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Information Arrival and Volatility: Evidence from the Saudi Stock Exchange (Tadawul)

Summary: This paper investigates the validation of the Mixture of Distributions Hypothesis (MDH) using trading volume and number of trades as contemporaneous proxies for information arrival in 15 sector indices of the Saudi Stock Exchange (Tadawul) using the TGARCH model. Findings provide strong evidence for the validity of the MDH for the Saudi market. Volatility persistence decreases when the trading volume and the number of trades are included in the conditional variance equation. The most striking finding is that contemporaneous number of trades is a better proxy for information arrival than trading volume, interacting with volatility in a manner anticipated under the MDH. This can be attributed to the unique characteristic of the Saudi equity market where only domestic investors are allowed to execute trade transactions. Further, the results reveal that the leverage effect was amplified, indicating a more pronounced asymmetric effect of bad news on volatility.

Key words: Volatility, Trading volume, Number of trades, MDH, Tadawul.

JEL: G14, G15.

The theoretical framework of volatility and information relationship is set on the Mixture of Distributions Hypothesis (MDH) which was proposed by Peter K. Clark (1973). The MDH is based on the assumption that all market participants receive information simultaneously and therefore the new price equilibrium is reached immediately with no partial equilibrium.

This paper investigates the validation of the MDH in the Saudi Stock Exchange (Tadawul). We estimate volatility by applying a TGARCH model using 15 sector indices from 2008 through 2012. The Saudi Stock Exchange possesses unique characteristics. For example; only the Saudi investors are allowed to invest in the stock market. However, the Saudi investors cannot access to all shares listed in the stock market. Only less than half of the listed shares are available to the Saudi investors for trading (free float) due to heavy government ownership or semi-government entities and passive shareholders (Arifur M. Rahmana, Shah Saeed Hassan Chowdhury, and Shibley M. Sadique 2015). Further, it is important to note that the Saudi Stock Exchange is the only stock market in the world that retail investors dominate more than 90% of the trade transactions.

The findings provide clear evidence in favor of the MDH. In comparison with trading volume and volatility relationship, the number of trades provides more explanatory power in reducing the volatility persistence than trading volume. This result can be attributed to the nature of the Saudi Stock Exchange where the retail investors dominate the stock market. In the presence of retail investor domination, retail investors may attempt to adopt camouflage strategy and split their trading activities into several small- and medium-sized transactions in order not to reveal their informational advantage. Such trading strategy provides retail investors information content that could significantly affect stock price volatility. Another possible explanation for why volatility is mainly driven by number of trades on the Saudi Stock Exchange could be related to the characteristics of retail investors. Since the majority of individual investors lack the necessary fundamental expertise to assess the stock value, they may ignore the risks associated with stock investment. This knowledge gap may also lead to mispricing of stocks and significant volatility.

The remainder of this paper is organized as follows: Section 1 presents literature review. Section 2 provides the data set. Section 3 describes the methodology. Section 4 discusses the empirical results and Section 5 offers a conclusion.

1. Literature Review

There is a large body of literature on the relationship between trading volume and volatility of financial assets. While some studies have focused on foreign exchange market (see Richard Payne 2003; Aditya Kaul and Stephen Sapp 2009; Antonio Portugal Duarte, Joao Sousa Andrade, and Adelaide Duarte 2010; Michael J. Moore and Payne 2011; Ramazan Gencay and Nikola Gradojević 2013; Gencay et al. 2015), the majority of the existing literature have examined the stock markets. Previous studies have documented a positive correlation between stock price volatility and trading volume, in accordance with MDH (Thomas Epps and Mary Lee Epps 1976; Goerge Tauchen and Mark Pitts 1983; Lawrence Harris 1986, 1987; Jonathan M. Karpoff 1987). However, some studies provided shortcomings of the MDH. For example; Christopher G. Lamoureux and William D. Lastrapes (1994) found that MDH failed to explain persistence of return volatility and trading volume. The latent information arrival process is unable to describe short-run dynamic dependencies in both stock trading volume and volatility. Using a generalized *method of moments (*GMM) estimator, Matthew Richardson and Tom Smith (1994) found that unobservable information tends to exhibit a small coefficient variation, positive skewness and large kurtosis. They argued that unobservable information follows weak MDH due to lognormally distributed information flow. Torben G. Andersen (1996) developed modified MDH and argued that standard MDH has a major limitation that it fails to consider the quality of information and how this information is revealed to the investors. In their seminal paper, David Easley et al. (1996) focused on the importance of asymmetric information and clarified how information-based trading differs between active and inactive stocks. They proposed a structural model to estimate the probability of informed trading (PIN). Using the number of buyer- and seller-initiated trades for each stock and each trading day, they found that high frequency stocks tend to have a higher probability information events and higher arrival rates of informed investors.

Despite the massive literature on the volatility-volume relationship, few researches have attempted to study the relationship between number of trades and volatility of stock returns. In their paper, Charles M. Jones, Gautam Kaul, and Marc L. Lipson (1994) used number of trades to address the question whether the positive volume-volatility relation is driven by the number of trades-volatility relation or the trade size-volatility relation. They reported that stock price volatility is determined by the number of trades per equally time-spaced intervals and the average trade size provided no additional explanatory power. This is an indication that only trade frequency affects price volatility. Consistent with Jones, Kaul, and Lipson (1994), Saji Gopinath and Chandrasekhar Krishnamurti (2001) and Roger D. Huang and Robert W. Masulis (2003) found a significant impact of number of trades on volatility on the NASDAQ and the London Stock Exchange, respectively. More recently, Pierre Giot, Sebastien Laurent, and Mikael Petitjean (2010) decomposed volatility into diffusive (continuous) and jumps (discontinuous) components using a sample of the largest 100 stocks traded on the NYSE. They reported that neither trade size nor order imbalance adds significantly more explanatory power beyond the number of trades, whatever the volatility component considered.

In the recent studies, Omid Sabbaghi (2011), Henryk Gurgul and Robert Syrek (2013), and Rachael Carroll and Colm Kearney (2015) found evidence to support the relationship between a contemporaneous volume and volatility in the developed markets. Consistent with the prior findings, a positive relationship between trading volume and volatility is also observed in the emerging markets (Cathy Ning and Tony S. Wirjanto 2009, for East-Asian stock markets; Boško Živković and Jelena Minović 2010, for frontier stock markets; Tianyi Wang and Zhuo Huang 2012; Yongjie Zhang et al. 2014, for the Chinese stock market; Kaliyaperumal Srinivasan, Krishna Murthy, and Salim Mohammed Al Hajiri 2016, for the Indian stock market).

For the Middle East and North Africa (MENA) region, Berna Okan, Onur Olgun, and Sefa Takmaz (2009) examined the relationship between volume and volatility for the Istanbul Stock Exchange (ISE)-30 futures index using daily data by applying GARCH, EGARCH and VAR models. They reported findings consistent with Sequential Information Arrival Hypothesis (SIAH) and rejected the MDH for the ISE-30 futures index. Sibel Celik (2013) examined the relationship between trading volume and return volatility within the scope of the MDH and the SIAH using intraday data from the ISE. He divided the data into two sub-samples in order to consider the effect of the global sub-prime crisis. The evidence was mixed for the crisis period, rejecting the MDH in the crisis period while the SIAH could not be strongly rejected. Hisham Farag and Robert Cressy (2010) used daily return data for 43 Egyptian listed companies to investigate whether information arrived to market participants simultaneously as proposed by the MDH or sequentially as proposed by the SIAH. They reported that volatility is best described by the TGARCH (1,1,1) asymmetric volatility model, using contemporaneous intraday volatility or trading volume as mixing variables, favoring the MDH against the SIAH. For the Amman Stock Exchange (ASE), Izz Eddien N. Ananzeh, Qasim M. Jdaitawi, and Ahmed M. Al Jayousi (2013) investigated the relationship between return volatility and trading volume using daily data for 27 individual stocks. They reported that trading volume significantly contributes to the return volatility process of stocks. On the other hand, trading volume has no significant impact on the reduction of the volatility persistence for majority of stocks, contradicting the MDH for the ASE. Kais Tissaoui and Chaker Aloui (2011) examined the dynamics of information flow between stock returns and trading volume in the Tunisian stock market (TSE) using intraday data. They reported results against to the MDH, where only a few Tunisian stocks displayed instantaneous correlations in mean and in variance between trading volume and stock returns.

Little is known about the empirical relationship between information arrival and volatility of the Saudi Stock Exchange. To our knowledge, Abdullah Alsubaie and Mohammad Najand (2009) is the only study that sheds some light on the volatility-volume relationship in the Saudi Stock Exchange. They tested the effect of trading volume on the persistence of the time-varying conditional volatility of returns utilizing the GARCH (1,1) model. They used intraday volatility and overnight indicators as proxies for information arrival, applying tests on five industry indices and a sample of 15 individual firms. Their results supported the MDH at the firm level, as contemporaneous volume largely reduced the persistence of volatility.

2. The Data Set

All data were obtained from the Tadawul Exchange which is the largest exchange in the Gulf and MENA regions. The 15 sector indices include Banks and Financial Services, Petrochemical Industries, Cement, Retail, Energy and Utilities, Agriculture and Food Industries, Telecommunication and Information Technology, Insurance, Multi-Investment, Industrial Investment, Building and Construction, Real Estate Development, Transport, Media and Publishing, and Hotel and Tourism. The sampling period was from April 5th 2008 through August 29th 2013. It should be noted that during the period under investigation, the Saudi exchange was closed to foreign investors. In June 2015, the market was opened to international investors, allowing only financial institutions with a minimum of $5 billion in assets and over five years of investment experience to qualify for registration with the Saudi Capital Market Authority as international investors.

The two proxies for information arrival were the contemporaneous trading volume and the number of trades. Trading volume is defined as the total number of traded shares in a given day. The number of trades is defined as the total number of executed trading transactions in a given day. Daily returns were calculated logarithmically as follows:

$$R_{(t)} = ln(P^{close}_{(t)} / P^{open}_{(t)}), \tag{1}$$

where $R_{(t)}$ is the daily return of a stock at time t, $P^{close}_{(t)}$ and $P^{open}_{(t)}$ refer to the opening price and closing price on trading day t. Closing and opening prices on the same trading day were used for calculating daily in order to have direct and contemporaneous matching of the variables used for information arrival, the daily trading volume and daily number of trades. According to Andrew Ellul, Hyun S. Shin, and Ian Tonks (2005), the opening and closing prices are important for traders and regulators, where the opening price assimilates information gathered overnight, and performs important information aggregation and price discovery functions, while the closing price serves as a benchmark for a variety of interested market participants.

3. Methodology

According to the MDH, dissemination of information is immediate and the contemporaneous variable of information arrival would impact volatility immediately. The MDH is based on the probabilistic mixture model. A mixture distribution is the probability distribution of a random variable generated from an underlying set of different random variables. Mixture models are used to identify the presence of a sub-population underlying an overall population and to make inferences about the sub-population provided only with observations of the overall population.

To investigate the volume-volatility relationship, Lamoureux and Lastrapes (1990) suggested using GARCH specification. The GARCH model of Tim Bollerslev (1986) is widely accepted as a simple and accurate tool for capturing the volatility dynamics of financial time series providing a parsimonious representation of the conditional variance. In this paper, we employed the TGARCH asymmetric model in order to investigate the leverage effect where higher volatility is associated with negative returns. The main advantage of TGARCH model is that it allows us to investigate the asymmetric response of volatility such as leverage effect, in which negative shocks have a greater impact on conditional volatility than positive shocks of the same magnitude. Since developing markets may show greater sensitivity and response to the unexpected large information shocks, TGARCH model helps us to capture the asymmetric volatility responses in the Saudi Stock Exchange. In the literature, some papers have already employed TGARCH to investigate the relationship between trading volume and volatility of stock returns (see among others, Mohamed Omran and Eric Girard 2007; Michaela Chocholatá 2011; Atsuyuki Naka and Ece Oral 2013).

During our preliminary study, we used EGARCH test. The results were very similar to those presented in Table 3, 4 and 5. However, the TGARCH (1,1) model produced more statistically significant results, indicating a better fit with the data for modeling volatility for the Saudi market. We have specified our model with ARCH and GARCH order of 1 and then set the threshold order to the value 1.We chose our specifications based on statistical significance of coefficients and the lowest Akaike Information Criterion (AIC).

The TGARCH model was introduced independently by a Lawrence R. Glosten, Ravi Jagannathan, and David E. Runkle (1993) and Jean-Michel Zakoïan (1994) and it has the following specification for the conditional variance:

$$h^2_t = \omega + \sum_{j=1}^{q} \beta_j h^2_{t-j} + \sum_{i=1}^{p} \alpha_i \varepsilon^2_{t-i} + \sum_{k=1}^{r} \gamma_k \varepsilon^2_{t-k} I_{t-k}, \quad (2)$$

where ω, α, β are non-negative parameters with $\alpha + \beta < 1$. $I_t = 1$ if $\varepsilon_t < 0$ and 0 otherwise. Good news is indicated when $\varepsilon_{t-i} > 0$ and has an impact on α_i. Bad news is indicated when $\varepsilon_{t-i} < 0$ and has an impact on $\alpha_i + \gamma_i$. If $\gamma_i \neq 0$, then there is an asymmetric news impact. If $\gamma_i > 0$, then volatility increases with bad news and there is leverage effect of the i-th order. The standard GARCH model is a special case of the TGARCH model if the threshold term is given a zero value.

The log likelihood function is used to estimate the parameters for the TGARCH (1,1) model:

$$I(\Theta)_t = ln\ (v/\lambda) - (1/2)|\ \varepsilon t/\ (h_t\ \lambda)|^{\ v} - (1 + (1/v))\ ln(2) - ln(\Gamma(1/v)) - 0.5\ ln(h^2_t). \quad (3)$$

Where λ = exp((-1/v) ln(2) + (1/2) ln(Γ(1/v) – (1/2) ln(Γ(3/v))), v is the tail thickness parameter, for $v = 2$, the errors are normally distributed.

The TGARCH (1,1) model with the additional regressors has the following forms:

$$h^2_t = \omega + \sum_{j=1}^{q} \beta_j\ h^2_{t-j} + \sum_{i=1}^{p} \alpha_i\ \varepsilon^2_{t-i} + \sum_{k=1}^{r} \gamma_k\ \varepsilon^2_{t-k} I_{t-k} + \sum_{l=1}^{s} \theta_l\ V. \quad (4)$$

Where V is the natural logarithm of daily trading volume.

$$h^2_t = \omega + \sum_{j=1}^{q} \beta_j\ h^2_{t-j} + \sum_{i=1}^{p} \alpha_i\ \varepsilon^2_{t-i} + \sum_{k=1}^{r} \gamma_k\ \varepsilon^2_{t-k} I_{t-k} + \sum_{l=1}^{s} \theta_l\ T. \quad (5)$$

Where T is the natural logarithm of daily number of trades.

The estimated parameter θ indicates the explanatory power of the proxy for information arrival. If θ is positive and statistically significant, the proxy for information arrival is serially correlated to the variance and has explanatory power. The ARCH parameter α represents the lagged squared residuals and the GARCH parameter β represents the lagged forecast variance. The sum ($\alpha + \beta$) provides a concise measure for the persistence of the variance. A value close to unity is an indication of high persistence of volatility and slow mean reversion. A low value of ($\alpha + \beta$) is an indication of faster decay of volatility to the long-term average and low persistence. As suggested by Lamoureux and Lastrapes (1990), if the proxy for information arrival is serially correlated to the variance then the sum of ($\alpha + \beta$) should be lower once volume or the number of trades is included in the variance equation. Ideally, the persistence of the variance as measured by ($\alpha + \beta$) should be small and statistically insignificant in the presence of an accurate proxy for information arrival in the variance equation. As stipulated by the MDH, if the proxy does not fully capture the rate of information arrival, then other exogenous variables must be present, hence some persistence will remain.

Further, the Augmented Dickey-Fuller (ADF) and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) unit root tests were used to test for stationarity and the ARCH heteroskedasticity test was used to investigate the presence of time varying volatility clustering.

4. Empirical Findings

Descriptive statistics are presented in Table 1. All indices are negatively skewed with long left tails. The indices have excess kurtosis, indicating fatter tails and higher peaks for the probability distribution. Normality of the distribution is rejected by the Jarque-Bera test for all indices. The lowest standard deviation is reported for the Energy and Utilities index with a value of 0.0129. In Saudi Arabia, the Energy and Utilities sector is considered as a defensive sector in the economy. The index includes natural gas and electricity companies, which enjoy a steady stream of revenues with prices that are not subject to large variations. The highest standard deviations are present for the Insurance and Petrochemical Industries with the values of 0.0215 and 0.0204, respectively. During the period under investigation, global oil prices were subject to large variations that were reflected in the high standard deviation of the Petrochemical Industries index.

Table 1 Descriptive Statistics for Sectorial Index Returns

Sector index	Mean	Median	Std. dev.	Skew.	Kurt.	Jarque-Bera
Agriculture	0.0004	0.0009	0.0154	-0.6461	13.4436	6219.838*
Banks	-0.0002	-0.0001	0.0149	-0.1854	12.5782	5160.580*
Construction	-0.0005	0.0008	0.0188	-1.0175	11.2563	4061.264*
Cement	0.0001	0.0000	0.0134	-0.5435	16.7979	10759.53*
Energy and utilities	-0.0001	0.0000	0.0129	-0.1227	14.8050	7830.628*
Real estate dev.	-0.0002	0.0001	0.0159	-0.7295	12.5774	5271.542*
Hotels and tourism	0.0006	0.0003	0.0196	-0.1449	8.6853	1820.155*
Industrial investment	0.0001	0.0006	0.0173	-0.8958	11.1379	3899.901*
Insurance	-0.0004	0.0004	0.0215	-0.9015	7.0050	1083.480*
Media and publishing	-0.0002	-0.0009	0.0197	-0.0532	8.0885	1454.971*
Multi-investment	-0.0002	0.0005	0.0194	-0.8553	9.7463	2720.596*
Petrochemical ind.	-0.0003	0.0004	0.0204	-0.7435	10.2619	3086.162*
Retail	0.0006	0.0006	0.0145	-0.6691	15.1592	8404.589*
Telecom	0.0000	0.0002	0.0147	-0.6402	14.0830	6991.224*
Transport	0.0000	0.0002	0.0189	-0.4195	10.4759	3178.617*

Note: Significance levels: * = 1%, ** = 5%, *** = 10%.

Source: Authors' own calculations[1].

Table 2 reports unit root and heteroscedascity test results for stock index returns. Similarly, Ki-Hong Choi et al. (2012) and Ananzeh (2015) used stock index returns for unit root tests in their papers. The stationarity of the sectorial stock index returns is verified by using Augmented Dickey-Fuller (ADF) and Kwiatowski-Phillips-Schmidt-Shin (KPSS) tests. The results show that the null hypothesis of the ADF unit root is rejected for all sectorial index returns. This result implies that all sectorial stock index returns are stationarity and mean reverting. The KPSS test complements the ADF test and the results of KPSS test also indicate that the sectorial stock index returns are stationary. Further, we test the heteroskedasticity of all sector indices. The null hypothesis of homoskedasticity is rejected for all sector index returns indicating heteroskedasticity and the presence of time varying volatility clustering and the suitability of applying GARCH methods.

[1] **The Saudi Stock Exchange (Tadawul).** 2014. Capital Market. Overview. http://tadawul.com.sa (accessed June 15, 2013).

Table 2 Results of Unit Root and Heteroskedasticity Tests for Stock Returns

Sector index	ADF		KPSS		Heteroskedasticity test
	Intercept	Intercept and trend	Intercept	Intercept and trend	*F*-statistic
Agriculture	-33.8638*	-33.8797*	0.1555	0.0462	224.6227*
Banks	-34.4397*	-34.4666*	0.1585	0.0456	133.7632*
Construction	-31.3329*	-31.3590*	0.1812	0.0382	200.4462*
Cement	-34.1680*	-34.3053	0.6021	0.1141	50.9353*
Energy and utilities	-41.7313*	-41.7379*	0.1544	0.1236	29.6602*
Real estate	-34.7638	-34.8954*	0.5882	0.0450	75.8657*
Hotels and tourism	-35.4844*	-35.5701*	0.4626	0.0556	47.9093*
Industrial investment	-22.6893*	-22.6897*	0.0857	0.0629	74.4823*
Insurance	-32.8853*	-32.9024*	0.1841	0.1032	60.0758*
Media and publishing	-32.6731*	-32.6988*	0.2638	0.0898	72.4310*
Multi-investment	-33.5435*	-33.6070*	0.3849	0.0998	72.3791*
Petrochemical ind.	-35.9729*	-36.0016*	0.2214	0.1370	41.2790*
Retail	-34.7798*	-34.8351*	0.3202	0.0351	90.5162*
Telecom	-35.1938*	-35.2504*	0.3262	0.0442	112.3796*
Transportation	-34.1672*	-26.7573*	0.3294	0.0578	150.8171*

Note: Significance levels: * = 1%, ** = 5%, *** = 10%. Critical values of KPSS tests constant and with trend at five percent level are 0.463 and 0.146 respectively.

Source: Authors' own calculations.

Table 3 displays the TGARCH output for all sector indices without including proxies for information arrival in the variance equation. The parameters α and β of the TGARCH model are positive and statistically significant for all sector indices. The γ parameter, which signifies the leverage effect was negative and significant at 10% level for the Energy and Utilities index. Further, the coefficients of γ are not statistically significant for the Real Estate Development and Transport indices. The presence of the leverage effect was rejected for those sectors. For all other indices, γ was positive and statistically significant and the presence of the leverage effect was accepted. The highest values of γ were for the Telecom and Agriculture indices with the values of 0.1621 and 0.1663 respectively indicating a strong presence of the leverage effect.

Table 3 Volatility Persistence without Trading Volume and Number of Trades

Sector	α	Γ	β	$\alpha+\beta$
Agriculture	0.0253*	0.1663*	0.8582*	0.8836
Banks	0.1199*	0.1304*	0.8139*	0.9338
Construction	0.0544*	0.0962*	0.8496*	0.9041
Cement	0.0907*	0.0584*	0.8593*	0.9500
Energy and utilities	0.0713*	-0.0138***	0.9223*	0.9937
Real estate	0.0688*	0.0035	0.9128*	0.9817
Hotels and tourism	0.0621*	0.0245**	0.8980*	0.9601
Industrial investment	0.0810*	0.0446*	0.8764*	0.9575
Insurance	0.0339*	0.0421*	0.9149*	0.9488
Media and publishing	0.1701*	0.0973*	0.6759*	0.8460
Multi-investment	0.0993*	0.1088*	0.7969*	0.8963
Petrochemical ind.	0.0431*	0.1323*	0.8772*	0.9204
Retail	0.0624*	0.0799*	0.8682*	0.9307
Telecom	0.0410*	0.1621*	0.8314*	0.8725
Transportation	0.0789*	0.0153	0.9028*	0.9817

Note: Significance levels: * = 1%, ** = 2%, *** = 10%.

Source: Authors' own calculations.

Table 4 indicates TGARCH results with trading volume. When contemporaneous volume was included as a proxy for information, the coefficients of contemporaneous trading volume θ were positive and significant for all sector indices except for the Cement and the Retail sector indices. The results reveal a striking fact that the degree of volatility persistence, indicated by ($\alpha + \beta$) decreased in all sectors as expected by the MDH. There is an average decrease of 11.43%, when trading volume was included. Comparing the results with those reported in in Table 3, before the inclusion of trading volume, the value of ($\alpha + \beta$) ranged from 0.8460 to 0.9937, however after the inclusion of trading volume it ranged from 0.5562 to 0.9494. This result is consistent with the findings of Alsubaie and Najand (2009), supporting the MDH, as contemporaneous volume largely reduces the persistence of volatility. In addition, when volume was included, there was an average increase of 76.64% in the value of the γ coefficients indicating a much stronger leverage effect.

Table 4 Volatility Persistence with Volume Traded

Sector	α	Γ	B	$\theta * 10^{-5}$	$\alpha + \beta$
Agriculture	0.0205***	0.1991*	0.8408*	0.2700*	0.8614
Banks	0.1126*	0.1616*	0.7920*	0.7100*	0.9047
Construction	0.0270***	0.1763*	0.8185*	0.9490*	0.8456
Cement	0.0908*	0.0593*	0.8585*	0.0037	0.9494
Energy and utilities	0.1843*	0.0702***	0.6654*	1.3000*	0.8497
Real estate dev.	0.0412**	0.4119*	0.6186*	2.2700*	0.6598
Hotels and tourism	0.0527*	0.0533*	0.8792*	0.3960*	0.9320
Industrial investment	0.0436*	0.1274*	0.8476*	0.8650*	0.8913
Insurance	0.0329*	0.0585*	0.8977*	0.5290*	0.9306
Media and publishing	0.4700*	0.1561**	0.0862*	6.8600*	0.5562
Multi-investment	0.0532*	0.3168*	0.6806*	3.0400*	0.7338
Petrochemical ind.	0.0255**	0.1718*	0.8553*	1.2000*	0.8809
Retail	0.0642*	0.0771*	0.8690*	-0.0227	0.9332
Telecom	0.0291**	0.1884*	0.8203*	0.3600*	0.8494
Transportation	0.1073*	0.1578 *	0.6966*	2.1500*	0.8040

Note: Significance levels: * = 1%, ** = 5%, *** = 10%.

Source: Authors' own calculations.

Table 5 reports the volatility persistence with the inclusion of number of trades as a proxy for information. The findings show that the impact of including the number of trades on the leverage effect was substantial. The γ coefficients were positive and statistically significant for 14 out of the 15 indices with the highest values for the Banks and the Real Estate Development sectors with the values of 0.2880 and 0.5003, respectively. When the number of trades was included in the variance equation, there was an average increase of 70.56% in the value of the γ coefficients indicating a much stronger leverage effect. Choi et. al (2012) also reported an increase in the asymmetric effect of bad news on volatility when a contemporaneous proxy for information was included. It seems that the leverage effect is amplified by the inclusion of a proxy for information arrival. The decrease in persistence is compensated for an increase in the leverage effect.

Similar to the results of trading volume, when contemporaneous number of trades was included as a proxy for information, the coefficients of θ were positive and significant for all sector indices except for the Cement and the Retail sector indices. For the Cement sector, θ was negative and statistically significant, indicating a negative serial correlation with volatility. For the Retail sector, θ was negative but not statistically significant. Including number of trades in the variance equation reduced the persistence by a greater degree than volume in 8 out of the 15 indices including Agriculture, Banks, Construction, Energy and Utilities, Real Estate Development, Multi-Investment, Petrochemical Industries, and Telecom. The persistence was reduced but not fully eliminated by the number of trades. This finding suggests the presence of other exogenous mixing variables affecting the variance. In particular, the volatility persistence decreased substantially in the Banks, Construction, Energy and Utilities, Real Estate Development, Media and Publishing, and the Multi-Investment sectors. The results imply that the persistence of the conditional heteroskedasticity is mostly absorbed by the number of trades largely in many sectors.

Overall, the findings provide evidence that the number of trades has greater impact on the variance, confirming the variable as a better proxy for information than trading volume. This result is in line with the findings reported by Jones, Kaul, and Lipson (1994), Choon C. Chan and Wai M. Fong (2006), and Giot, Laurent, and Petitjean (2010).

Table 5 Volatility of Persistence with Number of Trades

Sector	α	γ	B	$\theta * 10^{-5}$	$\alpha + \beta$
Agriculture	0.0192***	0.2073*	0.8365*	0.4470*	0.8557
Banks	0.1513*	0.2880*	0.4355*	4.5900*	0.5868
Construction	0.0092	0.2604*	0.7560*	1.9000*	0.7652
Cement	0.0891*	0.0501*	0.8664*	-0.0515**	0.9556
Energy and utilities	0.1822*	-0.0068	0.4574*	3.6800*	0.6397
Real estate dev.	0.0196	0.5003*	0.5755*	4.1500*	0.5952
Hotels and tourism	0.0541*	0.0440*	0.8870*	0.2930*	0.9412
Industrial investment	0.0636*	0.0742*	0.8637*	0.5610*	0.9273
Insurance	0.0339*	0.0495*	0.9056*	0.2650**	0.9395
Media and publishing	0.4685*	0.1326***	0.1534*	7.7100*	0.6219
Multi-investment	0.0564*	0.2799*	0.6674*	3.4600*	0.7239
Petrochemical ind.	0.1244*	0.1451*	0.7138*	3.3800*	0.8383
Retail	0.0651*	0.0761*	0.8691*	-0.0353	0.9343
Telecom	0.0255**	0.1994*	0.8000*	0.7760*	0.8255
Transportation	0.0298**	0.1786*	0.7861*	2.0200*	0.8160

Note: Significance levels: * = 1%, ** = 5%, *** = 10%.

Source: Authors' own calculations.

5. Conclusion

This paper tests the validity of the Mixture of Distributions Hypothesis in the Saudi Stock Exchange by exploring the use of contemporaneous trading volume and the number of trades as proxies for information arrival. Daily returns of 15 sector indices were used, covering the period from April 5th 2008 to August 29th 2013. The TGARCH (1,1) asymmetric model was applied to specify the variance with and without including the proxies of trading volume and number of trades for information arrival.

The Saudi Stock Exchange is a frontier market with special features that are very unique and different from other stock markets. The foreign investors are not allowed to trade stocks and retail investors constitute the main engine of the Saudi stock market. Further, free share float is limited and less than half of the listed shares are available for trading due to the government ownership and wealthy families' passive shares. In particular, this feature of the stock market makes the retail investors to trade certain shares continuously. In this context, the Saudi Stock Exchange provides a unique setting to assess the relationship among the trading volume, number of trades and volatility.

The findings of this paper reveal the fact that the persistence in the stock return volatility diminishes after incorporating trading volume and number of trades for the majority of the sector indices. The findings support the validity of MDH for the Saudi stock market. In addition, the number of trades provides better explanation for volatility due to its information content and drives the positive volume-volatility relationship. A possible explanation for this outcome could be attributed to the nature of the Saudi Stock Exchange, where the retail Saudi investors dominate the stock market. Since large-sized trades make the retail investors easy targets to trace, retail investors may adopt camouflage strategy by splitting large share trades into small and medium share trades. Such strategic behavior leads to the positive relationship between number of trades and stock prices. Another explanation for positive relationship between the number of trades and volatility can be linked to non-fundamental trading in the Saudi Stock Exchange. The knowledge gap of individual investors accompanied with their high risk appetite make investors to have more sentiment-driven decisions, which may increase the market volatility. The findings further suggest that the leverage effect was amplified, indicating a more pronounced asymmetric effect of bad news on volatility.

We believe that the findings can help international audience to understand the Saudi stock market, which is considered as a frontier market by the leading index providers such as MSCI, S&P and FTSE. In this regard, the current study contributes to the limited literature focusing on frontier markets and provides useful information to investors and policy makers. For future research, it would be interesting to use other proxies for information arrival such as PIN or the bid-ask spread to investigate the relationship between information arrival and volatility for the Saudi Stock Exchange.

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