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

Ezzat, Hassan and Kirkulak, Berna

6 February 2014

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

Hassan Ezzat
Maastricht School of Managment, Maastricht, the Netherlands
E-mail: hdezzat1@yahoo.com

Berna Kirkulak Uludag
Dokuz Eylul University, Faculty of Business, İzmir, Turkey
E-mail:berna.kirkulak@deu.edu.tr

Abstract

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 the Saudi Exchange (Tadawul). The sample comprises 15 sector indices from April 2008 to August 2013. The relationship between volatility and information arrival was modelled using TGARCH. The 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 of the paper 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 unique characteristic of the Saudi equity market where a large number of domestic investors generate a large number of trading transactions. This can be attributed to unique characteristic of the Saudi equity market where only the domestic investors are allowed to trade. Further, the results reveal that the leverage effect was amplified, indicating a more pronounced asymmetric effect of bad news on volatility, when the number of trade is included as a regressor in the variance equation.

Keywords: volatility, trading volume, number of trades, information arrival, MDH, Tadawul
JEL codes: C32, C52, G12, G15.

1. Introduction

The relationship between information arrival and volatility has been the focus of extensive empirical research. In his seminal paper, Karpoff (1987) proposed that information arrival helps to explain the dynamics of volatility in financial assets and can be considered the root cause of price adjustments for the informed traders. A significant problem in forecasting volatility lies in the fact that volatility is a latent variable that is unobservable (Patton, 2006). This means that volatility is not observed directly and can only be inferred from other variables that can be observed and measured directly. Information arrival is also a latent random variable that cannot be observed directly. In order to investigate the properties of a latent random variable, a proxy that is an accurate representation of the latent random variable must be used. In the case of volatility, the variance of a time series is well established as an accurate proxy and has been used as such for decades. On the other hand, for information arrival, many proxies have been suggested, however the debate is still ongoing as to what would be the best representation of information arrival as a random variable. Proxies that have been suggested include the volume of traded shares, the number of trades, and the average size of each trade, order imbalance, intraday volatility, and overnight indicators with varying degrees of success. Volume as a proxy for information arrival has received the biggest share in empirical research. However, the best proxy for information arrival might be market specific depending on the microstructure of each market and the volatility dynamics of the financial asset being investigated.

Two hypotheses have been proposed in an attempt to explain the relationship between information arrival and volatility. The first is the mixture of distributions hypothesis (MDH) proposed by Clark (1973) and later elaborated upon by Epps and Epps (1976) and Harris (1987). The second is the sequential information arrival hypothesis (SIAH) proposed by Copeland (1976). The MDH suggests that a contemporaneous positive relationship exists between trading volume and volatility driven by information arrival. It is assumed that all market participants receive information simultaneously and therefore the new price equilibrium is reached immediately with no partial equilibrium. According to the MDH, lagged volatility and volume do not Granger cause each other and therefore mutual forecasting is impossible. On the other hand, SIAH assumes that new information is disseminated to market participants sequentially with each participant reacting to the information as it is received resulting in a partial price equilibrium. The final price equilibrium is reached when the new information is fully disseminated to all market participants. The major implication of the SIAH is that lagged trading volume can be used to predict volatility.

The objective of this paper is to investigate the validation of the MDH using a sample of sector indices from the Saudi Stock Exchange. The current study extends the analysis of the role of trading volume and the number of trades in explaining the volume-volatility relation. We estimate volatility by using a TGARCH model that enables us to capture how information arrival impacts asymmetric volatility manifested by the leverage effect. The data contains 15 sector indices from 2008 through 2012. The Tadawul Exchange was selected for several reasons. First, it is the largest exchange in the Gulf region and one of the largest in the Middle East and North Africa (MENA) region. As of December 31st 2013, Tadawul had a market capitalization of approximately $474 billion with 163 publicly traded companies (Tadawul Exchange, 2013). Tadawul is a highly liquid exchange with a large number of market participants, high volume of trade, and an advanced microstructure that enables efficient trading. Second, Tadawul possesses a unique characteristic that makes it interesting to investigate. The exchange has been closed to foreign investors for 37 years and is currently dominated by domestic participants. The concentration of market participants within the domestic market allows for the rapid dissemination of information. Information propagates quickly among the domestic market participants and dissemination does not have to extend to different time zones or geographic locations. Finally, there is sparse empirical research on the linkage between information arrival and volatility related to the MENA region. Therefore, the contribution of this paper is expected to narrow the gap between research investigating information arrival and volatility on emerging markets and developing markets with emphasis on the MENA region.

The results of this paper highlight the relationship between volatility, volume and number of trades in the Saudi stock market. The findings provide clear evidence in favor of the MDH. Inclusion of trading volume and number of trades leads to a substantial reduction in the volatility persistence. In particular, the number of trades has more explanatory power in reducing the volatility persistence than trading volume.

The remainder of this paper is organized as follows: Section 2 presents a literature review. Section 3 provides the data set. Section 4 describes the methodology. Section 5 discusses the empirical results and Section 6 offers a conclusion.

2. Literature Review

Empirical studies indicate that information arrival is positively correlated with volatility. However, researchers are in disagreement on whether the causal relationship is contemporaneous or lagged and indeed what is the most appropriate proxy for information arrival. Using contemporaneous volume as a proxy for information arrival, Lamoureux and Lastrapes (1990) demonstrated that daily trading volume has significant explanatory power on the variance of daily returns. They reported that ARCH effects tend to disappear when volume is included in the variance equation specified by the GARCH model. Anderson (1996), Brailsford (1996), and Omran and McKenzie (2000) found evidence in support of a contemporaneous volume and volatility relation in the developed markets. Consistent with the prior findings, a positive relation between trading volume and volatility is also observed in the emerging markets (Ning and Wirjanto, 2009; Choi et. al.,2012)

Another proxy for information arrival was offered by Jones et al.(1994). In their paper, they 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 et al. (1994), Gopinath and Krishnamurti (2001) and Huang and Masulis (2003) found a significant impact of number of trades on volatility on the NASDAQ and the London Stock Exchange respectively. More recently, Gio et. al (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 number of trades, whatever the volatility component considered.

For the MENA region, Okan et al. (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 SIAH and rejected the MDH for the ISE-30 futures index. 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. Omran and Girard (2007) examined the change in speed of dissemination of order flow information on stock volatility in 79 traded companies on the Egyptian stock market. They reported that information size and direction have a negligible effect on conditional volatility which may indicate the presence of noise trading. They further showed that the persistence in volatility was not eliminated when lagged or contemporaneous trading volume was incorporated into a TGARCH model. Farag and 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 TGARCH (1,1,1) asymmetric volatility model, using contemporaneous intraday volatility or trading volume as mixing variables, favoring the MDH against the SIAH.

Little is known about the empirical relationship between information arrival and volatility of the Saudi Stock Exchange. Alsubaie and Najand (2008) investigated the volatility-volume relationship in the Tadawul Exchange and 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. Furthermore, Alzahranai et al. (2010) examined the price impact of block trades for the 124 companies listed on the Saudi Stock Exchange using high frequency intraday one minute data. They found a direct relationship between the size of the trades and the level of information asymmetry in the market.

3. The Data Set

All data were obtained from the Tadawul Exchange. The 15 sector indices were examined including 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. 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:

$$R(t) = \ln(P_{close}/P_{open}) \tag{1}$$

where R(t) is the return of any given day, Pclose is the closing price and Popen is the opening price. Closing and opening prices for each day were used for calculating daily returns instead of closing prices for consecutive days 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 Ellul et. al (2005), the opening and closing prices are important for traders and regulators where the open 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.

4. Methodology

In this paper, we tested the MDH for 15 sector indices from the Tadawul Exchange by following the approach suggested by Lamoureux and Lastrapes (1990). TGARCH was used to investigate the asymmetric response of volatility to information arrival. 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. The individual distributions of the underlying set of random variables are referred to as mixture components, when combined, produce the distribution of the random variable. Mixture models are used to identify the presence of a sub-population underlying an overall population and to make inferences about the subpopulation provided only with observations of the overall population. In our case, the overall population is the volatility described by the variance and the mixing variable generating the underlying mixture component distribution is represented by information arrival.

The GARCH model of 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 TGARCH model was introduced independently by aGlosten et al. (1993) and Zakoïan (1994) and it has the following specification for the conditional variance:

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

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 model

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

where $\lambda = \exp((-1/v)\ln(2) + (1/2)\ln(\Gamma(1/v) - (1/2)\ln(\Gamma(3/v)))$, v is the tail thickness parameter, for v=2, the errors are normally distributed.

The TGARCH model with the additional regressors had the following forms:

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

where V is the natural logarithm of daily trading volume.

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

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 (α + β) 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 (α + β) 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 (α + β) 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 (α + β) 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.

5. 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 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 Tadawul Sector Indices

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

Table 2 reports the results of ADF and KPSS unit root tests and the heteroskedasticity test. The results indicate that the null hypothesis of the ADF unit root is rejected for all indices indicating that that all time series are stationary and mean reverting. The KPSS test complements the ADF test and the results of KPSS test also indicate that the time series are stationary. Further, we test the heteroskedasticity of all sector indices. The null hypothesis of homoskedasticity is rejected for all sector indices indicating heteroskedasticity and the presence of time varying volatility clustering and the suitability of applying GARCH methods.

Table 2: Results of Unit Root and Heteroskedasticity Tests

	ADF		KPSS		Heteroskedasticity Test
Sector Index	**Intercept**	**Intercept and Trend**	**Intercept**	**Intercept and Trend**	**F-statistic**
Agriculture	-33.8638* (0.0000)	-33.8797* (0.0000)	0.1555	0.0462	224.6227* (0.0000)
Banks	-34.4397* (0.0000)	-34.4666* (0.0000)	0.1585	0.0456	133.7632* (0.0000)
Construction	-31.3329* (0.0000)	-31.3590* (0.0000)	0.1812	0.0382	200.4462* (0.0000)
Cement	-34.1680* (0.0000)	-34.3053 (0.0000)	0.6021	0.1141	50.9353* (0.0000)
Energy and Utilities	-41.7313* (0.0000)	-41.7379* (0.0000)	0.1544	0.1236	29.6602* (0.0000
Real Estate	-34.7638 (0.0000)	-34.8954* (0.0000)	0.5882	0.0450	75.8657* (0.0000)
Hotels and Tourism	-35.4844* (0.0000)	-35.5701* (0.0000)	0.4626	0.0556	47.9093* (0.0000)
Industrial Investment	-22.6893* (0.0000)	-22.6897* (0.0000)	0.0857	0.0629	74.4823* (0.0000)
Insurance	-32.8853* (0.0000)	-32.9024* (0.0000)	0.1841	0.1032	60.0758* (0.0000)
Media and Publishing	-32.6731* (0.0000)	-32.6988* (0.0000)	0.2638	0.0898	72.4310* (0.0000)
Multi-Investment	-33.5435* (0.0000)	-33.6070* (0.0000)	0.3849	0.0998	72.3791* (0.0000)
Petrochemical Ind.	-35.9729* (0.0000)	-36.0016* (0.0000)	0.2214	0.1370	41.2790* (0.0000)
Retail	-34.7798* (0.0000)	-34.8351* (0.0000)	0.3202	0.0351	90.5162* (0.0000)
Telecom	-35.1938* (0.0000)	-35.2504* (0.0000)	0.3262	0.0442	112.3796* (0.0000)
Transportation	-34.1672* (0.0000)	-26.7573* (0.0000)	0.3294	0.0578	150.8171* (0.0000)

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

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 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 Trade

Sector	α	γ	β	α + β
Agriculture	0.0253*	0.1663*	0.8582*	0.8836
	(0.0088)	(0.0000)	(0.0000)	
Banks	0.1199*	0.1304*	0.8139*	0.9338
	(0.0000)	(0.0000)	(0.0000)	
Construction	0.0544*	0.0962*	0.8496*	0.9041
	(0.0001)	(0.0000)	(0.0000)	
Cement	0.0907*	0.0584*	0.8593*	0.9500
	(0.0000)	(0.0009)	(0.0000)	
Energy and Utilities	0.0713*	-0.0138***	0.9223*	0.9937
	(0.0000)	(0.0670)	(0.0000)	
Real Estate Dev.	0.0688*	0.0035	0.9128*	0.9817
	(0.0000)	(0.6846)	(0.0000)	
Hotels and Tourism	0.0621*	0.0245**	0.8980*	0.9601
	(0.0000)	(0.0341)	(0.0000)	
Industrial Investment	0.0810*	0.0446*	0.8764*	0.9575
	(0.0000)	(0.0011)	(0.0000)	
Insurance	0.0339*	0.0421*	0.9149*	0.9488
	(0.0014)	(0.0002)	(0.0000)	
Media and Publishing	0.1701*	0.0973*	0.6759*	0.8460
	(0.0000)	(0.0077)	(0.0000)	
Multi-Investment	0.0993*	0.1088*	0.7969*	0.8963
	(0.0000)	(0.0000)	(0.0000)	
Petrochemical Ind	0.0431*	0.1323*	0.8772*	0.9204
	(0.0002)	(0.0000)	(0.0000)	
Retail	0.0624*	0.0799*	0.8682*	0.9307
	(0.0000)	(0.0000)	(0.0000)	
Telecom	0.0410*	0.1621*	0.8314*	0.8725
	(0.0005)	(0.0000)	(0.0000)	
Transport	0.0789*	0.0153	0.9028*	0.9817
	(0.0000)	(0.1256)	(0.0000)	

P values are in parenthesis. Significance levels: * = 1%, ** = 2%, *** = 10%.

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 (α + β) decreased in all sectors as expected by the MDH, with an average decrease of 11.43% when trading volume was included. Comparing the results in Table 3, before the inclusion of trading volume, the value of (α + β) 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 (2008) 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	β	θ $*10^{-5}$	α + β
Agriculture	0.0205***	0.1991*	0.8408*	0.2700*	0.8614
	(0.0600)	(0.0000)	(0.0000)	(0.0038)	
Banks	0.1126*	0.1616*	0.7920*	0.7100*	0.9047
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	
Construction	0.0270***	0.1763*	0.8185*	0.9490*	0.8456
	(0.0901)	(0.0000)	(0.0000)	(0.0000)	
Cement	0.0908*	0.0593*	0.8585*	0.0037	0.9494
	(0.0000)	(0.0008)	(0.0000)	(0.8767)	
Energy and Utilities	0.1843*	0.0702***	0.6654*	1.3000*	0.8497
	(0.0000)	(0.0598)	(0.0000)	(0.0000)	
Real Estate Dev.	0.0412**	0.4119*	0.6186*	2.2700*	0.6598
	(0.0200)	(0.0000)	(0.0000)	(0.0000)	
Hotels and Tourism	0.0527*	0.0533*	0.8792*	0.3960*	0.9320
	(0.0000)	(0.0008)	(0.0000)	(0.0002)	
Industrial Investment	0.0436*	0.1274*	0.8476*	0.8650*	0.8913
	(0.0015)	(0.0000)	(0.0000)	(0.0000)	
Insurance	0.0329*	0.0585*	0.8977*	0.5290*	0.9306
	(0.0033)	(0.0000)	(0.0000)	(0.0010)	
Media and Publishing	0.4700*	0.1561*	0.0862*	6.8600*	0.5562
	(0.0000)	(0.0380)	(0.0002)	(0.0000)	
Multi-Investment	0.0532*	0.3168*	0.6806*	3.0400*	0.7338
	(0.0026)	(0.0000)	(0.0000)	(0.0000)	
Petrochemical Ind.	0.0255**	0.1718*	0.8553*	1.2000*	0.8809
	(0.0199)	(0.0000)	(0.0000)	(0.0000)	
Retail	0.0642*	0.0771*	0.8690*	-0.0227	0.9332
	(0.0000)	(0.0000)	(0.0000)	(0.6858)	
Telecom	0.0291**	0.1884*	0.8203*	0.3600*	0.8494
	(0.0153)	(0.0000)	(0.0000)	(0.0000)	
Transportation	0.1073*	0.1578 *	0.6966*	2.1500*	0.8040
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	

P values are in parenthesis. Significance levels: * = 1%, ** = 5%, *** = 10%.

Table 5 reports the volatility persistence with the inclusion of number of trades as a proxy for information. As with trading volume, 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 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 by 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, Bnaks, Construction, Energy and Utilities, Real Estate Development, Multi-Investment, Petrochemical Industries, and Telecom. On average, persistence was reduced by 16.43% when number of trades was included compared to 11.43% with the inclusion of volume. The persistence was reduced but not fully eliminated by the number of trades which suggests the presence of other exogenous mixing variables impacting 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 effect largely in many sectors. These 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 et al. (1994), Chan and Fong (2006), and Gio et. al. (2010).

The Saudi equity market is characterized by large market size and trading volume relative to the number of listed companies combined with a lack of major institutional investors, who usually have a dominating presence in most markets and are the source of large volume trading. Further, 90% of total trading is initiated by individual investors (Alzahranai et. al (2010). These unique characteristics of the Saudi equity market may help to explain why number of trades is a better proxy for information than trading volume, where a large number of small investors generate a large number of trading transactions.

Table 5: Volatility of Persistence with Number of Trades

Sector	α	γ	β	θ $*10^{-5}$	$\alpha + \beta$
Agriculture	0.0192***	0.2073*	0.8365*	0.4470*	0.8557
	(0.0792)	(0.0000)	(0.0000)	(0.0000)	
Banks	0.1513*	0.2880*	0.4355*	4.5900*	0.5868
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	
Construction	0.0092	0.2604*	0.7560*	1.9000*	0.7652
	(0.6054)	(0.0000)	(0.0000)	(0.0000)	
Cement	0.0891	0.0501*	0.8664*	-0.0515**	0.9556
	(0.0000)	(0.0028)	(0.0000)	(0.0496)	
Energy and Utilities	0.1822	-0.0068	0.4574*	3.6800*	0.6397
	(0.000)	(0.8604)	(0.0000)	(0.0000)	
Real Estate Dev.	0.0196	0.5003*	0.5755*	4.1500*	0.5952
	(0.2425)	(0.0000)	(0.0000)	(0.0000)	
Hotels and Tourism	0.0541	0.0440*	0.8870*	0.2930*	0.9412
	(0.0000)	(0.0024)	(0.0000)	(0.0035)	
Industrial Investment	0.0636	0.0742*	0.8637*	0.5610*	0.9273
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	
Insurance	0.0339*	0.0495*	0.9056*	0.2650**	0.9395
	(0.0021)	(0.0001)	(0.0000)	(0.0135)	
Media and Publishing	0.4685*	0.1326***	0.1534*	7.7100*	0.6219
	(0.0000)	(0.0626)	(0.0000)	(0.0000)	
Multi-Investment	0.0564*	0.2799*	0.6674*	3.4600*	0.7239
	(0.0033)	(0.0000)	(0.0000)	(0.0000)	
Petrochemical Ind.	0.1244*	0.1451*	0.7138*	3.3800*	0.8383
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	
Retail	0.0651*	0.0761*	0.8691*	-0.0353	0.9343
	(0.0000)	(0.0000)	(0.0000)	(0.5163)	
Telecom	0.0255**	0.1994*	0.8000*	0.7760*	0.8255
	(0.0429)	(0.0000)	(0.0000)	(0.0000)	
Transportation	0.0298**	0.1786*	0.7861*	2.0200*	0.8160
	(0.0381)	(0.0000)	(0.0000)	(0.0000)	

p values are in parenthesis. Significance levels: * = 1%, ** = 5%, *** = 10%.

6. Conclusion

This paper tests the validity of the Mixture of Distributions Hypothesis (MDH) by exploring the use of contemporaneous trading volume and the number of trades as proxies for information arrival. Daily returns of 15 sector indices from the Tadawul Saudi Arabia Exchange were used, covering the period from April 5th 2008 to August 29th 2013. The TGARCH 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 findings reveal the fact that the persistence in return volatility diminishes after incorporating trading volume and number of trades for the majority of sector indices. There is a strong evidence for the validity of MDH for the Saudi stock market. The findings further suggest that the number of trades has more explanatory power as a proxy for information in 8 out of 15 sector indices, confirming the variable as a better proxy for information arrival than trading volume. A possible explanation for this outcome could be the lack of institutional investors in the Saudi equity market. Since Saudi equity market is closed to foreign investors, the large number of domestic individual investors, who generate 90% of total trade, hold a large number of trading transactions. It is also important to note that the leverage effect was amplified, indicating a more pronounced asymmetric effect of bad news on volatility.

References

Alsubaie, A., and Najand, M. (2009). Trading volume, time-varying conditional volatility, and asymmetric volatility spillover in the Saudi stock market, *Journal of Multinational Financial Management*, 19(2), 139-159.

Alzahranai, A., Gregoriou, A., Hudson, R., and Kyriacou, K. (2010). Price impact of block trades in the Saudi Stock Market, *Brunel University, Economics and Finance Working Paper Series*, No. 10-16.

Andersen, T. (1996). Return volatility and trading volume: an information flow interpretation of stochastic volatility, *Journal of Finance*, 51, 169-204.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity, *Journal of Econometrics,* 31, 307-327.

Brailsford, T. (1996). The empirical relationship between trading volume, returns and volatility, *Accounting and Finance*, 36, 89-111.

Celik, S. (2013). New Evidence on the Relation between Trading Volume and Volatility. *Business and Economic Research*, 3(1), 176-186.

Chan, K., and W. Fong (2006). Realized volatility and transactions, *Journal of Banking and Finance*, 30, 2063-2085.

Choi K. H., Z. H. Jiang, S. H. Kang, & S. M. Yoon, (2012). Relationship Between Trading Volume and Asymmetric Volatility in the Korean Stock Market, *Modern Economy*, *3*, 584-589.

Clark, P. (1973). A subordinated stochastic process model with finite variance for speculative prices, *Econometrica*, 41, 135-155.

Copeland, T. (1976). A model of asset trading under the assumption of sequential information arrival, *Journal of Finance*, 31, 1149-1168.

Ellul, A., Shin, H., and Tonks, I. (2005). Opening and closing the market: evidence from the London Stock Exchange, *Journal of Financial and Quantitative Analysis*, 40, 04, 779-801.

Epps, T. and Epps, M. (1976). The stochastic dependence of security price changes and transaction volumes: implications for the Mixture-of-Distributions hypothesis, *Econometrica*, 44, 305-321.

Farag, H. and Cressy, R. (2010). Information arrival modes and regime switching: An Egyptian tale, Birmingham Business Scholl, Working Paper.

Giot, P., S. Laurent, & M. Petitjean. (2010). Trading activity, realized volatility and jumps. *Journal of Empirical Finance,* 17(1), 168-175.

Glosten, L.R, R. Jagannathan, and D.E. Runkle. (1993). On the relation between expected value and the volatility of the nominal excess returns on stocks, *Journal of Finance* 48, 1779–1801.

Gopinath, S. and Krishnamurti, C. (2001). Number of transactions and volatility: an empirical study using high-frequency data from Nasdaq stocks, *The Journal of Financial Research*, 24, 205-218.

Harris, L. (1986). Cross-security tests of the Mixture of Distributions hypothesis, *Journal of Financial and Quantitative Analysis*, 21, 39-46.

Huang, R., and Masulis, R. (2003). Trading activity and stock price volatility: evidence from the London Stock Exchange, *Journal of Empirical Finance*, 10, 249-269.

Jones, C., G. Kaul, and M. Lipson (1994). Transactions, volume and volatility, *Review of Financial Studies*, 7, 631-651.

Karpoff, J. M. (1987). The Relation Between Price Changes and Trading Volume: A Survey, *Journal of Financial and Quantitative Analysis*, 22, 109-126.

Lamoureux, C.G. and W.D. Lastrapes, 1990. Heteroskedasticity in stock return data: Volume versus GARCH effects, *Journal of Finance*, 45, 221–229.

Ning, C., and Wirjanto, S. (2009). Extreme return-volume dependence in East-Asian stock markets: a copula approach, *Finance Research Letters*, 6(4), 202-209.

Okan B, Olgun O, & Takmaz S, (2009). Volume and volatility: a case of ISE-30 index futures, *International Research Journal of Finance and Economics*, 32, 93-103.

Omran, M. and McKenzie, E. (2000). Heteroskedasticity in stock returns data revisited: volume versus GARCH effects, *Applied Financial Economics*, 10, 553-560.

Omran, M. and Girard, E. (2007) On the Relationship Between Trading Volume and Stock Price Volatility in CASE. *Cairo and Alexandria Stock Exchanges Occasional Papers*, No. 1.

Patton, A. (2006). Volatility Forecast Comparison Using Imperfect Volatility Proxies. *Quantitative Finance Research Center*, Research Paper 175.

Tadawul Exchange. (2013) Annual Report.[online].Available at: http://www.tadawul.com.sa/Resources/Reports/Yearly_en.html[Accessed 31 January 2014].

Zakoian, J. (1994). Threshold Heteroskedasticity Model, *Journal of Economic Dynamics and Control,* 18, pp. 931-955.