Research Journal of

Business Management

ISSN 1819-1932

Academic Journals Inc.

www.academicjournals.com

Research Journal of Business Management 6 (1): 30-39, 2012
ISSN 1819-1932 / DOI: 10.3923/rjbm.2012.30.39

Relationship Between Stock Return and Trading Volume

[1]K. Ravichandran and [2]Sanjoy Bose
[1]School of Management, New York Institute of Technology, P.O. Box 5464, Abudhabi, UAE
[2]Department of Accounting and Finance, Abudhabi University, Abudhabi, UAE

Corresponding Author: K. Ravichandran, School of Management, New York Institute of Technology, P.O. Box 5464, Abudhabi, UAE

ABSTRACT

This study investigates the empirical relationship between trading volume and stock returns volatility in US stock Market during the period from May 2005 to May 2011 by using ARCH, GARCH, EGARCH, TARCH, PGARCH and Component ARCH models. The analysis showed that the recent news of trading volume can be used to improve the prediction of stock price volatility. This study also found the evidence of leverage and asymmetric effect of trading volume in stock market and indicated that bad news generate more impact on the volatility of the stock price in the market. Moreover, Random walk model dominated the forecasting performance and it is considered as the best model followed by the TGARCH model.

Key words: GARCH, volatility, EGARCH, TGARCH

INTRODUCTION

Pricing of securities depends on volatility of each asset. Therefore, price changes indicate the average reaction of investors to news. The arrival of new information makes investors to adapt their expectations and this is the main cause for price and return changes. Trading volume and volatility are indicators of the current stock market activity on one hand and a potential source of information for the future behavior of stock market on the other hand. Numerous papers have documented the fact that high stock market volume is associated with volatile returns. However, many theoretical and empirical studies are designed to work with the conditional variance in developed markets (Dimson and Marsh, 1990; McMillan *et al*., 2000). Various studies reported that there are significant relationships between volume and stock price movement and volatility. For example, Saatcioglu and Starks (1998) found that volume led stock prices changes in four out of the six emerging markets. Chan *et al*. (2000) found that trading volume for foreign stocks is strongly associated with NYSE opening price volatility. Griffin *et al*. (2007) investigated the dynamic relation between market-wide trading activity and returns in 46 markets and reported strong positive relationship between turnover and past returns. Recently, several authors have investigated the volatility of stock market by applying econometric models and suggested that, no single model is superior (Akgiray, 1989; Pagan and Schwert, 1990). Brailsford and Faff (1996) and Koutmos (1998) examined the predictive performance of several statistical methods with GARCH and TGARCH models for Australian stock exchange. Dimson and Marsh (1990) examined various technical methods of predicting the volatility of UK stock market returns and find that exponential smoothening and regression model performed.

The present study reinvestigates the effect of trading volume on volatility of the Nasdaq index in US stock market using GARCH model to see to what extent the stock market's reaction to the arrival of news changed when trading commenced. Further we also analysis the contemporaneous relationship between stock price volatility and trading volume. Also a few attempts were made to model the most prominent features of the time series of Nasdaq index such as volatility clustering, excess kurtosis and fat tailed by applying the most popular techniques proposed by Engle (1982). To capture the above characteristics, ARCH class of models were introduced by Engle (1982) and GARCH (Generalized Autoregressive Conditional Heteroskedasticity) by Bollerslev (1986) and Taylor (1986). Since the intrinsically symmetric GARCH model does not cope with the asymmetry issues or so called leverage effect, the Exponential Generalized Autoregressive Conditional Heteroskedasticity process (EGARCH) by Nelson (1991) is suggested. Finally, to capture asymmetries in terms of negative and positive shocks TGARCH (Threshold Generalized Autoregressive Conditional Heteroskedasticity) model was introduced by Zakoian (1994) and Glosten *et al.* (1993).

REVIEW OF LITERATURE

Random walk model: The random walk model is the simplest possible models, where the Ordinary Least Square (OLS) method are constructed on the assumption of constant variance. As per, efficient market hypothesis the competing market participants reflect information instantly hence are useless in predicting future prices. The basic model for estimating stock returns fluctuation by using OLS in the naïve random walk model is given below:

$$R_t = \mu + \varepsilon_t$$

where, μ is the mean value of the returns, it is expected to be insignificantly differ from zero and ε_t is the error term should not be serially correlated over time.

GARCH: Bollerslev (1986) extended Engle's ARCH model to the GARCH model and it is based on the assumption that forecasts of time varying variance depend on the lagged variance of the asset. An unexpected increase or decrease in returns at time t will generate an increase in the expected variability in the next period. The basic and most widespread model GARCH can be expressed as:

$$R_t = a \; bR_t \; -1 \; \varepsilon \, t$$

$$\varepsilon_t \mid I_t \; -1 \; N(0, h_t),$$

$$h_t = a_0 \Sigma_{i=1}^{p} {}^{\beta_i h_{t-1}} \; \Sigma^{\lambda_j u_{t-j2}}{}_{i=1}^{P}$$

where, $\lambda_j>0$, $\beta_i = 0$. The GARCH is weekly stationery $\Sigma\beta_i+\Sigma\lambda_j<1$, the latter two quantifying the persistence of shocks to volatility (Nelson, 1991).

In particular, volatility forecast are increased following a large positive and negative index return, the GARCH specification that capturing the well-documented volatility clustering evident in financial returns date (Engle, 1982).

TGARCH: In TGARCH model, it has been observed that positive and negative shocks of equal magnitude have a different impact on stock market volatility, which may be attributed to a leverage effect (Black, 1976). In the same sense, negative shocks are followed by higher volatility than positive shocks of the same magnitude (Engle and Ng, 1993). The threshold GARCH model was introduced by the works of Zakoian (1994) and Glosten *et al.* (1993). The main target of this model is to capture asymmetric in terms of negative and positive shocks and adds multiplicative dummy variable to check whether there is statistically significant different when shocks are negative. The conditional variance for the simple TGARCH model is defined by:

$$\begin{aligned}
&R_t\ a\ bR_{t-1}\ \varepsilon_t \\
&\varepsilon_t \mid I_{t-1}\ N(0, h_t), \\
&h_t = a_0\ \Sigma_{i=1}^{p\ \beta_i u_{2t-1}}\ \Sigma^{Q\ \lambda_j h_{t-j}}{}_{j=1}{}^{\delta u_{t-1} d_{2t-1}}
\end{aligned}$$

where, d_t takes the value of 1 if ε_t is negative and 0 otherwise. So good news and bad news have a different impact.

EGARCH: The Exponential GARCH model specifies conditional variance in logarithmic form, which means that there is no need to impose estimation constraints in order to avoid negative variance Nelson (1991). The mean and variance equation for this model is given by:

$$\begin{aligned}
&R_t = a\ bR_{t-1}\ \varepsilon_t \\
&\varepsilon_t \mid I_{t-1}\ N(0, h_t), \\
&\log h_t = a\ \Sigma^{\beta_j{}^q}{}_{j=1} \left|\frac{n_{t-j}}{\sqrt{h_{i-j}}}\right| \sum_{j=1}^{q} \lambda_j\ \frac{n_{t-j}}{\sqrt{h_{i-j}}} \sum_{i=1}^{p} \delta_i h_{t-1}
\end{aligned}$$

where, δ captures the asymmetric effect. The exponential nature of EGARCH ensures that the conditional variance is always positive even if the parameter values are negative; thus there is no need for parameter restrictions to impose non-negativity.

Smirlock and Starks (1985) found that the return-volume relation is asymmetric and later, Smirlock and Starks (1988) found a strong positive lagged relationship between volume and absolute price changes using individual stock data. Lee and Swaminathan (2000) used monthly returns and daily trading volume of all the firms listed on NYSE and American Exchange (AMEX) and find that momentum and trading volume appear to predict subsequent returns in the US equity market. Bekaert and Wu (2000) not only support this finding but also suggest that negative shocks generate a greater response in volatility than positive shocks of an equal magnitude, evidence of the speed of information transmission in markets. Thus, the findings of past studies are strong indications of information content of volatility on the markets, which could be used by investors to earn abnormal profit. Ratner and Leal (2001) examined the Latin American and Asian financial markets and find a positive contemporaneous relation between return and volume in these countries except India. At the same time they observed that there exists a bi-directional causal relation between return and volume. In summary, the return and volume are strongly related contemporaneously but there is little evidence that either can be used to predict the other. De Medeiros and Doornik (2006) investigated the empirical relationship between stock returns, return volatility and trading volume using data from the Brazilian stock market. The study found out there is a contemporaneous and dynamic relationship between return volatility and trading volume and return volatility contains information about upcoming trading volumes. Atmeh and

Dobbs (2006) investigated the performance of moving average trading rules in the Jordanian stock market and found that technical trading rules can help to predict market movements. Al-Khouri and Ajlouni (2007) reported that the price-limit technique was effective in reducing the volatility in the Amman stock exchange. Floros and Vougas (2007) used GARCH and GMM method to investigate the relationship between trading volume and returns in Greek stock index futures market and found that trading volume was used as the indicator of prices.

EMPIRICAL RESULTS AND ANALYSIS

The basic descriptive analysis of the time series of stock returns and trading volume is shown in Table 1. All returns are calculated as the first difference of the log of the daily closing price. Daily trading volume and stock return have positive kurtosis and high JB statistics that implies that the distribution is skewed to the right and they are leptokurtic((heavily tailed and sharp peaked), i.e., the frequency distribution assigns a higher probability to returns around zero as well as very high positive and negative returns. The Jarque-Bera statistic test indicates that the null hypothesis of normality is rejected and shows that all the series exhibit non-normality and indicates the presence of Heteroscedasticity. Hence, GARCH (1, 1) model is the suitable for testing of hypothesis.

The study here employs the unit root test to examine the time series properties of concerned variables. Unit root test describes whether a series is stationary or non-stationary. For the test of

Table 1: Diagnostic tests

	Mean	Std. Dev.	Skewness	Kurtosis	Jarque-bera	Probability
VOLUME	0.006316	1.561708	-0.37309	9.843999	2857.65	0
AAPL_PR	0.114373	2.489073	-0.50804	9.003068	2234.965	0
ACAS_PR	-0.21022	5.511311	-2.95134	42.51241	96229.85	0
AMAT_PR	-0.03393	2.371173	-0.37426	7.080998	1037.91	0
BIDU_PR	0.155735	4.833257	5.485321	134.4236	1048625	0
CMCSA_PR	-0.00708	2.28826	-0.341	13.78792	7044.743	0
CSCO_PR	-0.03018	2.160476	-0.90896	13.80388	7236.728	0
DELL_PR	-0.09325	2.440754	-0.62738	8.636016	2010.07	0
FITB_PR	-0.20879	5.39407	-2.67341	45.31016	109654.7	0
HBAN_PR	-0.21782	5.377047	-0.86657	17.75401	13305.44	0
INTC_PR	-0.02194	2.137301	-0.45419	8.069627	1599.312	0
JDSA_PR	-0.04166	3.952862	-0.81153	10.98002	3998.247	0
LVLT_PR	-0.12914	4.883423	-1.86109	27.00246	35570.44	0
MSFT_PR	-0.01462	1.917914	-0.14326	12.499	5445.13	0
MU_PR	-0.07951	3.825411	-0.53516	7.576845	1332.03	0
NVDA_PR	-0.01723	3.689643	-1.48576	18.97694	15922.57	0
NWSA_PR	-0.02526	2.605516	-0.28413	10.88353	3766.598	0
ORCL_PR	0.048772	1.992206	0.030073	7.563481	1255.814	0
QCOM_PR	0.004836	2.232546	-0.28102	9.9895	2964.48	0
QQQ_PR	0.017284	1.518291	-0.19849	9.726653	2737.57	0
RIMM_PR	-0.00886	3.437787	-1.03513	16.41648	11111.04	0
SIRI_PR	-0.21347	5.290021	-2.69152	51.21559	141909.7	0
SONS_PR	-0.10969	3.990461	-0.49759	7.745227	1417.311	0
STX_PR	-0.05545	3.362496	-0.80804	11.86214	4892.627	0
VSEA_PR	0.03393	3.135807	0.780843	14.08486	7555.331	0
YHOO_PR	-0.08447	2.871486	-0.63975	27.84657	37319.89	0

Table 2: Unit root tests

Variable	Coefficient	Std. Error	z-Statistic	Prob.
ACAS_PR	0.010838	0.008818	1.229159	0.2190
AMAT_PR	-0.029563	0.023451	-1.260646	0.2074
BIDU_PR	0.010800	0.011455	0.942794	0.3458
CMCSA_PR	-0.145992	0.023565	-6.195389	0.0000
CSCO_PR	-0.045689	0.018145	-2.518032	0.0118
DELL_PR	0.017139	0.016153	1.061081	0.2887
FITB_PR	-3.26E-05	0.009905	-0.003292	0.9974
HBAN_PR	-0.002760	0.009913	-0.278431	0.7807
INTC_PR	-0.142551	0.026750	-5.329069	0.0000
JDSA_PR	-0.004641	0.012678	-0.366048	0.7143
LVLT_PR	-0.016357	0.007740	-2.113220	0.0346
MSFT_PR	-0.180958	0.022671	-7.981961	0.0000
MU_PR	-0.012859	0.011210	-1.147061	0.2514
NVDA_PR	-0.022426	0.014270	-1.571493	0.1161
NWSA_PR	-0.110986	0.021951	-5.056033	0.0000
ORCL_PR	-0.125299	0.028608	-4.379823	0.0000
QCOM_PR	-0.141848	0.017289	-8.204279	0.0000
QQQ_PR	2.297559	0.079042	29.06754	0.0000
RIMM_PR	-0.006838	0.013353	-0.512098	0.6086
SIRI_PR	-0.007046	0.007577	-0.929915	0.3524
SONS_PR	-0.013536	0.009782	-1.383664	0.1665
STX_PR	-0.028338	0.011431	-2.478988	0.0132
VOLUME	0.033800	0.025619	1.319340	0.1871
VSEA_PR	-0.012363	0.014226	-0.869016	0.3848
YHOO_PR	-0.042838	0.014134	-3.030919	0.0024
C	0.071107	0.035541	2.000674	0.0454
Variance equation				
C	0.088014	0.018642	4.721367	0.0000
RESID(-1)^2	0.170797	0.018752	9.108358	0.0000
GARCH(-1)	0.808896	0.021062	38.40584	0.0000
R^2	0.609906	Mean dependent var.		0.114373
Adjusted R^2	0.603042	S.D. dependent var.		2.489073
S.E. of regression	1.568230	Akaike info. criterion		3.523520
Sum squared resid	3494.728	Schwarz criterion		3.629284
Log likelihood	-2520.267	Hannan-Quinn criter.		3.562992
Durbin-Watson stat	2.038683			

unit root the present study employees the Augmented Dickey Fuller test and KPSS test (Dickey and Fuller, 1981). ADF test is used to measure the stationarity of time series data which in turn tells whether regression can be done on the data or not. The output is presented in the Table 2. On observing the outputs of ADF and KPSS tests, it is seen that the ADF test statistic and KPSS test statistics for all is less than the critical values at 1, 5 and 10% confidence level. Both ADF and KPSS test statistics confirm that all prices have unit root (non-stationary). So, the null hypothesis is rejected and the data is found to be stationary.

We investigate that weather trading volume has an explanatory power for Indian stock market by fitting GARCH (1, 1) model with daily volume included in the conditional variance equation. It is evident from the Table 3 that parameter β is negative and statistical insignificant indicating that

Table 3: GARCH model with trading volume

Variables	Coefficient	Std. Error	z-Statistic	Prob.
ACAS_VOL	0.011049	0.009405	1.174772	0.2401
AMAT_VOL	-0.002565	0.019703	-0.130174	0.8964
BIDU_VOL	0.060097	0.011149	5.390473	0.0000
CMCSA_VOL	-0.010614	0.017017	-0.623713	0.5328
CSCO_VOL	0.066610	0.019221	3.465481	0.0005
DELL_VOL	0.010704	0.013410	0.798210	0.4247
FITB_VOL	0.065378	0.005522	11.83931	0.0000
HBAN_VOL	0.017120	0.012871	1.330160	0.1835
INTC_VOL	0.079096	0.021349	3.704922	0.0002
JDSA_VOL	0.014755	0.012064	1.223065	0.2213
LVLT_VOL	0.008611	0.004776	1.802997	0.0714
MSFT_VOL	0.009098	0.018008	0.505213	0.6134
MU_VOL	-0.030370	0.015525	-1.956233	0.0504
NVDA_VOL	0.021656	0.014907	1.452732	0.1463
NWSA_VOL	-0.018934	0.017581	-1.076954	0.2815
ORCL_VOL	0.040861	0.015923	2.566217	0.0103
QCOM_VOL	0.033267	0.014374	2.314317	0.0207
QQQ_VOL	0.339361	0.024256	13.99070	0.0000
RIMM_VOL	0.025875	0.012309	2.102202	0.0355
SIRI_VOL	0.011622	0.008975	1.294844	0.1954
SONS_VOL	-0.026373	0.011490	-2.295269	0.0217
VSEA_VOL	0.016551	0.010224	1.618873	0.1055
YHOO_VOL	0.007320	0.012519	0.584726	0.5587
C	1.566172	0.883356	1.772979	0.0762
Variance equation				
C	229.8119	28.67318	8.014875	0.0000
RESID(-1)^2	0.518683	0.039146	13.24983	0.0000
GARCH(-1)	0.465013	0.030792	15.10169	0.0000
R^2	0.220515	Mean dependent var.		6.045503
Adjusted R^2	0.207908	S.D. dependent var.		41.59402
S.E. of regression	37.01850	Akaike info. criterion		9.881431
Sum squared resid	1948665.	Schwarz criterion		9.979956
Log likelihood	-7117.275	Hannan-Quinn criter.		9.918202
Durbin-Watson stat	2.315061			

trading volume does not have GARCH effect in the stock market. Systematic variations in trading volume are assumed to be caused only by the arrival of new information. AIC and SIC criteria used in the study indicating lower for the regression which is quite reasonable and fit for our model. Further Durbin-Watson value is 2 suggests autocorrelation or specification errors. Since the Durbin-Watson statistic is greater than 2, the error terms are not auto correlated indicating that the statistical model is fit and appropriate.

LEVERAGE/ASYMMETRIC EFFECT

It is very often observed that downward movement of the markets is followed by higher volatilities than upward movement of the same magnitude. So it is important to use TARCH, EGARCH, PGARCH and component ARCH models to test asymmetric shocks to volatility. Sometimes the simple GARCH models cannot capture some important features of the data. To

Table 4: TARCH model with trading volume

Variables	Coefficient	Std. Error	t-Statistic	Prob.
ACAS_VOL	0.013850	0.012456	1.111973	0.2663
AMAT_VOL	-0.024123	0.026300	-0.917241	0.3592
BIDU_VOL	0.031144	0.015242	2.043259	0.0412
CMCSA_VOL	-0.011477	0.024774	-0.463261	0.6432
CSCO_VOL	0.069634	0.028382	2.453466	0.0143
DELL_VOL	0.002989	0.022133	0.135060	0.8926
FITB_VOL	0.001035	0.019397	0.053367	0.9574
HBAN_VOL	0.026121	0.016308	1.601759	0.1094
INTC_VOL	0.078384	0.030772	2.547252	0.0110
JDSA_VOL	0.021790	0.016737	1.301906	0.1932
LVLT_VOL	0.004948	0.007058	0.701023	0.4834
MSFT_VOL	0.007253	0.028176	0.257402	0.7969
MU_VOL	-0.017898	0.021945	-0.815568	0.4149
NVDA_VOL	0.025765	0.022416	1.149396	0.2506
NWSA_VOL	-0.010024	0.022721	-0.441168	0.6592
ORCL_VOL	0.022041	0.026374	0.835723	0.4035
QCOM_VOL	0.054863	0.026669	2.057157	0.0399
QQQ_VOL	0.334653	0.033787	9.904875	0.0000
RIMM_VOL	0.024277	0.017439	1.392130	0.1641
SIRI_VOL	0.005860	0.014098	0.415653	0.6777
SONS_VOL	-0.000361	0.014066	-0.025678	0.9795
VSEA_VOL	0.005403	0.010538	0.512702	0.6082
YHOO_VOL	0.011057	0.013835	0.799200	0.4243
C	1.105309	1.064036	1.038790	0.2991
R^2	0.233181	Mean dependent var.		6.045503
Adjusted R^2	0.220778	S.D. dependent var.		41.59402
S.E. of regression	36.71652	Akaike info. criterion		10.06079
Sum squared resid	1917002.	Schwarz criterion		10.14837
Log likelihood	-7249.950	Hannan-Quinn criter.		10.09347
F-statistic	18.80060	Durbin-Watson stat		2.323498
Prob. (F-statistic)	0.000000			

investigate the leverage effect we have used TARCH (1, 1) model introduced independently by Zakoian (1994). If the bad news has a greater impact on volatilities than good news, a leverage effect exists. ARCH model helps to explain the volatility of spot market when some degree asymmetric is present in the data.

TARCH model takes the leverage effect into account. The presence of leverage effect is seen in Table 4 which implies that every price changes are responding asymmetrically to the positive and negative news in the market. In the conditional variance equation; α, the coefficient for latest news which is statistically significant at 1% level indicating that the recent news has an impact on the volatility of the stock. Similarly β coefficient is insignificant and suggests that old news is not influencing the stock market volatility. Coefficient γ (parameter of volume) is positive and greater than 0 indicating the impact is asymmetric. The analysis shows that trading volume is associated with an increase in stock return volatility. Good news therefore induces more trading volume than bad news.

To test the leverage effect, EGARCH model is also used. Table 5 exhibited the existence of leverage effect and news impact is asymmetric (γ). As Coefficients γ is positive, greater than 0 and

Table 5: EGARCH model with trading volume

Variable	Coefficient	Std. Error	z-Statistic	Prob.
ACAS_VOL	0.005872	0.008054	0.729036	0.4660
AMAT_VOL	-0.000592	0.015777	-0.037545	0.9701
BIDU_VOL	0.056298	0.007796	7.221077	0.0000
CMCSA_VOL	0.009451	0.015284	0.618369	0.5363
CSCO_VOL	0.049505	0.013101	3.778637	0.0002
DELL_VOL	0.008571	0.013386	0.640304	0.5220
FITB_VOL	0.033539	0.005143	6.521425	0.0000
HBAN_VOL	0.028540	0.013461	2.120234	0.0340
INTC_VOL	0.068412	0.018758	3.646972	0.0003
JDSA_VOL	0.013061	0.009195	1.420493	0.1555
LVLT_VOL	0.002049	0.006304	0.325074	0.7451
MSFT_VOL	0.016014	0.011525	1.389522	0.1647
MU_VOL	0.009111	0.011611	0.784713	0.4326
NVDA_VOL	0.020374	0.014265	1.428274	0.1532
NWSA_VOL	-0.022309	0.016466	-1.354903	0.1754
ORCL_VOL	0.026939	0.012830	2.099720	0.0358
QCOM_VOL	0.071884	0.013187	5.450927	0.0000
QQQ_VOL	0.237567	0.014146	16.79383	0.0000
RIMM_VOL	0.015692	0.008277	1.895753	0.0580
SIRI_VOL	0.002298	0.008537	0.269140	0.7878
SONS_VOL	-0.008234	0.009834	-0.837331	0.4024
VSEA_VOL	0.008377	0.009536	0.878440	0.3797
YHOO_VOL	-0.005496	0.009743	-0.564136	0.5727
C	-4.900532	0.815259	-6.011010	0.0000
Variance equation				
C(25)	0.620353	0.133051	4.662525	0.0000
C(26)	0.284373	0.028022	10.14817	0.0000
C(27)	-0.550922	0.026340	-20.91570	0.0000
C(28)	0.885199	0.018359	48.21542	0.0000
R^2	0.200387	Mean dependent var.		6.045503
Adjusted R^2	0.187454	S.D. dependent var.		41.59402
S.E. of regression	37.49340	Akaike info. criterion		9.611608
Sum squared resid	1998984.	Schwarz criterion		9.713782
Log likelihood	-6921.192	Hannan-Quinn criter.		9.649741
Durbin-Watson stat	2.248608			

significant at 1% level, the analysis is suggesting that trading volume increases due to good news in the market. Coefficients γ shows a positive impact of volume on stock return also generate less impact on volatility of the market.

The empirical evidence in the Table 5 suggests the existence of leverage effect and news impact is asymmetric (γ). In the models with a significant power parameter we found δ smaller than 2, in concordance with Ding *et al.* (1993) results and the asymmetric estimated parameter γ is positive. So trading volume increased the stock return and decrease expected volatility in the market. This supports a positive correlation between trading volume and predictable volatility of stock returns. The analysis shows that the PARCH model which exhibits a low power effects but strong leverage effects in the market.

So far we have used TARCH, EGARCH and PARCH model to find the significance of the asymmetric effects. Alternatively it is also equally important to find the cross correlation between the squared standard residuals and lagged standardized residuals to know the impact of long run/short run movements in volatility.

CONCLUSION

This study examined the relationship between stock returns and trading volume and has used the GARCH (1, 1) model, asymmetric TARCH, EGARCH, PGARCH and CARCH model to empirically examine the persistence of shocks to volatility and to determine the asymmetry in the pattern of volatility. This paper specifically tested the hypothesis of variability in volatility, which implies that volatility is greater when stocks price are moving downwards than upwards. Statistical inferences are drawn from the data by means of significance tests and over all goodness of fit of all the models as reported by the Akaike info criterion &Schwarz criterion. The study found that the recent news has an impact on the volatility of the trading volume. Also, the past news coefficient is statistically insignificant and suggests that old news is not having influencing the trading volume volatility. So it is evident from the study that systematic variations in trading volume are assumed to be caused only by the arrival of new information. To predict volatility, we have used the asymmetric TARCH, EGARCH, PARCH and Component ARCH model and evidence suggests that leverage effects exist and the news impact is asymmetric. This implied that daily new information in market may have significant impact on price volatility. So the study concludes that bad news generate more impact on volatility of the stock return and trading volume. One explanation may be that normally investors have a higher aversion to downside risk, so they react faster to bad news.

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