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Does Trading Volume Transmit Information towards Stock Return and Volatility? A Developing Country Context

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Abstract

This paper examined the relationship between trading volume and return volatility of Dhaka Stock Exchange (DSE) using daily data for the period from January 27, 2013 to December 30, 2019. We conducted an empirical analysis by employing Threshold Generalized Autoregressive Conditional Heteroskedasticity (TGARCH) model, vector autoregressive (VAR) approach and Granger causality test. The empirical analysis showed the evidence of higher volatility persistence and shocks that take long time to dry out. We also found a negative and significant relationship between contemporaneous trading volume and return volatility and trading volume as a proxy of information arrival absorbs GARCH effect significantly. The observed negative relationship between trading volume and volatility signified that DSE is a thinly traded security market. Likewise, VAR model indicated a significant feedback relationship exists between return volatility and trading volume. Finally, Granger causality test indicates volume Granger cause return volatility and vice-versa. Thus, we conclude that trading volume is a functional tool for explaining return volatility dynamics in DSE.

Key Words: Return volatility, trading volume, TGARCH model, VAR approach and Granger causality test, DSE.

AMS Subject Classification: 91B24, 91B26.

1. Introduction

The discovery of the nexus between stock return volatility and trading volume is a matter of great interest to stock market investors and researchers. Two big barometers in the stock market are stock return and volume of trade. In particular, to understand the stock market microstructure, the nexus between volume of trade, market return and time varying volatility has been taken into consideration by stock market analysts and researchers (Mahajan and Singh, 2009). Aiming to explore the nexus between volatility and trading volume, we use volume as a proxy for the flow of information to the market. The nexus between the two dynamics- trading volume and stock return volatility is theoretically dependent on either the mixture of distribution hypothesis (MDH) or the sequential information arrival hypothesis (SIAH). When new information comes to the market, the SIAH postulates that traders modify trading strategies. According to SIAH, there is a lead-lag relationship is prevailed between volatility and volume of trade (Copeland, 1976). On the other hand, the MDH provides explanation of return volatility and trading volume by relating changes in price, volume and the degree of information arrival (Clark, 1973; Harris, 1987; Lamoureux & Lastrapes, 1990; Andersen, 1996; Omran & McKenzie, 2000). The MDH expresses that stock returns represent a stochastic mixing variable that is produced by a combination of distributions in which the information influxes into the market. MDH also postulates that volume and volatility are associated contemporaneously and positively, whereas a stochastic variable described as the flow of information is jointly guided. The influx of information to the market is not easily evident, so as a proxy for the arrival of information, trading volume in a stock market is considered, because entrance of new information ups and downs tend to trigger the trading volume (Clark, 1973).

Based on existing evidence, the original work of Granger and Morgenstern (1963) attempted to explore the connection between the regular price changes and the volume of trading for the period 1939 to 1961, and their findings reflect that there is no relationship between the volume of trading and the change in stock price. However, Ying (1966) performed a study on the NYSE S&P 500 composite stock price index and obtained a positive volume-price relationship. Using hourly and daily data, Crouch (1970) carried out an analysis and discovered a positive association between volume and returns. In the cotton future market, Clark (1973) analyzed the association between stock price and trading volume using regular data and found a positive relationship. A positive relationship was recorded by Epps and Epps (1976) using trading information. Using 4-day intervals and monthly data, Morgan (1976) found a positive relationship. Using daily data, Westerfield (1977), Cornell (1981), Harris (1984) and Rutledge (1984) showed a significant positive association between return and amount. Tauchen and Pitts (1983) analyzed the price volatility and volume connection on speculative markets, and recommended that the speed of new information delivery on the market, the reaction of investors to information, and the number of active traders on the market decide both trading volume and volatility. Smirlock and Starks (1985) showed a favorable lagged relationship between changes in price and volume using individual common stock transaction data. A positive nexus between volume and return volatility has been demonstrated by Karpoff (1987). Jain and Joh (1988) conducted an analysis on NYSE using the volume and return data of hourly trading and found a positive contemporary relationship. Lamoureux and Lastrapes (1990) investigated the association between trading volume and volatility of the U.S. stock market and a positive relationship has been found. The data contains the return and the volume of 20 actively traded stocks. In order to perform the analysis, the researchers used Autoregressive Conditional Heteroskedasticity (ARCH) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models, and incorporated contemporary trading volume as an independent variable in the variance equation. It is shown that regarding the variance of stock return, the daily trading volume has a substantial explanatory power. In addition, the insertion of volume in the variance equation decreases the volatility persistence, and the effect of ARCH tends to vanish. Hiemstra and Jones (1994) have documented a strong bi-directional non-linear causality in the NYSE using daily trading volume and stock return. A research on the U.S. market has been conducted by Gallo and Pacini (2000) and found that the volatility persistence decreased when trading volume was integrated into the GARCH model. The association between trading volume and return volatility on the New York, London and Tokyo markets was examined by Lee and Rui (2002) and found a positive significant association, while trading volume does not in all cases trigger Granger to generate stock return. Al-Saad (2004) on the Kuwait stock exchange, Kamath and Wang (2006) on the six Asian stock markets found the positive relationship. Likewise, in analyzing Korean stock market, An et al.

(2006) discovered a positive association between trading volume and price volatility. Extending the analysis in developed and developing markets, Girard and Biswas (2007) have concluded that the emerging markets have a larger reaction to big information shocks and unanticipated volume. They also argue that there is a negative association between trading volume and volatility in some developing countries whereas the relationship is positive in developed countries. Further, Leon (2007) has explored the similar analysis in the regional stock exchange of the West African Economic and Monetary Union. Using a VAR framework, the author checked the Granger causality between volatility of return and volume of trade; and found a one-way causality disseminating from trading volume towards returns volatility. The results of those tests show that trading volume has explanatory power for volatility of stock returns. Samman and Al-Jafari (2015) have drawn the similar conclusions on Muscat stock market.

Aiming to examine both the dynamic and contemporaneous relationships between trading volume and stock return volatility, Mahajan and Singh (2009) have investigated the Bombay Sensex index for the period 1996-2006. To conduct the test, trading volume is incorporated in mean GARCH(1,1) equation to capture the dynamic relationship. Furthermore, to test for Granger causality, they used a bi-variate VAR model. The empirical analysis has showed that there is a significant positive connotation between trading volume and volatility of return which indicates both the combination of distribution and hypothesis of sequential arrival information flow. When trading volume is included as a proxy for information arrivals in the conditional variance equation, the GARCH(1,1) model shows minor declines in persistent of variance over time, and α and β (ARCH & GARCH) effects remain noteworthy; which indicates the market inefficiency. The EGARCH(1,1) certifies the presence of leverage effect and signifies that trading volume has a positive impact on return volatility. Finally, they argue a considerable relationship of causality flowing from return volatility towards trading volume. Analyzing the same Indian Stock Market for an extended period from 2005-2010, Tripathy (2010) has documented that the trading volume related recent news would improve the stock price volatility prediction; however, the past news is found statistically insignificant, which suggests that old news does not influence the stock price volatility. Tripathy (2010) also indicated the presence of asymmetric and leverage effect of trading volume, which supports that compared to good news, bad news would influence more on the price volatility. The findings conclude that rather than symmetric GARCH models, asymmetric GARCH models provide better fit to capture the trading volume and price volatility relationship. While explaining the nature of Korea Exchange by using MDH method, Choi et al. (2012) observed that Korea stock market index shows strong volatility persistence and asymmetry. Incorporating GJR-GARCH and EGARCH models, their findings are same as Tripathy (2010) which certify that the contemporaneous trading volume positively affects the return volatility while lagged trading volume does not have such impact. Similarly, investigating in the U.S stock market, Ravichandran and Bose (2012) have documented that the recent news significantly affects the trading volume and stock price volatility while past news has no such influence. Therefore it is evident from the studies of Ravichandran and Bose (2012), Mahajan and Singh (2009), and Tripathy (2010) in the US, Korean and Indian stock markets respectively that systematic variations in the trading volume and as well as in return are presumed to be affected by the arrival of new information only not the past news. Thus, the recent news would be used to improve the stock price volatility prediction.

Attempts to explore the association between trading volume and return volatility are documented in recent literature also. Tapa and Hussin (2016) have investigated the Malaysian ACE market and their empirical results show a positive significant contemporaneous association between trading volume and stock return. The findings confirm the weak-form of the efficient market hypothesis (EMH). Based on selected African markets, and examining the stock return volatility dynamics, King and Botha (2015) have revealed that in capturing volatility through the conditional variance process, conventional GARCH effects act a significant role. However, examining the nature of Nairobi Security Exchange (NSE), Moyo et al. (2018) have found a positive but insignificant association between trading volume and return volatility which indicates that as a proxy for information flow, trading volume carry only a little source of volatility in stock returns. Studying the BRICS markets during and after the 2009 global financial crisis using GARCH model, Kishor and Singh (2017) have documented that although the crisis have some impact on the volatility patterns on BRICS markets, the specific market volatility is more inclined to the inherent nature of the respective markets.

Applying both the symmetric and asymmetric models of GARCH to Investigate the volatility patterns in Indian stock market, Singh and Tripathi (2016) have found the GARCH-M(1,1) and EGARCH(1,1) models as the most appropriate models to capture the symmetric and asymmetric return volatility. They have also found that the EGARCH(1,1) and TGARCH(1,1) models can identify the asymmetric leverage effect in a better way; and compared to positive shocks, negative shocks would have noteworthy effects on return volatility. Kumari et al. (2018) also supports the findings of Sing and Tripathi (2016). Investigating South African stock market, Marozva and Magwedere (2017) have also revealed the existence of leverage effect on the return volatility. However, in analyzing Saudi Stock Market by applying different symmetric and asymmetric GARCH models, Shaik and Syed (2019) have found a significant positive relationship between risk and returns though there is no proof for leverage effect in the return series. In other words, the asymmetric results indicate that the impact of negative shocks on return volatility do not significantly different than that of positive shocks. On the contrary, analyzing Chinese stocks, Ho et al. (2020) have found there is significant lead-lag association between arrival of the news and return volatility, while compared with negative news, positive news arrivals do affect the return volatility more strongly. Extending the analysis over 16 stock markets, Jin (2017) have found a significant negative association between contemporary stock market returns and volatility. Examining the lead-lag relationship between stock returns and volatility, the study has also documented the presence of leverage effect and volatility feedback which confirms the existence of a return-driven negative return-volatility relationship.

Using an extended GARCH model, in particular, a GARCH with modified Grey prediction model Chang et al. (2019) have investigated the transmission of return volatility for US stock and argued that the higher the sample size, the better GARCH models can capture the variations in return. Further examining the implied volatility index of five developed markets-the US, Japan, Germany, France, and the UK, Dai et al. (2020) have documented that the stock return volatility is more affected by the implied volatility of the stock market rather than any exogenous shocks. However, analysis based on Nasdaq100 indices, Dow Jones Industrial Average (DJIA), S&P Composite 500 (S&P500), and their respective implied volatility indices, VXN, VXD, and VIX, Kambouroudis et al. (2016) have argued that implied volatility performs worse than GARCH model, while asymmetric GARCH model incorporating realized and implied volatility through ARMA models provide better prediction results. On the basis of the experiences in different countries as outlined above, we may opine that trading volume has been identified as a vital source of information that significantly affect the return volatility.

1.1. Dhaka Stock Exchange (DSE) and Related Literature

Bangladesh has two stock exchanges, namely Dhaka Stock Exchange (DSE) which was established in 1954 as east Pakistan Stock Exchange association LTD but finally named DSE in 1964 and other one is Chittagong Stock Exchange (CSE), which was established in 1995. However, DSE is the momentous and main bourse in Bangladesh. It has been growing at a slow but steady rate up to now. Nonetheless, the market was in turmoil in 1990, 1996 and 2010. Total number of listed securities stood at 601 at the end of December 2020 of which 333 companies, 37 mutual funds, 221 Government Treasury bond, 8 debentures and 2 corporate bonds respectively (DSE, 2021b). The Market capitalization of DSE is BDT 4482.30 billion (US$ 77.391 billion) as at December 30, 2020 against (Tk.122.84 billion) US$ 2.192 billion as on December 30, 2004 (DSE, 2021a). The market capitalization accounted for 9.2% of its nominal GDP in June 2020. The market capitalization to GDP was ever highest of 28.5% in June 2010 and a record low of 4.2% in June 2006 (CEIC, 2021). Such oscillation proofs the disorder experienced by the DSE over time.

Prior literature has investigated the relationship between volume-return volatility in the context of various developed and developing nations. In the context of Bangladesh, studies are very limited on examining the stock return volatility. Rahman and Hossain (2008) have simply attempted to explain the trend of historical price volatility in Dhaka Stock Exchange (DSE) while Aziz and Uddin (2014) have identified the volatility nature by applying GARCH. Later, Hossain et. at. (2015) found the existence of leverage effect on return volatility by using ARIMA and GARCH model. In a different context, applying the days of a week (DoW) effect index, Rahman (2009), Iqbal and Roy (2015), Islam and Sultana (2015), and Hassan and Khan (2019) attempt to identify the specific days in a week, which could be more volatile in terms of stock return.

Based on the discussion above, and so far our knowledge, no attention has been given to investigate the impact of information arrival on the stock return as well as return volatility in DSE. We examine both the contemporaneous and dynamic impact of trading volume on return as well as return volatility. First, using daily stock index and contemporaneous trading volume of DSE, we attempt to identify the contemporaneous impact of trading volume on the return volatility by applying GARCH family models. The GARCH specification models the current variance as a function of past conditional variance and captures volatility shocks that persist over time (Ahmed et al. 2005). Second, to capture the dynamic (causal) association, if any, between trading volume and return as well as return volatility, the Granger causality is tested by applying a bi-variate vector autoregressive (VAR) model.

In this study, applying a GARCH approach, we find that there is a contemporaneous impact of trading volume on stock return in DSE. Furthermore, through a VAR approach, a bi-directional dynamic (causal) relationship is evidenced between trading volume and stock return which supports the significance of information arrivals while a noticeable one-way impact of trading volume on return volatility verifies the significance of privately available information.

The rest of the article is organized as follows. Section 2 portrays the details about the construction of the data sample and the methodology applied. Section 3 contains the analysis, and findings of the study. Finally, Section 4 represents the concluding remarks.

2. Data and Methodology

Examining the relationship between return volatility and trading volume, we use volume as a proxy for arrival of information to the market. Daily closing value of two major indicators of DSE, namely, DSE broad index (DSEX) and contemporaneous trading volume are analyzed. Our sample covers the period from January 27, 2013 to December 30, 2019 due to the fact that DSEX has been initiated from 2013. we calculate daily market returns as the first difference in logarithm in daily closing prices of DSEX index of successive days. That is,

$$r_t = logp_t \ - logp_{t-1} \tag{1}$$

Where r_t refers to the market return in period t, $p_t$indicates price index at day t and p_{t-1} refers to the price index at day $t-1$. To check the stationarity of data, we use Augmented Dickey–Fuller (Dickey and Fuller, 1979) and Phillips–Perron (Phillips and Perron, 1988) test statistics. Further, we have made a comparison of actual returns distribution to the Student's t-distribution and standardized normal distribution. Because, compared to normal distribution, student's t-distribution assumes a greater likelihood of large returns (Choi et.al, 2012).

2.1. TGARCH(1,1) model

ARCH (Engle, 1982) and the GARCH models (Bollerslev, 1986) are the most popular tools to analyze the volatility dynamics of financial time series. Particularly, GARCH model is advantageous due to its mechanism to make present conditional variance dependent on lags of its preceding conditional variance (Choi, 2012).

In order to measure the effect of trading volume on volatility, the daily contemporaneous volume needs to be added to the conditional variance equation and accordingly the TGARCH(1,1) model. The TGARCH model proposed by Zakoian (1994) is more or less similar to GJR-GARCH model, while the first one includes the conditional standard deviation in the model instead of the conditional variance. To model the asymmetry in stock return data, this model is used widely. It is assumed that when the squared error terms have opposite signs - positive and negative, the effect of the error terms on the conditional variance is different. Thus, GJR incorporates an indicator function that takes a value of 0 (zero) when conditional variance is positive and 1 (one), when the variance is negative. Further, the leverage term typically stands as and when the unconditional returns are skewed. The specification of conditional standard deviation under TGARCH(1,1) model can be written as follows:

Mean Equation:

$$r_t = \mu + \varepsilon_t; \quad \varepsilon_t \sim N(0, \sigma^2) \tag{2}$$

Variance Equation:

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \gamma d_{t-1} \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \phi V_t \tag{3}$$

Where, r_t represents realized return of DSE indices, μ is the mean of the returns, In variance equation, *The constant term*: ω, which represents long-run variance or average variance, *The* ε_{t-1}^2, is the lag of the squared residuals from the mean (the ARCH term),: σ_{t-1}^2, prior period forecast variance (the GARCH term),the term $d_{t-1}\varepsilon_{t-1}^2$ captures asymmetry (the leverage effect) where, $d_{t-1}$is a dummy variable and indicates $d_{t-1}=1$, if $\varepsilon_{t-1}<0$ and implies bad news and $d_{t-1}=0$, if $\varepsilon_{t-1} \geq 0$ and implies good news. In this model, good news ($\varepsilon_{t-1} \geq 0$) and bad news ($\varepsilon_{t-1}<0$) have different effect on conditional variance. In this model, good news ($\varepsilon_{t-1} \geq 0$) and bad news ($\varepsilon_{t-1}<0$) have different effect on conditional variance. The coefficient, γ is known as the leverage or asymmetry term. When γ =0, the model automatically converted to the standard GARCH form. Therefore, when shock is positive (good news), its impact on conditional variance (volatility) can be determine by α. But, a negative shock (bad news) has an impact on volatility of $\alpha+ \gamma$. If $\gamma>0$, then the leverage effect exists, and bad news ($\varepsilon_{t-1}<0$) increase the volatility than the good news ($\alpha+ \gamma>\alpha$). Hence, if the γ is positive and statistically significant, negative shocks have a larger effect on conditional variance (σ_t^2) than positive shocks. As a proxy for market information arrival, trading volume (V_t) is used. In this case, the coefficient of V_t, i.e., the ϕ measures the impact of volume on volatility. The sum of the coefficients α (ARCH effect) and β (GARCH effect) measures the degree of volatility persistence. As stated by the MDH, the GARCH effect can be explained if ϕ is significantly positive and at the same time α+β i.e. the sum of both the ARCH and GARCH effect is noticeably smaller than the persistence magnitude in the restricted version of the conditional volatility.

2.2. Vector Autoregressive (VAR) model

In addition, to examine the contemporaneous relationship through a GARCH process, we also analyze the dynamic (causal) relationship between trading volumes and stock return to investigate the price response to new arrival of information proxied by trading volume. To test the bi-causal relationship (Granger causality) between trading volume and stock return, we employ a bi-variate vector autoregressive (VAR) model. VAR aids to estimate the linear simultaneous association among the variables, and at the same time to test whether trading volume precedes volatility or vice-versa. The bi-variate VAR model can be written as follows:

$$r_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i r_{t-i} + \sum_{i=1}^{p} \phi_i V_{t-i} + \varepsilon_t \tag{4}$$

$$V_t = \beta_0 + \sum_{i=1}^{p} \beta_i V_{t-i} + \sum_{i=1}^{p} \gamma_i r_{t-i} + \varepsilon_t \tag{5}$$

Where, r_t represents stock return and V_t represents trading volume. The null hypothesis of stock return not to granger cause trading volume if the coefficients ϕ_i (i=1,2,……p) are all equal to 0 (zero) and volume not to granger cause return if the γ_i (i=1,2,………..p) are all equal to 0 (zero). If the coefficient ϕ and γ are significantly different from zero, there is a bi-variate feedback between trading volume and stock returns.

Further, with the trading acts of the informed traders, private information gradually reveals to the market and accordingly affects prices (Mahajan and Singh, 2009; De Medeiros and Doornik, 2008). To examine such market behavior, we employ another bi-variate VAR to test the bi-causal relationship (Granger causality) between trading volume and stock return volatility:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \sigma_{t-i}^2 + \sum_{i=1}^{p} \phi_i V_{t-i} + \varepsilon_t \tag{6}$$

$$V_t = \beta_0 + \sum_{i=1}^{p} \beta_i V_{t-i} + \sum_{i=1}^{p} \gamma_i \sigma_{t-i}^2 + \varepsilon_t \tag{7}$$

Where, σ_t^2 represents stock return volatility estimated from GARCH mean model and the remaining things are same as the equations (4) and (5).

3. Empirical Results and Discussion

Before presenting the econometric analysis, we perform stationarity tests of the data. Table 1 reports the unit root (ADF, PP) test results for daily return and trading volume. The results show we can reject the null hypothesis (H_0: series has unit root) at 1% level of significance meaning that both the return and trading volume series are stationary and eligible for applying econometric tools.

Table 1: Unit root tests for stock return and trading volume.

Test	Return		Trading volume	
	t-stat	p-value	t-stat	p-value
ADF	-35.90906	0.0000	-5.47572	0.0000
PP	-35.51022	0.0000	-7.00135	0.0000

3.1. Contemporaneous Relationship between Stock Return volatility and Trading Volume

The tests for contemporaneous relationships between trading volume and stock return volatility are performed following the process as described in Section 2.1 by applying the Eq(2) and Eq(3). The results are reported in Table 2.

Table 2: TGARCH(1,1) results with and without contemporaneous trading volume

	TGARCH(1,1) Restricted		TGARCH(1,1) Unrestricted	
	Normal	Student-t	Normal	Student-t
ω (constant)	1.24E-06***	1.33E-06***	8.13E-05***	8.15E-05***
	(0.0010)	(0.0011)	(0.0000)	(0.0000)
α (ARCH Effect)	0.117545***	0.119232***	0.153816***	0.193078***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ (Levarage Effect)	0.093721***	0.095561***	0.052013**	0.075206*
	(0.0001)	(0.0001)	(0.0314)	(0.0566)
β (GARCH Effect)	0.823987***	0.819594***	0.603044***	0.644708***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
φ(volume effect)	……….	……….	-3.87E-13***	-4.01E-13***
			(0.0000)	(0.0000)
$\alpha + \beta$	0.941532	0.938826	0.756860	0.837786

- This table reports the results of TGARCH(1,1) model (Eq 3):
  $\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \gamma d_{t-1} \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \phi V_t$
  Where, σ_t^2 represents stock return volatility produced from GARCH mean model (Eq 2) and V_t indicates logarithm of trading volume.
- Figures in parentheses are *p*-values.
- ***, ** and * denote 1%, 5% and 10% level of significance, respectively.

Table 2 summarizes the estimated coefficients of restricted (without trading volume) and unrestricted (with trading volume) versions of the TGARCH(1,1) model to compare the degree of persistence of volatility under both conditions. The results show that the estimated coefficients of restricted and unrestricted TGARCH(1,1) are significant under both normal distributions and student's *t*-distributions. The coefficients α and β represent ARCH and GARCH parameter.

We find that in all cases and under both specifications$\beta>\alpha$, implying the past volatility has significant influence to predict current volatility. The sum of $\alpha$and β is less than one but is very high (0.941532 and 0.938826) under restricted TGARCH(1,1) model. The very large value of $\alpha+\beta$ indicates that the volatility is persistent in DSE and shock dries out very slowly. However, when trading volume is incorporated in TGARCH(1,1) model under unrestricted version, the degree of volatility persistence ($\alpha+\beta$) dwindles sharply from 0.941532 and 0.938826 to0.756860 and 0.837786. Thus, the trading volume seems to absorb some GARCH effect (β) in volatility and this finding is consistent with the findings of earlier studies e.g. Choi (2012) in South Korea, Lamourerux and Lastrapes (1990) in the U.S market, Mahajan and Singh (2009) in India, De Medeiros and Doornik (2008) in Brazil. The γ coefficients are significant for restricted and unrestricted TGARCH(1,1) models, indicating leverage effect (asymmetric impact) on volatility i.e., compared to good news, bad news have greater impact on volatility. Further, the absolute magnitude of asymmetry coefficient (γ) decreases from 0.093721 and 0.095561 to 0.052013 and 0.075206 respectively after addition of the trading volume to the variance equation. It indicates the trading volume leads to reduce asymmetric volatility in DSE. The coefficients of V_t, i.e., the ϕ which measure the impact of volume on volatility are significant and negative. This finding also supports that the contemporaneous trading volume significantly explains volatility but the negative signs of the coefficients indicate DSE is a sallow and thinly traded securities market. This finding is supported by Tauchen and Pitts (1983) and Girard and Biswas (2007), where they explain that in mature and liquid markets, the relationship between volume and volatility should be positive if there is the presence of a large number of traders. While the negative relationship can be explained by thinly traded securities. Further, in sallow market, as much as the trading volume upsurges, the traders would expect more information to be accessible, which ultimately improves the market transparency and thereby diminishes uncertainty and price volatility. So, our findings support the MDH, and it can be argued that there are inefficient and thinly traded conditions persist in DSE.

3.2. Causality between Trading Volume, Stock Return, and Return Volatility

In this section, we extend our analysis to test the dynamic (causal) relation between trading volume and stock returns. By applying Granger (1963) causality test, we examine whether trading volume precedes stock returns or vice versa. Causality test is noteworthy as it would help comprehend the microstructure of stock market in a better way and can also have implications for other segments of financial market (De Medeiros and Doornik, 2008).

Table 3: The results of VAR(3) estimates on return model

Variables	$\boldsymbol{r_t}$	$\boldsymbol{V_t}$
r_{t-1}	0.10933***	7.33958***
	(0.0000)	(0.0000)
r_{t-2}	-0.00305	0.92190
	(0.9099)	(0.1340)
r_{t-3}	0.07227***	0.72694
	(0.0041)	(0.2041)
V_{t-1}	0.00244**	0.63574***
	(0.0322)	(0.0000)
V_{t-2}	-0.00378**	0.10276***
	(0.0047)	(0.0007)
V_{t-3}	0.00141	0.19136***
	(0.2058)	(0.0000)
C	-0.00129	1.30835
	(0.8659)	(0.0000)
R-squared	0.02533	0.87476
Adj. R-squared	0.02181	0.87431
F-statistic	7.18734***	1931.31***

- This table reports the results of VAR(3) model (Eq 4 & 5):

$$r_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i r_{t-i} + \sum_{i=1}^{p} \phi_i V_{t-i} + \varepsilon_t$$

$$V_t = \beta_0 + \sum_{i=1}^{p} \beta_i V_{t-i} + \sum_{i=1}^{p} \gamma_i r_{t-i} + \varepsilon_t$$

Where, r_t represents stock returns measured as log difference and V_t indicates logarithm of trading volume.

- Figures in parentheses are *p*-values.
- ***, ** and * denote 1%, 5% and 10% level of significance, respectively.

Formally, in line with Chen et al. (2001), x Granger-cause y, if the prediction of y using past x is more accurate than the prediction without using past x in the mean square error sense [i.e., if $\sigma^2(y_t|I_{t-1}) < \sigma^2(y_t|I_{t-1} - x_t)$, where I_t is the information set]. To advance the process, we begin with the estimation of a bi-variate VAR model with 3 lags based on the Schwarz Criteria (SC). It should also be noted that Akaike information criteria (AIC) and Hannan Quinn information criteria (HQ) suggest 8 and 4 lags, respectively. However, results of VAR at 3 lags produces better results, and the results are presented in Table 3.

Table 3 shows the results of the stock return equation (2^{nd} column), which confirms that the stock return is significantly affected by trading volume up to two lag at 5% level while results of the trading volume equation (3^{rd} column) supports that lagged return significantly affects the trading volume at 1% level. Thus, significant lead-lag relationship exists between trading volume and return in both ways in DSE. Furthermore, *F*-statistics of both of the models are significant at 1% level and accordingly, we can say both ϕ_i and γ_i are different from zero, which also confirms that there is a feedback relationship between stock return and trading volume.

Granger Causality test results confirms the dynamic relation more clearly. Panel A in Table 4 shows that the test results under the null hypothesis of volume does not Granger cause stock return and vice versa. The results support that trading volume significantly Granger cause stock returns because the null hypothesis (H_0: volume does not granger cause volatility) is rejected at 5% level of significance. Besides, return also significantly Granger cause volume at 1% level of significance. It indicates that causality between trading volume and stock return happens in both ways, even though more strongly from stock return to trading volume. The bi-causal relationship between stock return and trading volume would be considered as the proof that new information arrival follows a concurrent process. It indicates that, in most cases, short-term predictions of current as well as future stock return could be improved by knowing the recent trading volume information and vice versa. Moreover, this result also confirms that the changes in stock price have significant information content for the upcoming trading activities. Our findings support the arguments of previous studies (Mahajan and Singh, 2009; De Medeiros et al. 2008).

Table 4: Estimated results of the Granger Causality tests at lag 3

Null Hypothesis	*F*-statistic	Prob.
Panel A		
Trading volume does not cause stock return	2.83267	0.0371**
Stock return does not cause trading volume	51.1573	0.0000***
Panel B		
Trading volume does not cause return volatility	10.1080	0.0000***
Return volatility does not cause trading volume	0.79345	0.4975

***and ** denote 1%, and 5% level of significance, respectively.

Furthermore, as mentioned earlier, with the trading acts of the informed traders, private information gradually reveals to markets and accordingly influences stock prices. To examine such market behavior, we employ another bi-variate VAR model to test the bi-causal relationship (Granger causality) between trading volume and return volatility. The VAR(3) (volatility model) results are reported in Appendix (Table A1). The results support the evidence of one-way causal impact from trading volume to stock return volatility, although a bi-causal relationship is found between volume and return. This outcome is supported by Granger causality test as presented in Panel B of Table 4.

Thus, our results confirm that new information arrival follow a concurrent process in DSE as there is a bi-causal relationship between trading volume and stock return. In addition, one-way causal effect from trading volume to return volatility certifies that the trading activities of the informed traders disseminates private information to other traders, and thus significantly affects stock prices. It infers that the informed traders actively participate in the market only when they are well known about the private information, and accordingly, such trading activities carry information to other traders, and thereby affect the prices further. This indicates that the semi-strong form of market efficiency holds in the DSE since all sorts of information (public and private) is mirrored on the stock prices. The findings are in line with other emerging markets like India and Brazil (Mahajan and Singh, 2009; De Medeiros et al. 2008).

4. Conclusion

This study has investigated the persistence of volatility under with and without trading volume to show the impact of trading volume on return volatility. Besides, we examine the causal and feedback association between trading volume and return volatility under VAR framework. The findings show that volatility persistence of return is very high and there is a leverage effect, that is, bad news has larger impact on volatility than that of good news. The incorporation of contemporaneous trading volume in TGARCH(1,1) reduces the persistence of volatility as well as leverage effect significantly. It is also evidenced that there is a significant negative relationship between trading volume and return volatility. Such negative relationship indicates that the DSE is an inefficient and thinly traded securities market because trading volume acts as an important flow of information. When trading volume increases, the market participants think that more information will be available and thus, market transparency will increase, and uncertainty will reduce which will lead to lower volatility (negative sign of volume coefficient) in DSE. So, the contemporaneous trading volume has significant explanatory power to explain the return volatility. On the other hand, VAR model shows a significant causal and feedback relationship between trading volume and return volatility. Finally, Granger causality test indicates volume Granger cause return volatility and vice-versa.

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Appendix

Table A1: The results of VAR(3) estimates on volatility model

Variables	σ_t^2	V_t
σ_{t-1}^2	0.232272***	-48.35987
	(0.0000)	(0.1550)
σ_{t-2}^2	0.123142***	28.74351
	(0.0000)	(0.4059)
σ_{t-3}^2	0.110919***	-8.014161
	(0.0000)	(0.8113)
V_{t-1}	-8.42E-05***	0.766533***
	(0.0000)	(0.0000)
V_{t-2}	6.74E-05***	0.044585
	(0.0029)	(0.1536)
V_{t-3}	-6.59E-06	0.133275***
	(0.7111)	(0.0000)
C	0.000471	1.039269
	(0.0003)	(0.0000)
R-squared	0.137228	0.863373
Adj. R-squared	0.134107	0.862879
F-statistic	43.97851***	1747.258***

This table reports the results of VAR(3) model (Eq 6 & 7):

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \sigma_{t-i}^2 + \sum_{i=1}^{p} \phi_i V_{t-i} + \varepsilon_t$$

$$V_t = \beta_0 + \sum_{i=1}^{p} \beta_i V_{t-i} + \sum_{i=1}^{p} \gamma_i \sigma_{t-i}^2 + \varepsilon_t$$

Where, σ_t^2 represents stock return volatility estimated from GARCH mean model and V_t indicates logarithm of trading volume.

Figures in parentheses are *p*-values. ***, ** and * denote 1%, 5% and 10% level of significance, respectively.