JKAU: Islamic Econ., **Vol. 35** No. 1, pp: 41-55 (January 2022)
DOI:10.4197/Islec.35-1.3

Modelling the Relationship Between Trading Volume and Stock Returns Volatility for Islamic and Conventional Banks: The Case of Saudi Arabia

Karima Saci

Assistant Professor
Department of Banking and Finance
Hekma School of Business and Law
Dar Al-Hekma University, Jeddah, Kingdom of Saudi Arabia

Received: 21 February, Revised: 18 May 2021; 06 July 2021, Accepted: 14 July 2021

***ABSTRACT*.** Transparency to all parties involved in the investment process is believed to be of utmost importance in Islamic banking and finance. Hence, the trading volume and returns volatility relationship is assumed to be weaker for s*harīʿah*-compliant banks compared to the conventional counterparts. This study aims at investigating this relationship for the banking sector in Saudi Arabia. The Granger causality tests, GARCH and EGARCH models were utilized to examine the relationship between the daily stock returns volatility and trading volume over the period of January 2015 to April 2020. The findings of the paper support the mixture of distributions hypothesis. Future research could look into applying different types of GARCH models to examine stock returns volatility of Islamic and conventional banks for other countries in the GCC region.

KEYWORDS: Trading volume, Stock returns volatility, Granger causality tests, GARCH, EGARCH

JEL CLASSIFICATION: G12

KAUJIE CLASSIFICATION: I53

1. Introduction

The fundamental difference between conventional and Islamic banking is the prohibition of Ribaa and the emphasis on the compliance with the Sharia rules and ethical aspects in all financial transactions. Despite the slower observed growth in the Islamic finance industry in recent years, the Islamic banking sectors remains the main driver behind the industry`s growth. In terms of assets size, Saudi Arabia is the largest Islamic banking market in the GCC region worth US$ 409 billion, a market in which conventional and Islamic banks function together shoulder to shoulder (IRTI, 2020). This duality has called for an examination of whether or not Islamic banks stock returns are more transparent and informative compared to conventional banks (e.g. Alam & Rizvi, 2016, and Uddin *et al.,* 2018). High volatility tends to negatively impact the functioning of the banking sector and hence their economic performance. This paper aims at investigating the link between trading volume and stock returns volatility of Islamic and convectional daily returns in the Saudi dual banking industry over the period Jan 2015 to Apr 2020 with a total of 5361 daily observations.

2. Literature Review

Economists have long been investigating the relationship between trading volume and stock returns volatility. Ying (1966) was among the first researchers to look at the volume and price as joint components of a single market dynamics in which low trading volume tends to correlate with a drop in prices and vice versa. In addition, he claimed that a substantial increase in volume often precedes a major decrease or increase in prices. Subsequent studies in this field identified two alternative routes of explanation as to the price-volume link. The Mixture of Distributions Hypothesis (MDH) (Clark, 1973, Epps & Epps, 1976, Tauchen and Pitts, 1983 and Lamoureux & Lastrapes, 1990) was the one of the main theoretical rationalisations to suggest that returns volatility and trading volume are both driven by the flow of new information to the market, which justifies the contemporaneous positive correction between the two variables. A later contribution of Copeland (1976) and Jennings *et al.,* (1981) brought another explanation for the linkage. The Sequential Flow of Information Hypothesis (SIAH) assumes that traders are not informed simultaneously about the new arriving information; rather, they tend to respond to new information in a sequential manner before reaching the final new equilibrium. According to Boubaker & Makram (2011), this will cause a gradual increase in both trading volume and price movements. Hence, there is a room for the predictability of price volatility given the lagged nature to knowledge of trading volume in the process.

Recently, De Medeiros & Van Doornik (2008) investigated the link between daily return volatility and trading volume for a portfolio of 57 firms in the Brazilian stock market over the period of Jan 2000 to Dec 2005. Using unit-root tests, regression analysis, VAR and GARCH models as well as the Granger causality tests, they concluded that a significant contemporaneous relationship exists between return volatility and trading volume. Also, the dynamic nature of this relationship allowed for the predictability of one variable given knowledge of the other. Their results supported a strong mutual causality in both directions.

Ureche-Rangau & de Rorthays (2009) investigated the Chinese stock return volatility and trading volume relationship using 1305 daily observations of 36 stocks from the 9th Jul 2002 to 9th Jul 2007. The Bivariate Mixture Model BMM and GARCH (1,1) results showed the consistency of their findings with the (MDH) hypothesis in that the variables had the same multifractal behaviour despite the observed negative correlation which contradicted the direction of the relationship in the hypothesis.

Tripathy (2010) analysed the relationship between the daily trading volume and stock returns volatility in the Indian stock Market during the period from Jan 2005 to Jan 2010. Using various ARCH and GARCH models the author tested the variability in volatility and found that trading volume volatility to be more significant with recent news as opposed to past news where no significance was found. Hence, the improvement of stock returns predictability was present given the impact of new information.

Boubaker & Makram (2011) empirical work also supported the MDH hypothesis. They applied the ARCH and GARCH models to test the interlink between daily stock returns volatility and trading volume for the Tunisian stock market with the main 20 listed stocks from the 1st Jan 2008 to the 15th Feb 2010. The results showed that volatility persistence disappeared when trading volume is included as an explanatory variable. They also found that both measures of trading activity, intra-day volatility, and overnight indicators were good proxies when testing conditional volatility.

Kalu & Chinwe (2014) employed GARCH (1,1) and GARCH-X (1,1) models with All-Share Index daily returns and closing trading volume of the Nigerian stock market for the period from the 3rd Jan 2000 to 21st Jun 2011. Trading volume was used as the variable that measured new information arrival to the market. They also concluded that the variability of stock returns increased significantly with the number of information events.

The relationship between trading volume and stock returns volatility has also been studied in more mature markets. Miloudi *et al*., (2016) studied 128 French firms over the period from Apr 1996 to Oct 2014 with monthly observations for trading volumes and stock returns. They employed the GMM estimation, vector autoregression (VAR) with impulse response functions (IRF) analysis and Granger causality tests. Their results showed the existence of a positive and significant relation between market turnover and stock market returns but a statistically insignificant link between stock returns and market turnover, which implied that the lagged stock returns can be used to predict current market turnover, but not the other way around.

Al-Ajmi (2017) investigated the impact of the trading volume on the persistence of returns volatility of the Kuwait Stock Exchange using 7 sectoral indices and 20 individual listed companies. The study utilized the GARCH (1,1) model with daily observations from the 2nd Jan 2001 until the 16th Apr 2009. With the information flow proxied by the contemporaneous trading volume, the results of investigation concluded that the volume and returns are correlated with high persistence of volatility at both the sectoral and individual companies' level with a strong support for MDH hypothesis.

Naik *et al*., (2018) conducted a study using daily stock trading volume and returns volatility of South Africa over the period of 6th Jul 2006 to 31st Aug 2016. They used the EGARCH and Granger causality models to test the relationship. They found the speed to which the stock market responded to negative shocks was different compared to positive shocks with the first been more significant. Also, their findings support the MDH hypothesis in that the contemporaneous trading volume had a positive significant impact on stock return variability which allows for its potential predictability.

Miseman *et al.*, (2019) utilized the Granger causality tests and the GARCH (1,1) process to model the volatility of returns and the trading volumes for Malaysia, Indonesia and Singapore from Jan 2000 until Dec 2014 with 3600 daily observation for each country. The cross-market Granger causality results indicated that the variation of stock returns is significantly explained by the trading volumes of Malaysia and Singapore only. The Singapore market returns were also found to be related uni-directionally to the Indonesian market returns. A bi-directional causality was concluded for the relationship between the trading volumes and returns within the individual markets of Malaysian and Singapore. As for the GARCH (1,1) model, a significant positive contemporaneous relationship was found between trading volumes and stock returns in the three selected countries.

Given the current literature review, the investigations of the link between trading volume and stock returns volatility have reported a mixture of results, mostly supporting the Mixture of Distributions Hypothesis (MDH). No study has attempted examining the relationship between stock trading volume and returns volatility at the sectoral level for the Saudi stock market. This study aims at filing this gap by examining the Mixture of Distributions Hypothesis (MDH) in the Saudi banking sector.

3. Data and Methodology

There are currently twelve local banks operating in the Saudi banking sector four of which are fully Sharia compliant as per the table below.

Table (1). Saudi Banks, Type, Establishment, Branches and No of ATMs.

No.	Saudi Banks	Establishment	Branches	ATMs
Islamic Banks				
1	Al-Rajhi Bank*	1957	551	5,006
2	Bank Al-Jazira*	1975	79	618
3	Al-Bilad Bank*	2004	111	863
4	Alinma Bank*	2006	90	1,488
Conventional Banks				
5	Riyad Bank*	1957	321	2,588
6	Saudi Investment Bank	1976	48	500
7	Banque Saudi Fransi	1977	86	550
8	Saudi British Bank*	1978	75	925
9	Arab National Bank	1979	151	1,266
10	Samba Financial Group*	1980	72	520
11	The National Commercial Bank*	1953	401	3,729
12	Alawwal Bank	2008	65	560

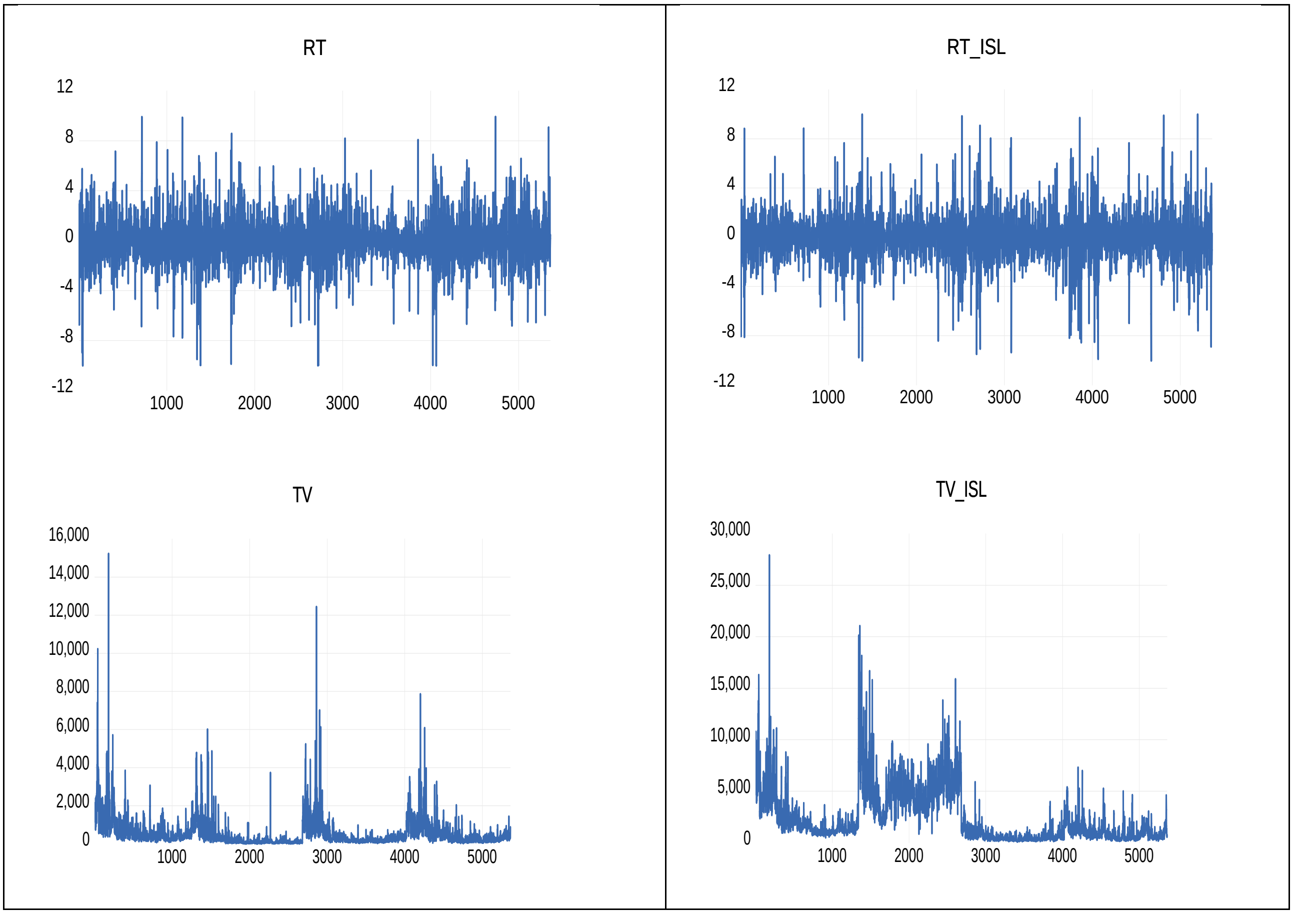
Source: * IRTI (2020) & SAMA (2018)

The sample of data used in this this study comprises of closing stock prices Pt and trading volumes of the 12 Saudi banks split into Islamic and conventional clusters. The sample period selected for this study is from Jan 2015 to 5 Apr 2020 with a daily frequency. From the values of the closing prices, the daily returns were calculated as $100 *[\ln(Pt) - \ln(Pt-1)]$. The number of shares traded are used to measure the trading volume. The variables are defined as follows:

Rt, returns of the conventional banks.
Rt_ISL, returns of the Islamic banks.
TV, The number of conventional shares traded.
TV_ISL, the number of Islamic shares traded.

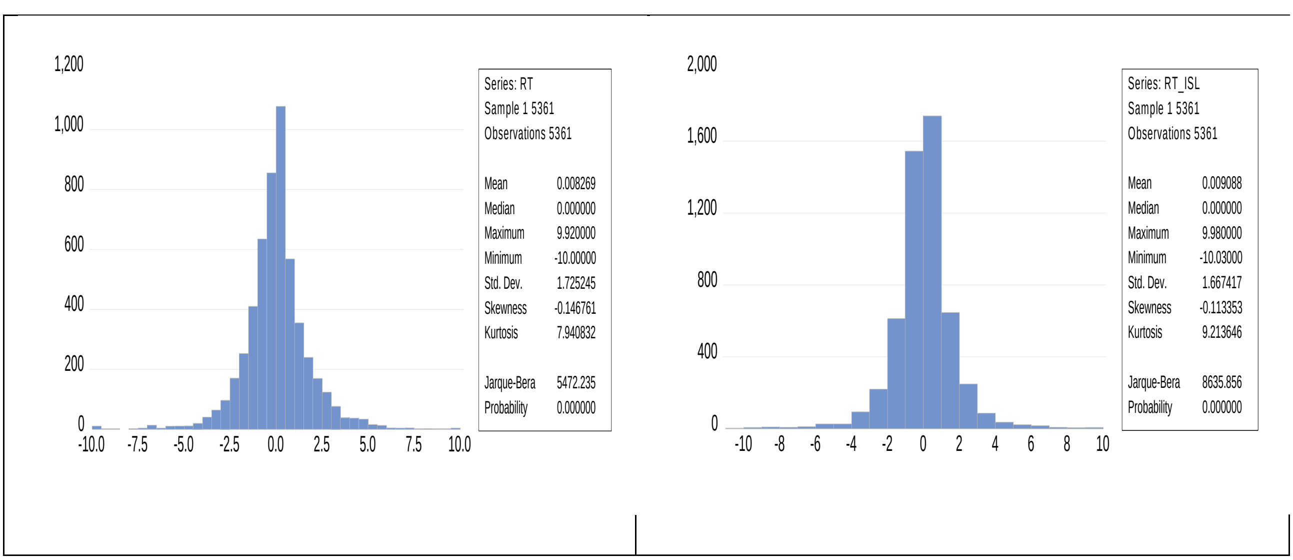
As it can be seen from the above figure that if the variance for one observation is high, it is likely that the variance of the next observation is also high and vice versa. These results suggest that the ARCH model can be applied to this data (Almarashi & Khan, 2019).

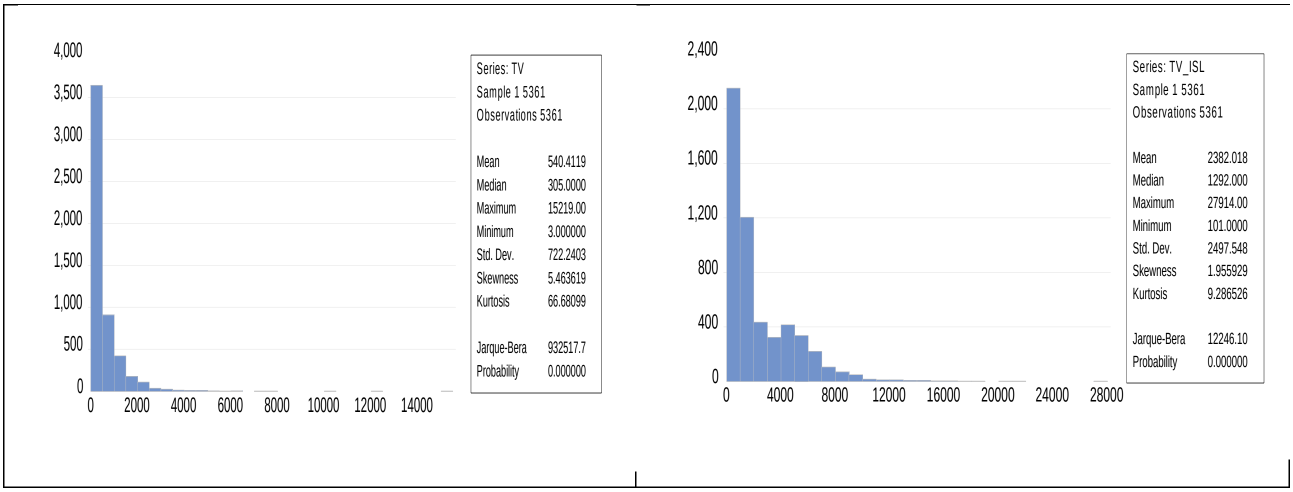
Figure 1. Saudi banks stock returns and trading volume from Jan 2015 to Arp 2020



Source: Author's Own

Figure 2. Descriptive Statistics of Saudi banks stock returns and trading volume from Jan 2015 to Arp 2020





Source: Author's own

The descriptive statistics from Figure 2 indicate that the variables are not normally distributed as the null hypothesis of normality at 1% level is rejected. The means are positive and standard deviations of the Islamic Banks's returns are lower than their conventional counterparts. Also, the variance appears to be smaller for some periods and larger for others which suggests that the variance changes auto-regressively and depends on the variance of the previous period.

3.1. Testing for Stationary

The time series data were tested for stationarity. The Augmented Dickey Fuller (ADF) and Phillips Perron(PP) Unit Root tests were used. The ADF Null hypothesis H0: ADF statistic> MacKinnon Critical Value (there is a unit root), and $H1$: ADF statistic < MacKinnon Critical Value (no root unit) (Tsay, 2005). The lag length being automatically selected based on Schwarz Information Criteria (SIC) with a maximum lag length of 32. Both the ADF and Phillips-Peron (PP) unit root tests (1988) included an intercept with no trend.

Table (2). Testing for the Stationarity of the variables.

Variable	Unit Root Test Critical Value	ADF Test Statistics	Phillips-Perron Test Statistic
Rt	-2.861884	-66.93431*	-66.97825*
Rt_ISL	-2.861884	-39.24619*	-68.99831*
TV	-2.861886	-5.997029*	-66.06274*
TV_ISL	-2.861886	-4.468563*	-23.43269*

*Denotes the rejection of the null hypothesis of a unit root at 5% level.

Source: Author's own

3.2. Granger Causality Tests

Following Naik *et al.,* (2018), Miseman *et al.,* (2019) and Hasbullah *et al.,* (2020), the Granger causality tests were used to investigate the direction of causality among the variables. There are several approaches to modelling causality in temporal systems. The original model by Granger (1969) was chosen for this study not only because it is a comprehensive framework for investigating the issue of the returns and trading volume, but also because the presence of causal ordering in the Granger's sense suggests predictability of variables (Murinde & Eng, 1994). The tests involve the estimation of the following lag distributed regressions for both Islamic and conventional data as follows:

$$x_t = \propto_0 + \sum_{i=1}^{m} \propto_i x_{t-1} + \sum_{i=1}^{n} \beta_i \, y_{t-1} + \varepsilon_t \qquad (1)$$

$$y_t = \gamma_0 + \sum_{i=1}^{m} \gamma_i \, x_{t-1} + \sum_{i=1}^{n} \delta_i \, y_{t-1} + \eta_t \qquad (2)$$

where, $\propto_0$ and γ_0 are the intercepts, and $\propto_i$, β_i, γ_i, δ_i are the parameters to be estimated, and ε_t and η_t are the white noise error terms. Table 3 shows the results of testing Granger causality the relationship between the returns and trading volume for Islamic and conventional banks in KSA.

Table (3). Granger Causality testing results.

Null Hypothesis:	Obs	F-Statistic	Prob.
RT_ISL does not Granger Cause TV_ISL	5360	4.20761	0.040*
TV_ISL does not Granger Cause RT_ISL		5.56656	0.010**
RT does not Granger Cause TV		9.50272	0.002**
TV does not Granger Cause RT		14.5651	0.000**

*Denotes the rejection of the null hypothesis at 5% level.
**Denotes the rejection of the null hypothesis at 1% level.

Source: Author's own

The results show that the P-values are less than 0.05, hence, the null hypothesis of no causality is rejected indicating the existence of a bilateral causality between trading volumes and returns at the 5% level of significance (Gujarati,1998 and Murinde & Eng, 1994). It is worth noting that the causality between Islamic banks returns and volume is the weakest though still significant at the 5% level. It is concluded that the volume has an effect on predicting the returns of both Islamic and conventional banks in KSA. The same results were reported by Miseman *et al.*, (2019) for both Malaysia and Singapore.

3.3. ARCH LM Test Heteroscedasticity Test

For high frequency data it is well established in the literature that Engle (1982) suggested the usage of autoregressive, conditionally heteroscedastic, or ARCH model. Engle (1982) who pioneered volatility modelling, suggested that for the GARCH- family models to be valid, there is a need for checking whether or not the series is characterized by the ARCH effect. The residuals are examined with the ARCH LM test to see if the variation appears to change. This tests whether the current variance of the disturbance term, σ_t^2, is conditional on recent values of the squares of the observed disturbances (e_{t-1}^2).

$$\sigma_t^2 = \delta_0 + \delta_1 e_{t-1}^2 + \delta_2 e_{t-1}^2 + \cdots + \delta_p e_{t-p}^2 + \varepsilon_t \ (3)$$

Table (4). Heteroskedasticity tests.
Heteroskedasticity Test: ARCH

RT		
F-statistic	451.4546	Prob. F(1,5357)
Obs*R-squared	416.5214	Prob. Chi-Square(1)
RT_ISL		
F-statistic	344.2481	Prob. F(1,5357)
Obs*R-squared	323.5828	Prob. Chi-Square(1)

Source: Author's own

The chi-squared and F-tests of H_0: $\delta_1 = \delta_2 = ... = \delta_p = 0$ are carried out. If the hypothesis is true, the variance is a constant and there are no ARCH effects. In table 4 above the chi-squared and F statistics are large with a small probability hence, the null hypothesis is rejected and the variance is not constant so the ARCH effect is present since the variance changes.

3.4 The GARCH(1,1) Model

Bollerslev (1986) extended the ARCH model to the GARCH version which is considered the most used model for volatility testing in finance, and in many cases, the only model estimated and reported in empirical work. The standard GARCH model allows the conditional variance to be dependent upon its previous own lags. The model is typically of the following form:

$$\sigma_t^2 = \omega + \beta\sigma_{t-1}^2 + \propto \varepsilon_{t-1}^2 \quad (4)$$

Where the variance σ_t^2 of the time series today is equal to a constant ω, plus some amount α of the lagged residual ε_{t-1}^2 plus some amount β of its own lags. According to Namugaya *et al.*, (2014) the GARCH (1,1) outperformed the other GARCH models when it comes to modelling the volatility of the returns. This was also confirmed by Abdullah *et al.*, (2017).

The model consists of the two equations:
The Mean equations:

$$R_t = C_r + a_i R_{t-1} + b_j TV_t + \varepsilon_{1t} \quad (5)$$

$$R_{ISL_t} = C_x + c_i R_{ISL_{t-1}} + d_j TV_{ISL_t} + \varepsilon_{2t} \quad (6)$$

Table (5). GARCH(1,1) model for RT.

Dependent Variable: RT

Method: ML ARCH - Normal distribution (Marquardt / EViews legacy)
Included observations: 5360 after adjustments

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.024333	0.023340	1.042529	0.2972
RT(-1)	0.085606	0.014926	5.735493	0.0000
TV	0.000130	2.35E-05	5.515568	0.0000
Variance Equation				
C	0.177785	0.012640	14.06477	0.0000
RESID(-1)^2	0.181293	0.008857	20.46970	0.0000
GARCH(-1)	0.771249	0.009759	79.03065	0.0000

Source: Author's own

The above mean equation indicates that the contemporaneous trading volume is positive and highly statistically significant at 1%, level. The variance equation for Rt is:

var = 0.177785+ 0.181293 e(-1)^2 +0.771249 var(-1)

(0.000) (0.0000) (0.0000)

Here the ARCH and GARCH terms are both positive and significant which is consistent with Attari et al., (2012) and Al-Ajmi (2017). Jena (2016) stated that according to Lamoureux and Lastrapes (1990) and Najand and Yung (1991), the more the sum of the coefficients, α and β approaches one, the further the volatility shocks endure into the future. Hence, the effect of a shock on volatility is more persistent over time as the total of the parameters of α and β approaches one, while with a small value of α and β, such a shock has little effect.

The estimates of α and β in table 5 are 0.181293 and 0.771249 and their sum is 0.952542 which is close to 1, showing that the estimated model is stable indicating high level of volatility persistence. Since only the squared residuals are considered in the equation the sign of the residuals or shocks have no effects. However, large changes in the conditional variance on previous or past information are typically followed by large changes which tends to be driven by bad news and small changes are also followed by small changes usually associated with positive shocks. In both cases the future volatility in the market is impacted.

Table (6). GARCH(1,1) model for RT_ISL.

Dependent Variable: RT_ISL
Method: ML ARCH - Normal distribution (Marquardt / EViews legacy)
Included observations: 5360 after adjustments

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.047269	0.020350	2.322880	0.0202
RT_ISL(-1)	0.061289	0.014575	4.205170	0.0000
TV_ISL	0.000203	2.82E-05	5.312132	0.0000
Variance Equation				
C	0.236272	0.013566	17.41607	0.0000
RESID(-1)^2	0.212623	0.010339	20.56588	0.0000
GARCH(-1)	0.721408	0.010528	68.52428	0.0000

Source: Author's own

The variance equation for Rt_ISL is:

var = 0.236272+ 0.212623 e(-1)2 +0.721408 var(-1)

(0.000) (0.0000) (0.0000)

In table 6 above the ARCH and GARCH terms are also both significant. The estimates of α and β are 0.212623 and 0.721408 so that their sum is 0.934031 which shows a high level of volatility persistence that is slightly less than the one present for the conventional banks. Also, the estimated model is stable and good enough to be used to model the returns volatility.

The results indicate that the degree of persistence of volatility as measured by the sum of the parameters α and β is high for both conventional and Islamic banks' returns with the persistence being over 0.90. Kalu O & Chinwe (2014) as well as Al-Ajmi (2017) reported the same level of persistence for the Nigerian Stock Exchange (NSE) All-Share Index and for the sample of sectors and companies listed on the Kuwait stock exchange respectively.

3.5. GARCH Model Diagnostics

For the GARCH (1,1) model to be valid the ARCH test for Heteroskedasticity as well as the standardized ACF/PACF squared residual Corelogram plots are used to see whether there are serial correlations or not in the residuals. The LM tests for ARCH effects in the standardised residuals. This tests whether the GARCH model has removed the original ARCH effects. The null hypothesis is that the variance of the standardised residuals is constant. The test with 12 lags gives:

Table (7). Heteroskedasticity test of the GARCH(1,1) model.

Heteroskedasticity Test ARCH

RT			
F-statistic	0.019475	Prob. F(1,5357)	0.8890
Obs*R-squared	0.019482	Prob. Chi-Square(1)	0.8890
RT_ISL			
F-statistic	0.022107	Prob. F(1,5357)	0.8818
Obs*R-squared	0.022115	Prob. Chi-Square(1)	0.8818

Source: Author's own

The above high probabilities show that the GARCH (1,1) model has resulted in the variance being constant.

Figure 3: AC, PAC & Q-statistics with 12 lags

Dependent Variable: RT

Included observations: 5360 after adjustments

Lag	AC	PAC	Q-Stat	Prob*
1	0.004	0.004	0.0962	0.756
2	-0.005	-0.005	0.2430	0.886
3	-0.023	-0.023	3.0726	0.381
4	-0.008	-0.008	3.4432	0.487
5	-0.005	-0.005	3.5564	0.615
6	-0.000	-0.001	3.5576	0.736
7	-0.018	-0.019	5.3732	0.615
8	0.002	0.001	5.3854	0.716
9	-0.025	-0.025	8.7821	0.458
10	0.015	0.014	9.9548	0.444
11	0.011	0.011	10.655	0.473
12	-0.006	-0.007	10.838	0.543

Dependent Variable: RT_ISL

Included observations: 5360 after adjustments

Lag	AC	PAC	Q-Stat	Prob*
1	-0.002	-0.002	0.0195	0.889
2	-0.010	-0.010	0.5413	0.763
3	-0.024	-0.024	3.7158	0.294
4	-0.009	-0.009	4.1449	0.387
5	-0.000	-0.001	4.1454	0.529
6	-0.020	-0.021	6.2917	0.391
7	-0.023	-0.024	9.1166	0.244
8	0.024	0.023	12.229	0.141
9	-0.003	-0.004	12.278	0.198
10	-0.015	-0.016	13.444	0.200
11	0.005	0.005	13.567	0.258
12	-0.013	-0.013	14.462	0.272

Source: Author's own

From Figure 3 it can be seen that AC and PAC are not significant, which is shown by the probability value of the Ljung-Box statistic that is greater than the confidence level of 0.05 hence, it can be concluded that the standardised residuals are random so the GARCH (1,1) model is valid.

3.6. The EGARCH Model

According to McAleer & Hafner (2014), despite the fact that the ARCH and GARCH models are the most widely used to investigate volatility with a symmetry that implies a similar effect of equal magnitude of stocks on volatility, the Exponential GARCH (EGARCH) model is better able to account for to the asymmetric effect on volatility caused by negative and positive shocks. The model also allows unrestricted estimation of the parameters (Nelson, 1991). The logarithm of the conditional variance is explained as follows:

$$ln\sigma_t^2 = \omega + \beta\, ln(\sigma_{t-1}^2) + \gamma \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \left[\frac{|\varepsilon_{t-1}|}{\sqrt{\sigma^2{}_{t-1}}} - \sqrt{\frac{2}{\pi}} \right] \tag{7}$$

The parameter β represents the persistence in conditional volatility. The α captures the symmetric effect of the model, which is the GARCH effect. The γ parameter measures the asymmetry or the leverage effect. If $\gamma = 0$, then the model is symmetric. When $\gamma < 0$, then positive shocks generate less volatility than negative shocks. If $\gamma > 0$, then positive shocks are more destabilizing than the negative ones.

Table (8). EGARCH(1,1) model for RT.

Dependent Variable: RT
Method: ML ARCH - Normal distribution (Marquardt / EViews legacy)
Included observations: 5360 after adjustments
Convergence achieved after 22 iterations
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(4) + C(5)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(6)
*RESID(-1)/@SQRT(GARCH(-1)) + C(7)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.021217	0.022746	-0.932777	0.3509
RT(-1)	0.090759	0.014210	6.387160	0.0000
TV	0.000132	2.27E-05	5.793007	0.0000
Variance Equation				
C(4)	-0.171977	0.007084	-24.27791	0.0000
C(5)	0.331176	0.011907	27.81455	0.0000
C(6)	0.016365	0.007997	2.046239	0.0027
C(7)	0.924825	0.005062	182.6852	0.0000

Source: author's own

Table (9). EGARCH (1,1) model for RT_ISL.

Dependent Variable: RT_ISL
Method: ML ARCH - Normal distribution (Marquardt / EViews legacy)
Sample (adjusted): 2 5361
Included observations: 5360 after adjustments
Convergence achieved after 21 iterations
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(4) + C(5)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(6)
*RESID(-1)/@SQRT(GARCH(-1)) + C(7)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.072435	0.017975	4.029846	0.0001
RT_ISL(-1)	0.059883	0.013815	4.334727	0.0000
TV_ISL	2.73E-05	1.27E-05	2.146288	0.0218
Variance Equation				
C(4)	-0.175406	0.007678	-22.84479	0.0000
C(5)	0.342718	0.012420	27.59411	0.0000
C(6)	0.023098	0.008129	2.841311	0.0045
C(7)	0.915618	0.005209	175.7890	0.0000

Source: Author's own

In table 8 the coefficient C(6) which measures the asymmetry of the variable shows a positive value, which suggests that good news are more destabilizing than bad news for the Saudi conventional banks. The coefficient C(5) that estimates ARCH effects is statistically significant which this confirms the appropriateness the GARCH model estimated above. The same is observed with the GARCH coefficient C(7).

Very similar findings were recorded for the Saudi Islamic banks with the estimation of the EGARCH model. The measure of asymmetry is positive and significant. Both the ARCH and GARCH effects are also significant confirming the validity of the estimated GARCH model.

Table (10). Heteroskedasticity test of the EGARCH (1,1) model.

Heteroskedasticity Test: ARCH			
RT			
F-statistic	1.037416	Prob. F(12,5335)	0.4105
Obs*R-squared	12.45027	Prob. Chi-Square(12)	0.4102
RT_ISL			
F-statistic	1.266718	Prob. F(12,5334)	0.2310
Obs*R-squared	15.19436	Prob. Chi-Square(12)	0.2310

Source: author's own

The above probability values are high, hence, the null hypothesis of no ARCH effect is accepted validating the results of the EGARCH model for both the Islamic and conventional banks. Overall, the same pattern of asymmetry is observed cross the board in the banking sector of Saudi Arabia, regardless of the dual nature of this sector.

4. Summary and Conclusions

This paper empirically examined and compared the stock returns volatility for the Saudi listed Islamic and conventional banks. Using a sample of 5361 daily observation from Jan 2015 to Apr 2020, the Granger causality tests were used. It was found that a bilateral causality between trading volumes and returns exists at the 5% level of significance indicating that rising market returns go with rising volumes and vice versa for both Islamic and conventional banks. No differences were observed between the behaviour of Islamic and conventional banks returns.

The results also confirmed that the contemporaneous trading volume is an important variable in explaining the volatility dynamics of the returns which supports the mixture of distributions hypothesis. The findings suggest that one of the factors causing high serial dependence in stock returns is the existence of conditional heteroscedasticity or volatility in stock returns which also showed that GARCH (1,1) is an appropriate representation of conditional variance suggesting that volatility helps to explain the returns. The EGARCH model confirmed the results of the GARCH model and suggested that positive shocks are more destabilizing than negative shocks for both the Islamic and conventional banks returns. The finding of positive contemporaneous relationships supports similar previous investigations (e.g. Ureche-Rangau & de Rorthays, 2009, Tripathy, 2010, Al-Ajmi, 2017 and Miseman *et al.,* 2019). Finally, future research could look into applying different types of GARCH models to examine stock return volatility of Islamic and conventional banks for other countries in the GCC region.

References

Abdullah, S.M, et.al. (2017). Modeling and forecasting exchange rate volatility in Bangladesh using GARCH models: a comparison based on normal and Student's t-error distribution. *Financial Innovation volume* 3, Article number: 18.

Al-Ajmi, J. (2017). Trading volume and volatility in the Boursa Kuwait. *The British Accounting Review*, **10**: 0890-8389.

Alam, N.S. and **Rizvi, S.A.R.** (2016). Do Islamic stock indices perform better than conventional counterparts? An empirical investigation of sectoral efficiency. *Review of Financial Economics, Elsevier*, **31**: 108-114.

Almarashi, M. and **Khan, K.** (2019). Assessing Volatility Modelling using three Error Distributions. *European Online Journal of Natural and Social Sciences*, **8**(**1**): 36-42.

Attari, M.I.J., et.al. (2012). The Dynamic Relationship between Stock Volatility and Trading Volume. *Asian Economic and Financial Review*, **2**(**8**): 1085-109.

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

Boubaker, A. and **Makram, B.** (2011). The empirical relationship between stock returns volatility and trading volume: evidence on the Tunis stock market. *International Journal of Management Science and Engineering Management*, **6**(**5**): 374-381.

Clark P. (1973). A Subordinated Stochastic Process Model with Finite Variance for Speculative Prices. *Econometrica*, **41**: 135-155.

Copeland T.E. (1976). A Model of Asset Trading under the Assumption of Sequential Information Arrival. *Journal of Finance*, **31**(**4**): 135-155.

De Medeiros, O. and **Van Doornik, B.** (2008). The Empirical Relationship Between Stock Returns, Return Volatility and Trading Volume in the Brazilian Stock Market. *Brazilian Business Review*, **5**(**1**): 01-17.

Engle, R.F. (1982). Autoregressive conditional heteroskedasticity with estimates of the variance of U.K. inflation. *Econometrica*, **50**: 987-1008.

Epps T.W. and **Epps M.L.** (1976). The Stochastic Dependence of Security Price Changes and Transaction Volumes: Implications for the Mixture of Distribution Hypothesis. *Econometrica*, **44**: 305-321.

Gujarati, D.N. (1998). Causality in Economics In, Basic Econometrics 3rd edition, 620-624. McGRAW-HILL INC. New York.

Granger, C.J. (1969). Investigating Causal Relationships by Econometrics Models and Cross Spectral Methods. *Econometrica*, **37**: 425-435.

Hasbullah, E.S, et al. (2020). The GARCH Model Volatility of Sharia Stocks Associated Causality with Market Index. *International Journal of Quantitative Research and Modeling*, **1**(**1**): 18-28

Islamic Research and Training Institute IRTI. (2020). Islamic Finance in Saudi Arabia: Leading the Way to Vision 2030. Islamic Development Bank.

Jena, S.K. (2016). Sequential Information Arrival Hypothesis: More Evidence from the Indian Derivatives Market, *The Journal of Business Perspective*. **20**(**2**): 101–110.

Jennings, R.H, et. al. (1981). An Equilibrium Model of Asset Trading with Sequential Information Arrival. *Journal of Finance*, **36**: 143-161.

Kalu., E.K. and **Chinwe, O.C.** (2014). The Relationship Between Stock Returns Volatility and Trading Volume in Nigeria. *Business Systems & Economics*, **4**(**2**): 115-125.

Lamoureux C.G. and **Lastrapes W.D.** (1990). Heteroscedasticity in stock return data: Vol-ume versus GARCH effects. *Journal of Finance*, **45**(**1**): 221-229.

McAleer, M. and **Hafner, C.A.** (2014) one line derivation of EGARCH,. *Econometrics*, **2**(**2**): 92-97.

Miloudi, A, et.al. (2016). Relationships between Trading Volume, Stock Returns and Volatility: Evidence from the French Stock Market. Bankers. Markets & Investors nº 144 September 16.

Miseman. M.R, et al. (2019). The Dynamic Relationship Between Trading Volume, Stock Return and Volatility-Domestic and Cross Country: South Asian Markets. *Finance, Accounting and Business Analysis*.**1**(**1**): 1-21.

Murinde, V. and **Eng, F.S.H.** (1994). Financial Development and Economic Growth in Singapore: demand following or supply-leading? *Applied Financial Economics*, **4**(**6**): 391-404.

Najand, M. and **Yung, K.** (1991). A GARCH examination of the relationship between volume and price variability in futures markets. *Journal of Futures Markets*, **1**(**5**): 613-621.

Naik, P.K, et.al. (2018). The Relationship between Stock Market Volatility and Trading Volume: Evidence from South Africa. *The Journal of Developing Areas*, **52**(**1**): 99-114.

Namugaya, J., et.al. (2014). Modelling Volatility of Stock Returns: Is GARCH(1,1) Enough?. *International Journal of Sciences: Basic and Applied Research*, **16**(**2**): 216-223.

Nelson, D.B. (1991). Conditional heteroskedasticity in asset returns: A new approach. *Econometrica*, **59**: 347-370.

Phillips, P. and **Perron, P.** (1988) Testing for a Unit Root in Time Series Regression. *Biometrika*. **75**: 335-346.

SAMA, (2018). Saudi Arabian Monetary Authority: 54th Annual Report 2018.

Tauchen, G. and **Pitts M.** (1983). The Price Variability-volume Relationship on Speculative Markets. *Econometrica*, **51**(**2**): 485-505.

Tripathy, N. (2010). The Empirical Relationship between Trading Volumes & Stock Return Volatility in Indian Stock Market. *European Journal of Economics, Finance and Administrative Sciences*, ISSN 1450-2275 Issue **24**.

Tsay, R.S. (2005). Analysis of Financial Time Serie, Second Edition, USA: John Wiley & Sons, Inc.

Uddin, G.S, et.al.(2018) Time-varying evidence of efficiency, decoupling, and diversification of conventional and Islamic stocks. *International Review of Finance*. Anal., **56**: 167-180.

Ureche-Rangau, L. and **Rorthays, Q. D.** (2009). More on the volatility-trading volume relationship in emerging markets: The Chinese stock market. *Journal of Applied Statistics*, **36**(**7**): 779-799.

Ying, C. (1966), Stock Market Prices and Volume of Sales. *Econometric*a, **34**: 676-686.

Karima Saci is an assistant professor and the Chair of the Banking and Finance Department at Dar Al-Hekma University, Jeddah, KSA. She attained her MSc in International Banking and Finance from Liverpool John Moores University in the UK. She completed her PhD in Banking and Finance in 2006 from the same university where she worked as a senior lecturer for five years before joining Effat University, KSA in 2011 as the Chair of the Finance Department. In 2016 she obtained her professional Certification as an Islamic Banker. She also completed her Postgraduate Certificate in Teaching and Learning in Higher Education in the UK.

Email: karimasaci@gmail.com

نمذجة العلاقة بين حجم التداول وتقلب عوائد الأسهم للبنوك الإسلامية والتقليدية: حالة المملكة العربية السعودية

كريمة ساسي

قسم المصرفية والتمويل - كلية الأعمال والقانون

جامعة دار الحكمة - جدة - المملكة العربية السعودية

المستخلص. يُعتقد أن الشفافية لجميع الأطراف المشاركة في عملية الاستثمار ذات أهمية قصوى في الصيرفة والتمويل الإسلامي. ومن ثم، يُفترض أن تكون علاقة تقلب حجم التداول والعوائد أقل بالنسبة للبنوك المتوافقة مع الشريعة الإسلامية مقارنة بنظيرتها التقليدية. تهدف الدراسة إلى التعرف على هذه العلاقة في القطاع المصرفي في المملكة العربية السعودية. للوصول للنتائج المرجوة استخدام البحث اختبارات جرانجر (Granger) السببية، ونماذج جارش (GARCH) و (EGARCH) لفحص العلاقة بين تقلب عوائد الأسهم اليومية وحجم التداول خلال الفترة يناير ٢٠١٥– أبريل ٢٠٢٠. تدعم نتائج الورقة فرضية وصول المعلومات المتسلسلة، والتي أظهرت عدم وجود فرق بين سلوك البنوك الإسلامية ونظريتها التقليدية. في ضوء النتائج المُتوصل إليها يظهر من الأهمية بمكان توسيع نطاق الدراسة باستخدام نماذج (GARCH) المختلفة لفحص علاقة تقلب حجم التداول وعوائد الأسهم بالنسبة للبنوك الإسلامية والتقليدية على مستوى دول مجلس التعاون الخليجي الأخرى.

الكلمات الدَّالة: حجم التداول، تقلبات عائد الأسهم، اختبارات جرانجر (Granger) السببية، نموذج جارش (GARCH) ،أي جارش (EGARCH)

تصنيف JEL: G12

تصنيف KAUJIE: I53