Impact of Noise Trading on Volatility in Indian Stock Market using EGARCH Model

1. Ms. Savita

Ph.D Scholar, IKG-PTU Kapurthala

2. Dr. Suresh K. Dhameja
Professor and Head

Entrepreneurship Development and Industrial Coordination Deptt.

National Institute of Technical Teachers Training and Research (NITTTR)

Abstract:

The impact of noise is considered one of the key reasons for the inefficiency of information and the variations in stock prices and returns. This study covers all the 50 companies of Nifty 50 and finds out the impact of noise trading on volatility. Empirical evidence for the EGARCH model demonstrates that there exists an asymmetry feature in the considered stocks. The change in the residual term is taken as a basis for error. The results provide evidence that the leverage effect exists in the Indian stock market and stock market volatility is sensitive to positive and negative shocks. The study concluded that irrational investors (noise traders) play a significant role in stock market volatility, as EGARCH Models show the implications.

Keywords: Noise trading, Stock market, Volatility, Asymmetry effect, EGARCH.

Introduction:

Noise trading and volatility:

Whilst earlier research has ignored the importance of noise traders, more recent analysis has discussed how such traders acting on a noisy signal, can contribute to systematic risk and affect asset prices in equilibrium. For example, De Long, Shleifer, Summers, and Waldmann (1990) show that if risk-averse arbitrageurs know that prices may deviate further away from fundamentals before they join closer, they may take smaller positions. Earlier, previous researches only provide a theoretical model, explaining the relevance of investor sentiments in asset pricing. Before the global financial crisis, markets were following the efficient market theory, which is based on three fundamental conditions: uncorrelated errors, investor rationality and, unlimited arbitrage. Although this theory was well accepted and has been applied for a long time. Some of the assumptions of efficient market hypothesis need discussion and investors' rationality is one such assumption. Several factors affect traders' decision making such as studying the economic condition, the cycle of the industry, the company's position, and financial statements. In addition to the above, some other factors affect traders' decision making i.e., their experience, information collected from friends, relatives, and co-workers. The global financial crisis has highlighted some of the gaps in the traditional theories of financial markets. Traditional theories couldn't contribute positively to the solution of the crisis. The crisis thus, highlighted the need for behavioral finance as it covers the importance of understanding the role of human behavior (psychology) in financial markets. It has been observed that many traders in the financial market depend mainly on the information and rumors collected through friends, co-workers, or family and most importantly by copying others.

Shiller (1984) classified the traders into two major groups: the first group are those denominated smart money traders, i.e., the purely rational traders, who trade on fundamental information, and the second group are the noise traders who mainly act on rumors and news before taking their investment decisions. Shleifer and Summers (1990) defined the noise traders as the category of traders in the financial markets who think that they possess a lot of important information that enables them to make good decisions. While the reality is different. These traders lack information, and most of their decisions are based on their feelings, intuitions, whims, and desires, and some misperceptions.

Noise trader models define the concept of noise trader as a subset of investors who do not make investment decisions based on a company's fundamental information and are capable of affecting stock prices by way of unpredictable changes in their sentiments. The return volatility in financial markets depends heavily on the nature, behavior, and desires of the trader. The behavior of traders in the financial market is usually divided into two types: the first type which is characterized by those who like to enter and exit the market very quickly upon realizing profits, even if profits are few, who are the so-called short-term traders and the second type of traders who like to stay in the market and don't leave it before making high profits known as long term traders.

It will be interesting to check the impact of noise trading on volatility. DSSW (1990) concluded that, there are four effects of investor sentiments on stock returns and volatility. The first effect is due to the trading by bullish or bearish investors which takes the price away from the fundamental value. The second effect is the outcome of the changes in the market risk due to the changes in noise traders' demand for stocks based on their sentiments. Consequently, in the case of a bullish market, where the first effect is more than the second effect, the mean return will be higher and vice versa. On the other hand, in the case of a bearish market, where the mean return is always lower while both the effects build up. Specifically, these two effects represent the short-run effect of noise trading on excess returns due to the concurrent changes in investor sentiments. The third effect captures the variations in stock prices due to the variations of noise traders' misperceptions about the risk. It has been observed that, when a majority of noise traders are more bullish (bearish) than the average number, they bid up (down) the stock price. Consequently, the more numerous the noise traders are compared to smart investors, the more volatile the stock prices. The fourth effect demonstrates the deviations of stock prices from its fundamental value. The justification is that average misperceptions of noise traders associated with shifts in sentiments are not zero. The position of informed investors reduces as a result of an increase in such misperceptions about stock's risk among noise traders. Consequently, the returns are higher when this effect is more than the third effect and vice versa. Specifically, these two effects capture the long-run impact of noise trading on excess returns associated with the impact of the shift in sentiments on the formation of future volatilities of stock returns.

Literature Review

Khasawneh, O. A. H. (2017). Investigated the behavior of traders at the Amman Stock Exchange (ASE). Various aspects of volatility like market return, timeframe, and classification have been covered by the researchers. Market returns for the period from 1/1/1992 to 31/12/2015 have been included. Daily closing prices of free float have been taken for study and the GARCH technique was applied. The study concluded that there is a presence of noise traders at the exchange. The study reached the following conclusions. Firstly, that the traders in the Amman Stock Exchange are noise traders and it put a significant impact on volatility in the market.

Zhang, W., Li, X., Shen, D., & Teglio, A. (2016). Used R^2 as proxy for firm focussed returns deviation and examined its affect on information efficiency. It has been further investigated that the usage of the proxy used in the study depends on environment, whether it is improved or deteriorated. The research also contributed in the prevailing literature on resolving out the most appropriate representative for firm specific returns.

XiaomingXu, Vikash Ramiah& Imad Moosa & Sinclair Davidson used BAPM, CAPM along IANM to measure noise trader risk, overreaction, under reaction & information pricing error in the Shenzen Stock market in China. IANM model as a base which was proposed by Ramiah& Davidson (2010). Morgan Kelly tries to test the Smart money – noise trader model, on the behavior of different groups of investors. It is done by comparing the behavior of actual investors with the predictions of the Smart money – noise trader model. Paritosh Chandra Sinhadevelops a new theory of herding behavior and extends the models of Banerjee (1992) and Bikhchandani, Hirshleifer, and Welch (1992).

Berkman, H., & Koch, P. D. (2008). Investigated the data from the Australian Stock Exchange. Daily movements for noise calculation have been found positively related to volume and are negatively related to risk spread. In the noise measure, movements are positively related to the arrival pace of irrational traders. It has also been concluded that the proxies available for the study are useful for measuring daily noise.

Verma, R., & Verma, P. (2007). investigated the impact of fundamental and noise trading on the volatility of stock returns as suggested by DSSW (1990). A multivariate EGARCH technique is applied. Initially, the applied model has been found consistent with the previous studies that the behavior of individual and institutional investors has a significant impact on stock market volatility. It has also been found that the bullish reaction put more effect on market sentiment. The study also suggested that retail investors act like positive feedback traders. Findings also suggested that institutional investors do not follow individual investors but individual investors follow institutional investors.

Engle, R. F., & Ng, V. K. (1993). Studied the impact of new news arrival on volatility. Regular data from Japanese stock has been considered and various ARCH techniques were applied. The techniques that have been applied also highlight the irregularity of the volatility in response to news arrival. The study also indicates that the EGARCH model can also be used to predict the variation, the only issue is that the variability provided by EGARCH is too high.

Day, T. E., & Lewis, C. M. (1992). Focused on the examination of information content with GARCH and E- GARCH techniques of conditional volatility. Within-sample evidence supported the belief that the conditional volatility calculations using GARCH and EGARCH models indicate incremental information as compared to implied volatility. Out-of-sample evaluation of the relative predictive power of the volatility forecasts to ex-post volatility has also been performed. It proved that it is very difficult to predict weekly volatility. It couldn't be concluded from the study that a better forecast window is provided by GARCH than EGARCH. Different behavioral finance literature studies emphasize that some investors are not completely rational and their demand for risky assets depends on their beliefs or attitudes that are not fully justified by the fundamental news(Tversky and Kahneman, 1974; Kahneman, 2003; Gilovich, Vallone, and Tversky, 1985; Rabin, 2002; Read, Loewenstein and Rabin,1999; Forlani, 2002; Lerner, Gonzales, Small and Fischoff, 2003; Alwathainani, 2012; Corredor, Ferrer and Santamaria, 2013).

Chou, R. Y. (1988). Examined matter of volatility existence and its impact on risk patterns in the stock market. GARCH model was applied to US market data for a period ranging from 1962-1985. The estimation results show that in 1974 there was a drop in the market index due to an increase in volatility.

Black (1986) argues that investors who act irrationally act on noise and such investors are called "noise traders". Theoretically, noise trading matters only if the prejudices regarding investors in processing information tend to be the same; and vice versa, if all investors trade at random, their transactions are canceled and there is no aggregate change in demand. However, empirical research and experiments in psychology and behavioral finance find evidence that prejudices tend to be similar, and investors tend to make similar mistakes. Consequently, changes in the demand for stocks, which are not dependent on fundamental factors, can affect volatility and prices (Chen and Wu, 2009; Franken, Van Strien, Nijs and Muris, 2008; Kilborn, 2002; Meier and Sprenger,2007, Sanders, Irwin and Leuthold, 2000, 2003).

Literature also provides evidence on quantifying noise and check its influence on the market, the first model for measuring trading noise was called the noise trading model. It was proposed by J. B. Delong, referring to the DSSW model. The model was created based on: rational traders and noise traders were on the market. The noise traders traded according to the noise that filled the market and then presented the risk. About the impact of noise, Q. Zhang and S. E. Young believed that the positive changes were stronger than the passive changes.At the empirical level, much of the research has measured trade-in noise. These studies typically measured noise trading using the behavioral asset valuation model (BAPM) and the capital stock valuation model (CAPM).

Research Methodology

The study is descriptive and makes an effort to examine the impact of noise trading behavior on the stock volatility in the market. Data for this study is collected from the Prowess and Bloomberg software. The Nifty 50 Index is taken for the study from January 2007 to December 2017. The variables include daily stock prices of the firms taken for data analysis, daily returns of stocks and market, Change in beta, risk-free rate (91-days treasury bills rates (collected from Bloomberg)).

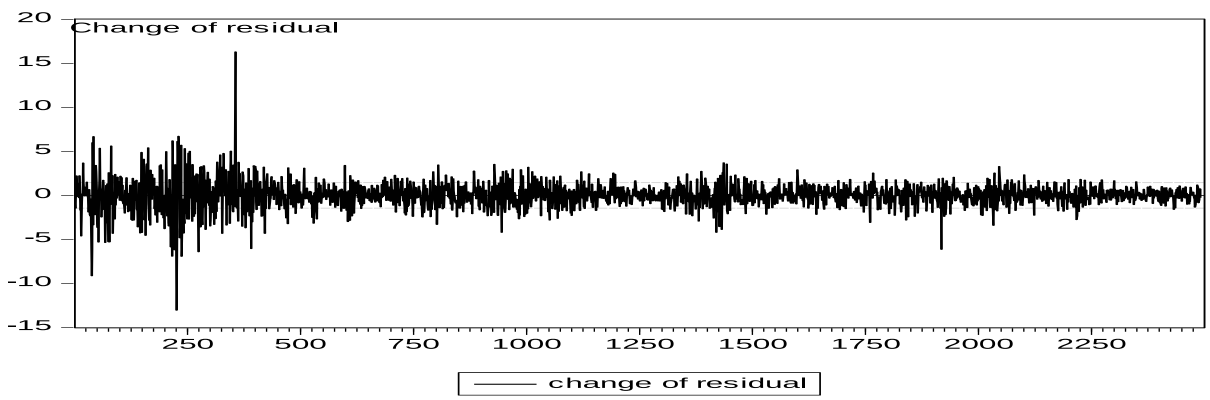
Proxy for Noise: The change in beta of the companies for the three market indices considered in the study is used as proxy for showing presence of inefficiency of the market and hence the presence of noise traders in the stock market. The difference in the slope coefficients can be considered as the proxy for noise traders risk.The difference in the slope coefficients (beta) of the companies is known as the behavioural error (ΔBEit) which can be explained with the help of different firm related factors, market sentiments, portfolio balancing, noise trading and liquidity trades etc.

Null hypothesis: "There exists no significant effect of the noise trading behaviour of the investors on the asset price volatility in the Indian stock market"

Econometric Methodology:

Residual Diagnostic:

Heteroscedasticity will make an evident impact to variance ratio and the time series model.Fig -1 Shows high volatility of yield in one period & low fluctuations in another period. The movements of returns are both negative & positive. It is also seen that returns fluctuate around mean value, but close to zero. The normal trend of stock returns is that larger fluctuations tend to cluster together followed by a period of calmness. This shows that Heteroscedasticity exists in residual.



ARCH LM:

The next test which is used to test the presence of noise traders in the market is ARCH LM test. The ARCH LM test is basically used to examine the presence of volatility clustering in the stock returns. It is believed that the high volatility in stock returns are followed by high volatility and low volatility in stock returns are followed by low volatility. The involvement of noise traders if persist in the stock may lead to volatility. The results of ARCH LM test applied on all the selected companies in the study are shown below:

Table 1:Test result of ARCH LM:

Company	F-statistic	T x R^2
Adani	72.06821 (.000)	70.10034 (.000)
Asian	72.40439 (.000)	70.57888
Axis	182.5091 (.000)	171.1587 0.000
Bajaj	50.97956 (.000)	50.07845
Bharat Petroleum	31.99715 (.000)	31.64837 (.000)
Bharti Airtel	91.63000 (.000)	88.70899 (.000)
Bharti Infra	91.63000 (.000)	88.70899 (.000)
Cipla	21.88192 (.000)	21.72325 (.000)
Coal India	9.532094 (.002)	9.491748 (.002)
Dr. Reddy	39.53645 (.000)	38.99866 (.000)
Eicher Motors	305.3087 (.000)	274.6994 (.000)
GAIL	25.61707 (.000)	25.39672 (.000)
Grasim Industries	10.39908 (0.001)	10.36709 (0.001)
HCL	56.69786 (.000)	55.58097 (.000)
HDFC Bank	57.87156 (.000)	56.70758 (.000)
Hero Motors	100.8910 (.000)	97.35406 (.000)
Hindalco	262.2915 (.000)	239.3990 (.000)
Hind Petroleum	59.87166 (.000)	58.62524 (.000)
Hindustan Unilever	142.1021 (.000)	135.1461 (.000)
Housing Development Fin	67.39442 (.000)	65.81330 (.000)
ICICI	203.4978 (.000)	189.4720 (.000)
India Bulls Housing Fin	11.06926 (.000)	10.97817 (.000)
Indian Oil	176.4929 (.000)	165.8604 (.000)
Indus bank	276.1451	250.8780

	(.000)	(.000)
Infosys	24.39931 (.000)	24.20017 (.000)
ITC	73.20037 (.000)	71.33445 (.000)
Kotak Mahindra	141.5414 (.000)	134.6393 (.000)
Larsen & Turbo	99.85852 (.000)	96.39309 (.000)
Lupin	38.71807 (.000)	38.20274 (.000)
Ma & Ma	114.4323 (.000)	109.8932 (.000)
Maruti Suzuki	65.18022 (.000)	63.70164 (.000)
NTPC	83.34608 (.000)	80.92758 (.000)
ONGC	52.48324 (.000)	51.52759 (.000)
Power Grid Corp	186.8329 (.000)	174.1268 (.000)
Reliance	106.7218 (.000)	102.7681 (.000)
SBI	29.46369 (.000)	29.16938 (.000)
Sun Pharma	150.7249 (.000)	142.9163 (.000)
Tata Motors	220.2830 (.000)	203.9295 (.000)
Tata Steel	240.0009 (.000)	220.7035 (.000)
TCS	160.8479 (.000)	151.9789 (.000)
TECH Mahindra	92.54762 (.000)	89.56812 (.000)
Titan	72.56777 (.000)	70.73399 (.000)
Ultra	50.61334 (.000)	49.72527 (.000)
UPL Ltd.	257.8229 (.000)	235.6735 (.000)
Vedanta	48.92355 (.000)	48.09447 (.000)
Wipro	166.3607 (.000)	156.8875 (.000)
Yes Bank	155.3728 (.000)	147.0852 (.000)
ZEE Ent.	23.46138 (.000)	23.27785 (.000)

Due to Heteroscedasticity presence ARCH test can be used. The result of ARCH-LM test is given in the table. It shows that one can reject the null hypothesis as the p value < 0.05 for all the companies. Both the F version & LM statistic significant which shows the presence of ARCH effect in the residuals. Hence it can be concluded that the significant volatility clustering is present in the stock returns. This means high volatility in stock returns are followed by high volatility and low volatility in stock returns are followed by low volatility.

The volatility clustering in the stock returns also indicate the involvement of noise traders in the stock markets.

Application of EGARCH: Noise trading & Volatility

The EGARCH model is the further extension of the GARCH models. The EGARCH model is also known as exponential GARCH where the log of the variance is considered as the dependent variable. The EGARCH model can be expressed as below:

$$\ln(\sigma 2t)=\omega+\alpha(|zt-1|-E[|zt-1|])+\gamma zt-1+\beta \ln(\sigma 2t-1)$$

The EGARCH model does not need any constraint on the parameters. This is because the equation is on the log of variance rather than variance. The variance is positive so the non-negative assumption is automatically satisfied. This also the main benefit of the EGARCH model.The likelihood of maximization without restrictions is providing faster and reliable optimizations. The EGARCH model not only captures the GARCH model but also observe the leverage. The asymmetry arises because the increase in risk was supposed to come from the increased leverage brought by a negative shock. In the study the EGARCH model with noise trading as an exogenous variable is used. The difference in beta is considered as the measure of noise trading in the stock market for the companies selected in the study. The results of the EGARCH (1,1) model are shown below in the table.

Table 2:Result of EGARCH Model: Noise Trading and Volatility

	Log(Garch)			C(7)		
Company	**Coefficient**	**Z static**	**Prob**	**Coefficient**	**Z static**	**Prob**
Adani	-.0015	-1.378	.168	-.002	-4.720	.000
Asian	-0.0010	-1.252	.210	-0.024	-2.592	.009
Axis	-0.0008	-1.159	.264	-0.044	-5.185	.000
Bajaj	0.001	-1.388	.164	-0.037	-5.498	.000
Bharat Petroleum	0.000	0.699	.484	-0.023	-3.633	.000
Bharti Airtel	-0.001	-1.102	.270	-0.002	-1.669	.094
Bharti Infra	-0.000	-0.645	.518	-0.020	-1.248	.211
Cipla	-1.590	-0.017	.985	-0.010	-1.580	.113
Coal India	-0.002	-1.648	.099	0.023	3.168	.001
Dr. Reddy	-0.0003	-0.493	.622	-0.020	-2.575	.010
Eicher Motors	-0.0017	-1.837	.060	-0.102	-6.686	.000
GAIL	0.001	1.359	.174	-0.024	-5.430	.000
Grasim Industries	0.0005	1.019	.307	-0.006	-1.214	.224
HCL	0.0002	0.359	.719	-0.031	-3.929	.000
HDFC Bank	-0.0003	-0.887	.374	-0.02	-3.869	.000
Hero Motors	0.0007	0.961	.336	0.005	0.612	.540
Hindalco	0.0013	1.166	.243	-0.044	-4.87	.000
Hind Petroleum	-6.37	-0.046	.962	0.001	-0.207	.836
Hindustan Unilever	-0.001	-1.274	.202	-0.017	-1.153	.248
Housing Development	-0.0005	-1.231	.218	-0.058	-6.264	.000
ICICI	-0.0001	-0.299	.764	-0.079	-10.604	.000
India Bulls Housing Fin	0.001	0.767	.442	0.025	1.176	.239
Indian Oil	6.73	0.100	.919	-0.011	-1.174	.240
Indus bank	-0.0015	-4.193	.000	-0.055	-6.892	.000
Infosys	-0.001	-2.177	.029	0.028	2.190	.028
ITC	0.001	1.658	.097	-0.008	-2.791	.005
Kotak Mahindra	-0.0002	-0.570	.568	-0.026	-3.684	.000

Larsen & Turbo	0.0002	0.303	.761	-0.029	-3.612	.003
Lupin	0.0002	0.414	.671	-0.041	-5.927	.000
Ma & Ma	0.0002	0.414	.670	-0.041	-5.127	.000
Maruti Suzuki	-0.0006	-0.95	0.33	-0.037	-5.921	.000
NTPC	0.000	0.258	0.796	0.007	1.227	.219
ONGC	0.0004	0.646	.518	-0.028	-4.38	.000
Power Grid Corp	-8.73	-0.179	0.857	-0.0036	-4.107	.000
Reliance	-0.0003	0.471	.637	-0.006	-1.053	.292
SBI	-0.000	-0.137	.891	-0.023	-1.778	0.075
Sun Pharma	-0.001	-1.124	.260	0.002	0.190	.849
Tata Motors	0.001	1.350	.181	-0.038	-6.58	.000
Tata Steel	0.001	1.44	.148	-0.040	-5.542	.000
TCS	0.007	1.230	.218	-0.028	-4.163	.000
TECH Mahindra	0.001	1.253	.210	-0.024	-3.326	.000
Titan	-0.003	-3.195	.001	-0.027	-3.232	.001
Ultra	-0.000	-0.240	.810	-0.051	-5.307	.000
UPL Ltd.	-0.000	-0.156	.875	-0.028	-2.470	.013
Vedanta	0.001	1.636	.101	-0.035	-6.886	.000
Wipro	0.000	0.406	.684	0.009	1.102	.311
Yes Bank	-0.008	-1.331	.183	-0.062	-7.506	.000
ZEE Ent.	-0.002	-2.895	.003	0.016	2.630	.008

The results indicate that the p-value of z statistics of the exogenous variable i.e. change in beta is found to be less than a five percent level of significance in the case of most of the companies. Thus it can be concluded in the results that the noise trading in the majority of the companies significantly influences the underlying stock volatility. The results also indicate the presence of leverage effect in the volatility. The impact of negative shocks is found to be significantly higher than positive shocks. The price movement in these stocks is not efficient due to the involvement of noise traders as well as the asymmetric nature of the volatility. Thus it can be concluded in the study that the underlying volatility in the stocks does not only have the leverage effects but also influences by the behavior of noise traders in the market.

Conclusion:

This article has measured the modelling of the stock returns volatility in the Indian Stock Exchange for ten years. Empirical evidence suggested that the EGARCH model presents a better description and more frugal representation than the GARCH model. The EGARCH (1,1) model with exogenous variables does not only examine the nature of volatility and asymmetric volatility but can also play a significant role in analyzing the impact of noise trading on the stock volatility. EGARCH model is used to capture the conditional volatility and possible leverage effects. The analysis shows that there is asymmetry meaning bad news has bigger magnitude of variance & makes larger fluctuations in stock prices than to positive shocks or good news. γ is positive for one company i.e. India bulls show that good news has greater impact as compared to bad news. The stock prices have ARCH effect and due to this EGARCH model has been fitted effectively.

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