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Research Paper

An Empirical Investigation of Trading Volume and Return Volatility Sectors of the Tunisia Stock Exchange

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ABSTRACT: *This study examines the relationship in terms of sector between the trading volumes, stock market return volatility of four sectors of the Tunisian Stock Exchange. The sectors are the financial companies, consumer services, consumer goods and industry. It employs daily data from 2013 to 2017 and adopted the GARCH model. To make the analysis more rigorous, this paper splits trading volume into unexpected and expected activity, in order to examine the impact of each component on volatility. The results indicate that the return volatility is best described by a GARCH (1,1) specification. The study shows again that the persistence in volatility is not eliminated when total trading volume is incorporated into a GARCH model. It is also found that the impact of unexpected trading activity on stock return volatility is greater than expected activity.*
KEYWORDS: *GARCH mode, Return, Sectors, Volatility, Volume.*

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I. INTRODUCTION

Tunisian stock market is the only official stock exchange in Tunisia. It has undergone a remarkable evolution during these last few years. It is the first institution operating in the financial sector to obtain the ISO 27001 certification, in Tunisia, which attests that the information security management system meets the most stringent international practices (Annual Report of Tunis Stock Exchange in 2016). End-of-year 2016, the market capitalization of the market stood at 19.300 million dinars against 3.840 million dinars at the end of 2005, recording an increase of 400%, equivalent to 15.460 million dinars. The financial companies still dominate the market capitalization with a share of 62%, at the end of 2005, against 49% at the end of 2016. On the other hand, the exchange maintained sustained growth in terms of the trading volume and the market index. The trading volume on the stock exchange increased to reach 1740,7 million dinars in 2016 against 701 million dinars in 2005, recording an increase of 148%. During the same period the market index (Tunindex) closed the year 2016 at the point 5488,77; against 1335,29 point at the beginning of 2005, recording an increase of 311%.

Trading volume, volatility and returns, were widely investigated on financial markets (e.g Lamoureux and Lastrapes, 1990, Sharma et al., 1996, Huang and Yang, 2001, Hsieh, 2014, Kartsaklas, 2017 and Bouras et al., 2018). These variables are among the most important indicators for investors. They help them in portfolio management decisions (see Apergis et al., 2017 and Bouras et al., 2018). Lamoureux and Lastrapes (1990) assumed that the trading volume is an indirect indicator of the rate of information receipt. They empirically tested that the daily stock returns are generated by a mixture of distributions, in which the mixing variable (daily volumes) is hypothesized to be the rate of information receipt. Lamoureux and Lastrapes (1990) applied the GARCH model for a sample of 20 stocks for 375 days during 1980. Lamoureux and Lastrapes (1990) found that GARCH effects disappear with the introduction of the trading volume in the variance equation. They confirmed that the trading volume does not play its role as an information keeper. Sharma et al., (1996) criticized the work of Lamoureax and Lastrapes (1990). Indeed, the work of Lamoureax and Lastrapes (1990) was carried out on individual stocks, based on a micro level study. According to Sharma et al., (1996), the volatility of an individual asset is influenced by specific factors (specific risk) of the asset, as well as by market factors (systematic risk). They asserted that these two factors affect both trading volume and return volatility for individual stocks. This double influence make trading volume a good proxy for information flow. But it affects the conditional volatility model which makes the GARCH effect disappear for individual shares, as Lamoureax and Lastrapes (1990) found.

Contrary to Lamoureax and Lastrapes (1990), Sharma et al., (1996) focused on a macro level. They studied the GARCH effects in the market index returns and volume data for four years. The results suggested that market returns are strongly related to the GARCH model in the absence of volume as a mixing variable. The insertion of volume as a proxy for information arrival in the conditional variance model describes well the GARCH effects in stock returns. Indeed, the GARCH effects did not vanish as a result of that insertion.

Huang and Yang (2001) focused on a macro and micro level. They studied an empirical investigation of trading volume and return volatility using 5-min interval stock returns of the Taiwan stock index. Their results showed that the persistence of stock volatility remained dominant after the stochastic mixing variable was included in the variance equation. Similar results were also found for individual stocks in the sample. Girard and Omran (2009) analyzed the link between volatility and volume in 79 trading companies at the Cairo and Alexandria Stock Exchange over a period from January 1998 to May 2005. They found that the persistence in volatility was not eliminated when lagged or contemporaneous trading volume was incorporated into a GARCH model. Bouras et al., (2018) analyzed the role of country-specific and global geopolitical risks (GPRs) on the returns and volatility of 18 emerging market economies. They used a panel Generalized Autoregressive Conditional Heteroskedasticity (GARCH) approach. Their results showed that the persistence of stock volatility remained dominant after the stochastic mixing variable (GPRs) was included in the variance equation. Indeed, the coefficients of ARCH and GARCH terms were found to be statistically significant. The volatility was highly persistent since the sum of the ARCH and GARCH parameter coefficients were always close to one.

This study applies the methodology initially developed by Lamoureux and Lastrapes (1990), then applied by Sharma et al., (1996), Arago and Nieto, (2005), Girard and Omran (2009) and Bouras et al., (2018). It investigates the extent to which trading volume explains the GARCH effects for market returns. The main difference between this study and the other studies is the use of sectoral indicators. Our study is carried out on sectors while the other studies focus on individual stocks and market indicators. The sectors are the financial companies, consumer services, consumer goods and industry.

The rest of the paper is structured as follows: section 2 describes the data. Section 3 develops the econometric methodology. Section 4 presents the results. Section 5 summarizes and concludes the paper.

II. DATA

To study the relationship between return volatility and volume, our study uses daily returns and trading volume for the four sectors listed at Tunisia Stock Exchange for the period January 2, 2013 to December 31, 2017. The return of each sector index and sectoral volume data are provided by Tunisia Stock Exchange. The daily rate of return corresponding to sectoral index i for day t, $(r_{i,t})$, is the continuously compounded return defined as follows:

$$r_{i,t} = 100 \times \ln\left(\frac{S_{i,t}}{S_{ti-1}}\right) \rightarrow (1)$$

Where $(S_{i,t})$ is the daily closing sectoral index at the time t.

The volume parameter for each sector i for day t, $(v_{i,t})$, is measured as follows:

$$v_{i,t} = \ln\left(\frac{Vol_{i,t}}{Vol_{i,t-1}}\right) \rightarrow (2)$$

Where $(v_{i,t})$, is the daily return of trading volume. $(Vol_{i,t})$, denotes the level of trading volume for sector i on day t. Enders (1995) and Sabbaghi (2011) denoted that the daily return of trading volume pushes GARCH models to be econometrically estimated.

Table 1. Descriptive statistics of daily return for each sector

		Financial Companies	Consumer Services	Consumer Goods	Industry
Mean		0.030413	-0.018258	0.063565	-0.021704
Maximum		2.050207	2.627572	4.496341	2.255222
Minimum		-3.014003	-5.211879	-4.869462	-4.191643
Std. Dev.		0.428865	0.587354	0.850846	0.630431
Skewness		0.098790	-0.258703	0.449948	-0.038308
Kurtosis		6.934954	8.776872	7.546152	5.407034
Jarque-Bera		805.8974***	1746.474***	1115.030***	301.1002***
Q(36)		86.510***	47.748*	57.391***	39.840*
ADF Test	Intercept	-29.751***	-21.88367	-30.485***	-32.626***
	Trend and Intercept	-29.760***	-21.887***	-30.473***	-32.687***
PP Test	Intercept	-29.816***	-33.549***	-30.540***	-32.670***
	Trend and Intercept	-29.824***	-33.553***	-30.528***	-32.720***

Note: Jarque-Bera (J-B) is the test statistic for the null hypothesis of normality in sample returns distributions. Q(36) statistics test serial correlations up to a 36th lag length. The critical value for the ADF and PP tests are –3.436 (without trend) and –3.966 (with trend), at the 1% significance level, respectively. Significance levels: ***1%, **5%, *10%.

Table 1 presents the basic descriptive statistics for daily return. The average sectoral returns range from -0.021704 (industry) to 0.063565 (consumer goods). The statistics show that the averages daily return of consumer services and industry are negative during the study period. The average daily return of financial companies and consumer goods are positive. The average daily return of the second sector is higher, but it also entails more risk. This is confirmed by the standard deviation results. The standard deviation of consumer goods is higher than the other sectors.

Table 2. Descriptive statistics of daily return of trading volume for each sector

		Financial Companies	Consumer Services	Consumer Goods	Industry
Mean		0.001530	0.006898	0.004679	0.004680
Maximum		4.918573	5.620525	5.620525	5.620525
Minimum		-4.422133	-6.023804	-4.740687	-4.740687
Std. Dev.		0.920677	0.927748	0.905130	0.905050
Skewness		-0.165194	0.036669	0.144358	0.144232
Kurtosis		7.442615	9.070087	8.010131	8.013114
Jarque-Bera		1028.684***	1913.198***	1307.509***	1309.054***
Q(36)		254.57***	230.07***	276.73***	276.55***
ADF Test	Intercept	-17.26753	-22.437***	-23.604***	-23.592***
	Trend and Intercept	-17.263***	-22.427***	-23.600***	-23.589***
PP Test	Intercept	-223.23***	-124.12***	-134.91***	-135.16***
	Trend and Intercept	-223.70***	-123.67***	-135.10***	-135.37***

Note: Jarque-Bera (J-B) is the test statistic for the null hypothesis of normality in sample returns distributions. Q(36) statistics test serial correlations up to a 36th lag length. The critical value for the ADF and PP tests are –3.436 (without trend) and –3.966 (with trend), at the 1% significance level, respectively. Significance levels: ***1%, **5%, *10%.

Table 2 reports the per sector summary statistics of the daily return of trading volume. It shows that the consumer services sector has the highest average transaction volume compared to other sectors, with value equal to 0.006898. Among the 4 sectors consumer services sector presents also the largest fluctuations around its mean, as reflected by the standard deviation, with value equal to 0.927748. On the contrary, financial companies sector has the lowest average transaction volume, with value equal to 0.001530.

For all series, the measures of skewness are all strictly different from zero; which means that the series are asymmetric. The measures of kurtosis are strictly greater than three (3), which means that the distributions are leptokurtic. The Jarque-Bera normality test rejects normality of all series at 1% level.

In order to guarantee the goodness of fit of the model and to enable the results be relevant, some diagnostic tests are conducted. This paper tests the stationarity of returns and trading volume. It employs both the augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test. The null hypothesis that returns and trading volume are non stationary is rejected at the 1% significance level, indicating that both trading volume and returns are stationary. In addition, the autocorrelation coefficient (Q) up to 36 lags is statistically significant which indicates that all series suffer from serial correlation. These results suggest the proper application of the GARCH model (see, Arago and Nieto, 2005 ; Girard and Omran, 2009 and Sabbaghi, 2011).

III. ECONOMETRIC METHODOLOGY

This section exhibits the empirical analysis adopted to evaluate the relationship in terms of sectors between the trading volume, stock market returns and volatility of four sectors of the Tunisian Stock Exchange. The GARCH model of Bollerslev (1986), which is a generalization of the ARCH model developed by Engle (1982), is applied. Similarly to Arago and Nieto (2005), Girard and Omran (2009) and Bouras et al., (2018) the model is estimated, using the maximum likelihood method and assuming the hypothesis of generalized error distribution, which is the distribution likely to take into account the asymmetrical and leptokurtic characteristics of financial series.

First, the paper identifies the variance of return on the stock exchange index simply explained by the lags in conditional and unconditional variance using the specification included in (3)–(5).

$$r_{i,t} = \rho_{t-j} + \varepsilon_{i,t} \rightarrow (3)$$

$$\varepsilon_{i,t} / (\Phi_{i,t-1}) \approx N(0, h_{i,t}) \rightarrow (4)$$

$$h_{i,t} = \alpha_{i,0} + \alpha_{i,1}\varepsilon_{i,t-1}^2 + \alpha_{i,2} h_{i,t-1} \rightarrow (5)$$

Where

$(r_{i,t})$ is the daily sector index return (i),

$(\rho_{i,t-j})$ is the AR (p) term in the mean equation in order to account for the time dependence in returns; according to Rachev et al., (2007) if the conditional mean is not specified adequately, then the construction of consistent estimates of the true conditional variance process would not be possible and statistical inference and empirical analysis might be wrong. They added that the conditional mean is typically captured by AR or ARMA model.

$(h_{i,t})$ represents the term for the conditional variance at time t,

$(\alpha_{i,1})$ represents the new information coefficient for ARCH term,

$(\alpha_{i,2})$ represents the volatility persistence coefficient related to GARCH term.

$(\Phi_{i,t-1})$ represents the variables included in the set of available information

Second, following Girard and Omran (2009) work, this study includes the delayed trading volume indicator in the conditional variance equation in a second model.

$$h_{i,t} = \alpha_{i,0} + \alpha_{i,1}\varepsilon^2_{i,t-1} + \alpha_{i,2}h_{i,t-1} + \gamma_i \cdot v_{i,t} \rightarrow (6)$$

Where $(v_{i,t-1})$ is the delayed trading volume for each sector (i). Lagged volume is used for representing contemporaneous volume to avoid the problem of simultaneity since lagged values of endogenous variables are classified as predetermined (Girard and Omran, 2009).

Third, this paper examines whether an unexpected activity produces more information and thus have a larger effect on return volatility than an expected activity. According to Arago and Nieto (2005), Girard and Omran (2009) and Kartsaklas (2017), trading volume can be divided into two components: a first component that corresponds to trading caused by the existence of new information (surprise) called unexpected activity; a second component corresponding to normal market activity called expected activity. Our study applies ARMA(p,q) processes to split up activity into expected and unexpected components as follows:

$$Ev_{i,t} = \sum_{j=1}^{p}\beta_{i,j}v_{i,t-j} + \sum_{j=1}^{q}\delta_{i,j}\varepsilon_{i,t-j} + \varepsilon_{i,t} \rightarrow (7)$$

$$Uv_{i,t} = v_{i,t} - Ev_{i,t} \rightarrow (8)$$

$(Ev_{i,t})$ and $(Uv_{i,t})$ represent the expected and unexpected components of volume respectively.

To investigate lag structures, our study applies the Akaike information criteria. Each sector has a series of daily volume, expected volume and unexpected volume.

In order to examine the impact of unexpected and expected volume on volatility, the following model estimates conditional volatility using transformation trading activity components.

$$h_{i,t} = \alpha_{i,0} + \alpha_{i,1}\varepsilon^2_{i,t-1} + \alpha_{i,2}h_{i,t-1} + \gamma_{i,1} \cdot Ev_{i,t-1} + \gamma_{i,2} \cdot Uv_{i,t-1} \rightarrow (9)$$

Finally, in order to detect the component causing the persistence of volatility, the following models are estimated.

$$h_{i,t} = \alpha_{i,0} + \alpha_{i,1}\varepsilon^2_{i,t-1} + \alpha_{i,2}h_{i,t-1} + \gamma_{i,1} \cdot Ev_{i,t-1} \rightarrow (10)$$

$$h_{i,t} = \alpha_{i,0} + \alpha_{i,1}\varepsilon^2_{i,t-1} + \alpha_{i,2}h_{i,t-1} + \gamma_{i,2} \cdot Uv_{i,t-1} \rightarrow (11)$$

As noted by Lamoureax and Lastrapes (1990) and Sharma et al., (1996) the sum $(\alpha_1 + \alpha_2)$ is a measure of the persistence of a shock to the variance of returns taking values between 0 and 1. The more this sum approaches unity, the greater is the persistence of shocks to volatility. As noted by Engle and Bollerslev (1986), if this sum equals one, this implies that shocks to the conditional variance persist over future horizons.

IV. EMPIRICAL RESULTS

This paper aims to analyze the relationship in terms of sector between the trading volumes, stock market returns and volatility of four sectors of the Tunisian Stock Exchange. It also conduces the analysis based on expected and unexpected volume. The adequate conditional mean for the each series sector index return is determined by comparing different lag lengths using Akaike Information Criteria. The conditional mean is found to be AR (1) for each sector index return. AR (1) has the lowest AIC criterion.

The results are presented as follows: Table 3 reports results of the estimated GARCH(1,1) model without the inclusion of volume in the conditional variance. Table 4 reports results of the estimated GARCH(1,1) model with the inclusion of total volume traded in the conditional variance. Table 5 reports results of the estimated GARCH(1,1) model with the inclusion of expected and unexpected trading volume in the conditional variance. Within each table, results are presented by sector.

Table 3. Volatility persistence without volume : $h_{i,t} = \alpha_{i,0} + \alpha_{i,1}\varepsilon_{i,t-1}^2 + \alpha_{i,2}h_{i,t-1}$

Sector (i)	Financial Companies		Consumer Services		Consumer Goods		Industry	
	h_t	P-value	h_t	P-value	h_t	P-value	h_t	P-value
α_1	0.266692***	0.0000	0.104527**	0.0250	0.214812***	0.0000	0.154237***	0.0008
α_2	0.452541***	0.0000	0.530823***	0.0029	0.734862***	0.0000	0.527799***	0.0002
$\alpha_1 + \alpha_2$	0,719233	-	0,63535	-	0,949674	-	0,682036	-
γ	-	-	-	-	-	-	-	-
γ_1	-	-	-	-	-	-	-	-
γ_2	-	-	-	-	-	-	-	-
Log L	-606.3632	-	-1043.343	-	-1335.932	-	-1144.971	-
LM(1)	0.256350	0.6124	0.228447	0.6324	0.238171	0.6253	0.015607	0.9005
Q(12)	18.560	0.169	20.956	0.151	12.547	0.324	8.6623	0.653
Q²(12)	4.7283	0.966	7.6623	0.811	7.3056	0.837	3.7251	0.988

Notes: Log-L is the maximum value of the log-likelihood function. Q(12) and Q² (12) are the Ljung- Box Q-statistics on standardized residuals and squared standardized residuals of order 12. LM(1) is the Engle's (1982) Lagranger multipliers test for the existence of ARCH effects, it is distributed with a χ^2 (1) under the null of no autocorrelation. Significance levels: ***1%, **5%, *10%.

The results show strong evidence that the sectoral index returns can be characterized by a GARCH(1,1) model with GED distributed residuals since for each sector and each model, Q(12), Q² (12), are insignificant. In addition, ARCH-LM test results show the absence of ARCH effects. Regarding volatility, the GARCH model parameters (α_1) and (α_2) are all positive and statistically significant at the 1% confidence level for all periods. This means that the GARCH model is a good representation of the behavior of daily stock returns, for it manages to successfully capture the temporal dependence of the return volatility of sectoral indices. A perusal of Table 3 indicates that the four sectors exhibit a high degree of persistence $(\alpha_1 + \alpha_2 > 0.5)$. It ranges from 0,63535 to 0,949674, but it is less than one. It indicates the persistence of past volatility in explaining current volatility.

Table 4. Volatility persistence with total trading volume $h_{i,t} = \alpha_{i,0} + \alpha_{i,1}\varepsilon_{i,t-1}^2 + \alpha_{i,2}h_{i,t-1} + \gamma_i \cdot v_{i,t-1}$

Sector (i)	Financial Companies		Consumer Services		Consumer Goods		Industry	
	h_t	P-value	h_t	P-value	h_t	P-value	h_t	P-value
α_1	0.220784***	0.0000	0.074654***	0.0022	0.186821***	0.0000	0.152119***	0.0010
α_2	0.536527***	0.0000	0.643071***	0.0000	0.759935***	0.0000	0.539564***	0.0001
$\alpha_1 + \alpha_2$	0,757311	-	0,717725	-	0,946756	-	0,691683	-
γ	0.025919***	0.0000	0.034360***	0.0000	0.094114***	0.0001	0.004261*	0.0718
γ_1	-	-	-	-	-	-	-	-
γ_2	-	-	-	-	-	-	-	-
Log L	-600.5246	-	-1086.678	-	-1331.919	-	-1143.933	-
LM(1)	0.081207	0.7755	0.061181	0.8045	0.725099	0.3942	0.013996	0.9058
Q(12)	18.299	0.175	21.906	0.139	13.443	0.265	8.4890	0.669
Q²(12)	5.1079	0.954	9.0230	0.701	9.4357	0.665	3.8279	0.986

Notes: Log-L is the maximum value of the log-likelihood function. Q(12) and Q² (12) are the Ljung- Box Q-statistics on standardized residuals and squared standardized residuals of order 12. LM(1) is the Engle's (1982) Lagranger multipliers test for the existence of ARCH effects, it is distributed with a χ^2 (1) under the null of no autocorrelation. Significance levels: ***1%, **5%, *10%.

By including the contemporaneous indicator of volume into the conditional variance table 4, the model with volume yields a positive and statistically significant relationship between volume and return volatility. Table 4 clearly indicates that the persistence of return volatility does not vanish for all sectors even after volume variable is included in the variance equation. Similarly to Huang and Yang (2001), after including the proxy for daily information arrivals (volume indicator), the ARCH effect $(\alpha_{i,1})$ decreases. It proves that part of the persistence of sectoral return index volatility can be explained by information arrivals. On the other hand, the study shows an increase in the volatility persistence when trading volume is included in the variance equation, since the sum $(\alpha_1 + \alpha_2)$ of the GARCH parameters becomes higher, compared to the model without the proxy variable. This finding concerns: financial companies, consumer services, and industry. Consumer goods volatility persistence is marginally reduced when trading volume is included in the variance equation. Its value is 0,949674 without volume as compared to 0,946756 with volume, which implies that the GARCH effect is not eliminated. This contradicts the findings of Lamoureux and Lastrapes (1990), who argued that GARCH effects disappear with the inclusion of volume in the conditional variance equation. But, this finding is consistent with the results obtained by Sharma et al. (1996), Arago and Nieto (2005), Girard and Omran (2009), Sabbaghi (2011) and Bouras et al., (2018), who found a high degree persistence in volatility since the sum of the ARCH and GARCH parameter coefficients are always high, when volume is excluded and included from the variance equation.

Table 5. Volatility persistence with expected and unexpected trading volume

$$h_{i,t} = \alpha_{i,0} + \alpha_{i,1}\varepsilon^2_{i,t-1} + \alpha_{i,2}h_{i,t-1} + \gamma_{i,1} \cdot Ev_{i,t-1} + \gamma_{i,2} \cdot Uv_{i,t-1}$$

Sector (i)	**Financial Companies**		**Consumer Services**		**Consumer Goods**		**Industry**	
	h_t	P-value	h_t	P-value	h_t	P-value	h_t	P-value
α_1	0.232087***	0.0000	0.055310***	0.0004	0.227366***	0.0000	0.147171***	0.0007
α_2	0.444886***	0.0000	0.755344***	0.0000	0.699377***	0.0000	0.557598***	0.0000
$\alpha_1+\alpha_2$	0,676973	-	0,810654	-	0,926743	-	0,704769	-
γ	-	-	-	-	-	-	-	-
γ_1	0.013258	0.2567	-0.028115	0.1273	-0.037601	0.3225	-0.010082	0.7558
γ_2	0.049369***	0.0000	0.032823*	0.0628	0.058092*	0.0825	0.050247**	0.0219
Log L	-593.7735	-	-1082.276	-	-1326.503	-	-1137.413	-
LM(1)	0.308831	0.5781	0.004412	0.9470	0.305848	0.5800	0.000954	0.9753
Q(12)	18.481	0.171	21.439	0.174	12.421	0.333	7.3233	0.772
Q²(12)	4.7209	0.967	8.6304	0.734	9.8502	0.629	4.1260	0.981

Notes: Log-L is the maximum value of the log-likelihood function. Q(12) and Q² (12) are the Ljung- Box Q-statistics on standardized residuals and squared standardized residuals of order 12. LM(1) is the Engle's (1982) Lagranger multipliers test for the existence of ARCH effects, it is distributed with a χ² (1) under the null of no autocorrelation. Significance levels: ***1%, **5%, *10%.
Volumes are partitioned into expected and unexpected components using an ARMA (p,q) model. For each sector the AIC criteria is employed to determine the more adequate specification.

Equation (9) investigates the impact of expected and unexpected trading activity on stock return volatility. The paper splits trading volume into expected and unexpected components using an ARMA(p,q) process to each sector series. The adequate ARMA process is selected using the AIC criteria. It is found to be ARMA(1,1) for each sector trading volume. A perusal of Table 5 indicates that all sectors have positive and significant coefficients associated with unexpected volume. However, the coefficients associated with expected volume are not significant for all sectors. These results are consistent with the empirical findings of Girard and Omran (2009). According to Girard and Omran (2009), these results suggest that unexpected volume always convey most of the information associated with trading volume. By examining the persistence of volatility, the sum $(\alpha_1+\alpha_2)$ data from Table 5, the study notes that the volatility persistence coefficient is high $(\alpha_1+\alpha_2 > 0.5)$ which implies that the GARCH effect is not eliminated, when trading volume is decomposed into expected and unexpected components. This finding affects all market sectors.

Table 6. Volatility persistence with expected trading volume $h_{i,t} = \alpha_{i,0} + \alpha_{i,1}\varepsilon^2_{i,t-1} + \alpha_{i,2}h_{i,t-1} + \gamma_{i,1} \cdot Ev_{i,t-1}$

Sector (i)	**Financial Companies**		**Consumer Services**		**Consumer Goods**		**Industry**	
	h_t	P-value	h_t	P-value	h_t	P-value	h_t	P-value
α_1	0.253762***	0.0000	0.072409***	0.0007	0.119254***	0.0000	0.149878***	0.0007
α_2	0.334671***	0.0005	0.629339***	0.0000	0.528993***	0.0000	0.560374***	0.0000
$\alpha_1+\alpha_2$	0,588433	-	0,701748	-	0,648247	-	0,710252	-
γ	-	-	-	-	-	-	-	-
γ_1	-0.059683***	0.0000	-0.058370***	0.0000	-0.191261***	0.0000	-0.042239*	0.0811
γ_2	-	-	-	-	-	-	-	-
Log L	-595.4097	-	-1082.985	-	-1456.187	-	-1142.916	-
LM(1)	0.591995	0.4414	0.109101	0.7410	7.514860	0.162	0.023717	0.8775
Q(12)	18.672	0.067*	20.263	0.142	12.324	0.340	14.119	0.293
Q²(12)	5.1877	0.951	10.161	0.602	39.765	0.100	4.9834	0.959

Notes: Log-L is the maximum value of the log-likelihood function. Q(12) and Q² (12) are the Ljung- Box Q-statistics on standardized residuals and squared standardized residuals of order 12. LM(1) is the Engle's (1982) Lagranger multipliers test for the existence of ARCH effects, it is distributed with a χ² (1) under the null of no autocorrelation. Significance levels: ***1%, **5%, *10%.
Volumes are partitioned into expected and unexpected components using an ARMA (p,q) model. For each sector the AIC criteria is employed to determine the more adequate specification.

Table 7. Volatility persistence with unexpected trading volume $h_{i,t} = \alpha_{i,0} + \alpha_{i,1}\varepsilon_{i,t-1}^2 + \alpha_{i,2}h_{i,t-1} + \gamma_{i,2} \cdot Uv_{i,t-1}$

Sector (i)	Financial Companies		Consumer Services		Consumer Goods		Industry	
	h_t	P-value	h_t	P-value	h_t	P-value	h_t	P-value
α_1	0.210476***	0.0000	0.053739***	0.0006	0.126212***	0.0000	0.139865***	0.0009
α_2	0.554329***	0.0000	0.748645***	0.0000	0.826880***	0.0000	0.596039***	0.0000
$\alpha_1 + \alpha_2$	0,764805	-	0,802384	-	0,953092	-	0,735904	-
γ	-	-	-	-	-	-	-	-
γ_1	-	-	-	-	-	-	-	-
γ_2	0.031008***	0.0003	0.039049***	0.0000	0.062759***	0.0000	0.044291**	0.0284
Log L	-599.5233	-	-1085.121	-	-1418.764	-	-1142.404	-
LM(1)	0.112116	0.7376	0.003784	0.9509	2.512170	0.1130	0.000203	0.9886
Q(12)	17.504*	0.094	20.377	0.140	8.1564	0.699	13.467	0.336
Q²(12)	5.1708	0.952	7.5602	0.818	10.207	0.598	4.6471	0.969

Notes: Log-L is the maximum value of the log-likelihood function. Q(12) and Q² (12) are the Ljung- Box Q-statistics on standardized residuals and squared standardized residuals of order 12. LM(1) is the Engle's (1982) Lagranger multipliers test for the existence of ARCH effects, it is distributed with a χ^2 (1) under the null of no autocorrelation. Significance levels: ***1%, **5%, *10%.

Volumes are partitioned into expected and unexpected components using an ARMA (p,q) model. For each sector the AIC criteria is employed to determine the more adequate specification.

Finally, the paper tries to detect clearly the component having a higher effect on the volatility persistence. On the one hand, only expected volume is included in the variance equation (10). On the other hand, only unexpected volume is included in the variance equation (11). A perusal of Table 6 and Table 7 indicates that the coefficients associated with expected volume (10) are negative and significant, for all sectors. But, the ones associated with unexpected volume (11) are positive and significant. The negative relationship between expected volume and volatility indicates that variance decreases with an increase in expected volume or normal activity. However, the positive relationship between unexpected volume and volatility indicates that variance increases with an increase in surprises activity or unexpected volume. This finding affects all sectors of the market. Moreover, the study shows an increase in the volatility persistence when unexpected trading volume is included in the variance equation, since the sum $(\alpha_1 + \alpha_2)$ of the GARCH parameters becomes higher, compared to the model with expected trading volume in the variance equation. This finding affects all sectors of the market. To conclude, the impact of unexpected trading activity on stock return volatility is greater than expected activity. This finding confirms a similar result already reported by Arago and Nieto (2005).

V. CONCLUSION

In this research, the paper investigates the relationships in terms of sector between stock returns, trading volume and return volatility, in Tunisian Stock Exchange. The sectors are the financial companies, consumer services, consumer goods and industry. It uses daily data from 2013 to 2017 and adopted the GARCH model. The volatility persistence in the Tunisian stock market exhibits characteristics similar to those found in many of the major developed and emerging stock markets (See Sharma et al., 1996, Huang and Yang, 2001, Arago and Nieto, (2005), Girard and Omran, (2009) and Bouras et al., 2018). Indeed, ARCH and GARCH effects remain significant when total trading volume is incorporated into a GARCH model. This finding affects all sectors of the market. Next, the study splits trading volume into unexpected and expected activity, in order to examine the impact of each component on volatility. The results show an increase in the volatility persistence when unexpected trading volume is included in the variance equation, compared to the model with expected trading volume in the variance equation. Consequently, the impact of unexpected trading activity on stock return volatility is greater than expected activity. This finding confirms a similar result already reported by Arago and Nieto (2005). When unexpected trading volume is removed, and only expected trading volume is introduced in the variance equation, the study shows a reduction in the volatility persistence but GARCH effects do not disappear. This finding suggests that there may be other variables, other than unexpected volume, that contribute to the persistence of volatility.

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