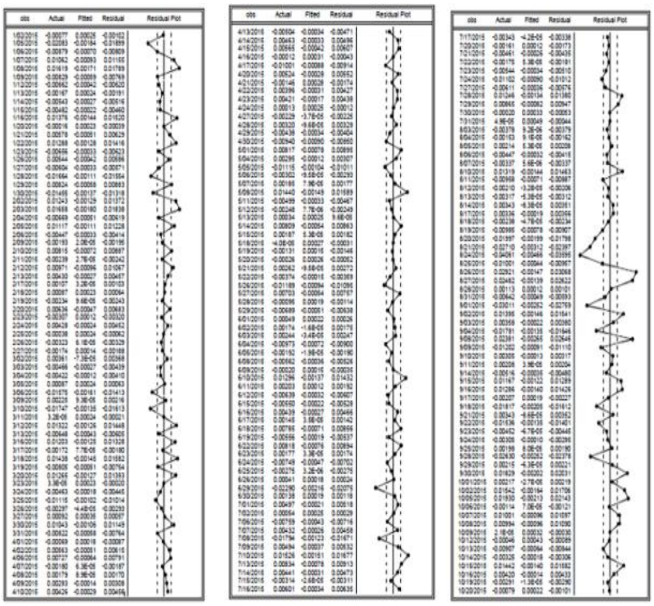
Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-48.6994	0.0000	3	2415
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-39.6402	0.0000	3	2415
ADF - Fisher Chi-square	402.703	0.0000	3	2415
PP - Fisher Chi-square	515.849	0.0000	3	2418

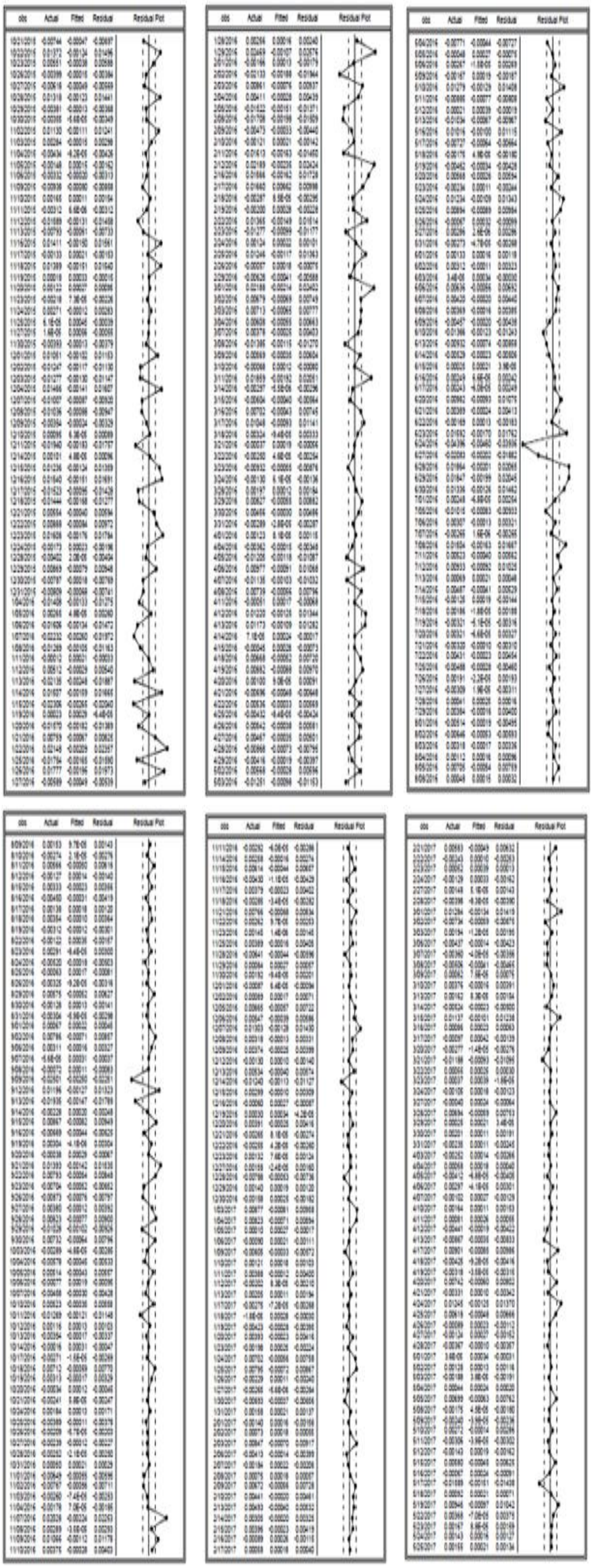
** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.

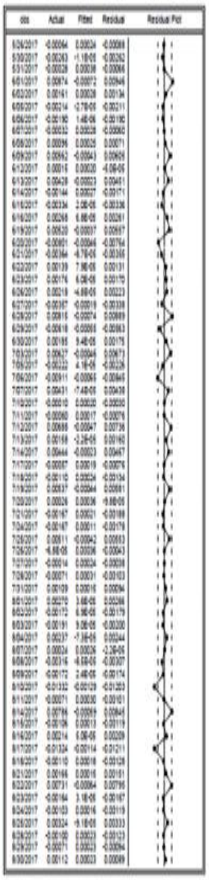
I. *Interpretation*

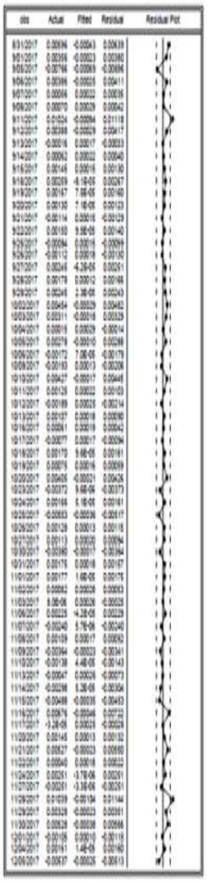
Probability value should be less than **0.05**, all the values in from the analysis among 2415 observations shows less than 0.05. Hence null hypothesis is rejected and it is significant.

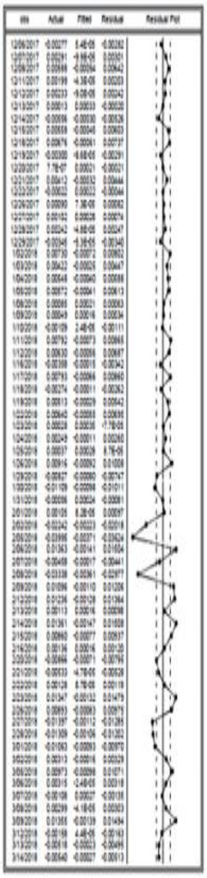
E. *Actual, Fitted and Residual Analysis*

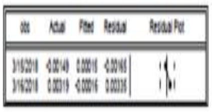


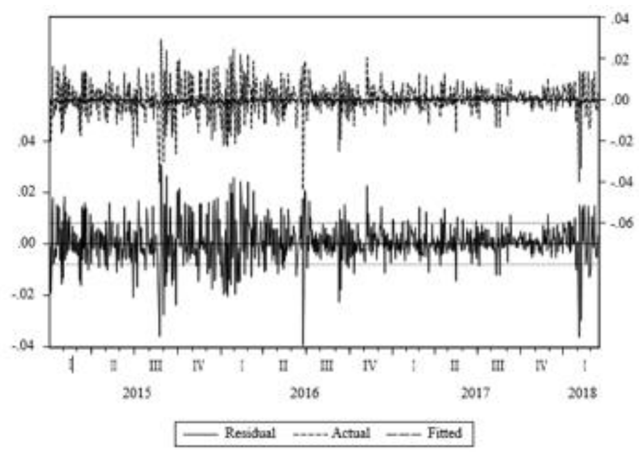












In the residual plot is nothing but the difference between the actual and predicted value and in this study, it is identified that performance of the selected companies was good on the whole year except 22 odd days starting from 02nd January 2015 – 31st December 2015 and in 2016 the performance was not good on 24 working days among which the performance on June 24th was really bad. 2017 was a good year where the overall performance was good except 3 days and in 2018 the performance was not good for 6 days dated till 16th march 2018 (3 months).

F. *Granger Causality Test*

Pairwise Granger Causality Tests
Date: 11/01/18 Time: 11:02
Sample: 1/02/2015 3/16/2018
Lags: 2

Null Hypothesis:	Obs	F-Statistic	Prob.
HV does not Granger Cause ARMS	805	6.89925	0.0011
ARMS does not Granger Cause HV		0.72404	0.4851
NYSE_INDEX does not Granger Cause ARMS	805	3.28011	0.0381
ARMS does not Granger Cause NYSE_INDEX		0.55701	0.5731
NYSE_INDEX does not Granger Cause HV	805	6.02893	0.002
HV does not Granger Cause NYSE_INDEX		0.83470	0.434

I. Interpretation

Granger causality Test is used to test the causality between two variables. The method is a probabilistic account of causality; it uses empirical data sets to find patterns of correlation. Causality is closely related to the idea of cause-and-effect, although it isn't exactly the same. A variable X is causal to variable Y if X is the cause of Y or Y is the cause of X. However, with Granger causality, you aren't testing a true cause-and-effect relationship. The probability value should be greater than 0.01, then null hypothesis is accepted. In this analysis the probability value should be less than 0.05, then only we can reject null hypothesis. In this analysis we cannot reject HV does not cause ARMS, NYSE does not cause ARMS and NYSE does not cause HV as they show significant value, hence it is accepted.

VI. FINDINGS

1. The analysis helps in testing the validity and reliability of the data set used in the study saying the data are distributed normally and it also has both significant and non-significant values.
2. We can also say that the historical volatility and ARMS index helps in determining the future value of NYSE index as both the actual and predicted values are similar.
3. It is also proven that both the dependent variables act as independent variable for the other in determining the price range fluctuations of the market.

VII. CONCLUSION

There are various methods and models used in earlier studies for analyzing the current market fluctuations and predicting their future movements, some studies concentrate on short run and some on long run. The method of analysis proposed in this study is to verify the use of historical volatility and ARMS index (whose values are computed from NYSE index) in determining present and future movement of the market in short run and also their impact on one another in order to analyze its flexibility, reliability and accuracy. We can conclude by saying that apart from unpredictable or any sudden event change in the market, the method of analysis proposed in this study will help in determining the price range fluctuations of the market.

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