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The Relationship between Trading Volume, Volatility and Stock Market Returns: During a Pre- and Post Revolution on Tunisian Stock Exchange

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Abstract This paper investigates the relationships between trading volume, volatility and stock market returns, by using daily data of the Tunisian stock exchange, during its pre and post revolution period from January 2006 to December 2015. The results indicate that the return volatility is best described by a GARCH (1,1) specification. We have included volume in the conditional variance equation as an additional explanatory variable in the GARCH model, to examine if volume can capture GARCH effects. Our results show that the persistence in volatility remains in return series even after volume is included in the model as an explanatory variable. This finding holds during the pre and post revolution period.

Keywords: *trading volume, return volatility, Tunisian stock market, GARCH model*

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1. Introduction

Relationships between trading volume, volatility and Stock Market Returns, have been widely investigated in empirical studies using different methodologies in both emerging and developed market such [1-6].

This paper aims at studying the dynamics of the relationship between trading volume, volatility and market return in the Tunisian Stock Exchange. The study is carried out on the Tunisian Stock Exchange with a sample period covering a long period, ten years on daily basis starting from January 2006 to December 2015. GARCH model is employed to determine the dynamics of the relationship between trading volume and market return.

This paper is organized as follows. Section 2 reviews and discusses previous empirical research. Section 3 provides data, some descriptive statistics and briefly describes the methodology. Section 4 shows results. Section 5 concludes the paper.

2. Literature Review

The literature on the relationship between trading volume, volatility and market return is well documented. Reference [1] studies contemporaneous and dynamic relationships between trading volume and returns in the French stock market. [1] uses a monthly value-weighted portfolio of 128 French firms covering at least 90% of the French market capitalization from April 1996 to October 2014. The period is divided into two sub-periods of nearly 10 years. The authors find a positive relationship between market turnover and stock market returns for the total sample and the first sub-sample (1996-2005). For the second sub-period (2005-2014), there were no statistical relations between turnover and returns.

[3] examines the relationship between trading volume, volatility and stock market returns for a pre- and post crisis on Kuala Lumpur Stock Exchange. The investigation period starts on January 2, 1990 and ends on December 26, 2000, a period of 11 years. The results indicate that the return volatility is best described by a GARCH (1,1) specification. Current volatility can be explained by past volatility that tends to persist over time. [3] adds volume as an additional explanatory variable in the GARCH model to examine if volume can capture GARCH effects. This approach is used by [7] in Treasury-bond futures markets, [8] for Crude Oil Futures Markets, [5] in NYSE, [9] in Taiwan Stock Market, [4] in the US stock market, [2] in eight international stock exchange and [6] in eight African stock markets. The results of [3] are consistent with results of [2,5,7,8,9] and [6] in South Africa, Morocco, Egypt and Botswana stock market, their results show that the persistence in volatility remains in return series even after volume is included in the model as an explanatory variable. This finding holds for contemporaneous volume when it is included in the variance equation. But, this result is not consistent with the findings of [4] who found that GARCH effects disappears with the introduction of the trading volume in the variance equation, thus

confirming that the trading volume is not playing its role of information keeper. The study of [4] is carried out on individual stocks (20 actively traded shares from the US market), focusing, therefore, on a micro level of study. According to [5] the volatility of an individual asset is influenced by specific factors (specific risk) of the asset, as much as by market factors (systematic risk). Both these factors have an effect on the trading volume. It is this double influence on both variables that might make trading volume a good proxy for information flow and affect the conditional volatility model so much so as to make the GARCH effect disappear for individual shares, as [4] found.

[10] and [11] investigated the relationship between return volatility and trading volume as a proxy for the arrival of information to the market, based respectively on Korean stock market and Pakistan stock exchange. To measure this relationship they use the GJR-GARCH and exponential GARCH (EGARCH) models. Indeed, according to [10] and [11] the GARCH model only captures the shocks that are symmetric and ignores asymmetric shocks in volatility. This implies that the volatility shocks may have different effect as good or bad news on volatility. So this defect of GARCH model is fulfilled by Exponential GARCH (EGARCH) and the GJR-GARCH models. According to [11] the inclusion of contemporaneous trading volume in the GJR-GARCH and EGARCH models results in a positive relationship between trading volume and volatility, second, when contemporaneous and lagged trading volumes are included in the conditional variance equation, the former is positively correlated with volatility but the latter is not. The major finding of [10] includes that negative shock has a greater impact on volatility and investors are more prone to the negative news whereas according to GJR-GARCH good news has greater impact on stock return and there is a strong relationship exist between the trading volume, stock return and stock volatility.

3. Research Methods

3.1. Data and Descriptive Statistics

We use the daily TUNINDEX closing price and trading volume from January 2, 2006 to December 31, 2015, all of which are collected from Tunisian Stock Exchange database. The sample period is chosen in order to include the Tunisian revolution period. The analysis period is divided into three sub-periods: (1) pre-revolution – January 2, 2006 to June 30, 2010; during revolution –July 1, 2010 to June 30, 2011 and post-revolution – July 1, 2011 to December 31, 2015. Similarly to [3,5,11] stock returns are expressed in percentages:

$$r_t = 100 \times \ln\left(\frac{Tun_t}{Tun_{t-1}}\right) \tag{1}$$

where (r_m) is the daily market returns, (Tun_t) is the daily closing index at the time t.

Trading volume in day t is expressed as equation (2):

$$V_t = \ln\left(\frac{Vol_t}{Vol_{t-1}}\right) \tag{2}$$

Table 1, shows the basic descriptive statistics for the three sub-periods relating to the daily return and trading volume. The statistics show that the averages of the daily return and trading volume for the period before the revolution are much better than the averages of the samples for the period after the revolution. The sample mean of return is negative during revolution; which means that this variable has decreased on average during this period. 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. The autocorrelation coefficient (Q) up to 36 lags is statistically significant which indicates that all series suffer from serial correlation.

Table 1. Descriptive statistics of return and volume for pre, during and post revolution

	r_t	V_t
Pre-revolution Period: January 2, 2006 to June 30, 2010		
Mean	0.099494	0.366841
Maximum	3.185152	4.175047
Minimum	-5.001519	-4.895798
Std. Dev.	0.573794	0.762399
Q(36)	127.84***	295.79***
Skewness	-0.531943	0.132785
Kurtosis	13.79437	9.603205
Jarque-Bera	4501.228***	2025.328***
During revolution Period: July 1, 2010 to June 30, 2011		
Mean	-0.058389	0.002069
Maximum	4.108560	2.972600
Minimum	-4.143924	-2.752213
Std. Dev.	1.041004	0.587537
Q(36)	76.67***	100.40***
Skewness	-0.284546	-0.093251
Kurtosis	7.764378	7.934992
Jarque-Bera	226.3944***	239.8245***
Post-revolution Perio: July 1, 2011 to December 31, 2015		
Mean	0.015716	0.000805
Maximum	1.780768	5.538098
Minimum	-3.757202	-4.197107
Std. Dev.	0.445133	0.791869
Q(36)	93.94***	244.12***
Skewness	-0.722107	0.180893
Kurtosis	10.48741	9.679734
Jarque-Bera	2713.528***	2088.321***

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

Additionally, we tested the stationarity of returns and trading volume. We employed both the augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test. Table 2 provides the results. The null hypothesis that returns and trading volume are non stationary was rejected at the 1% significance level, indicating that both trading volume and returns are stationary.

Table 2. Unit root tests for returns and trading volume.

		r_t	V_t
Pre-revolution Period : January 2, 2006 to June 30, 2010			
ADF Test	Intercept	-26.62***	-17.59***
	Trend and Intercept	-26.61***	-17.58***
PP Test	Intercept	-26.70***	-181.25***
	Trend and Intercept	-26.69***	-180.76***
During revolution Period : July 1, 2010 to June 30, 2011			
ADF Test	Intercept	-10.52***	-10.48***
	Trend and Intercept	-10.53***	-10.44***
PP Test	Intercept	-10.52***	-39.00***
	Trend and Intercept	-10.50***	-38.88***
Post-revolution Period : July 1, 2011 to December 31, 2015			
ADF Test	Intercept	-27.42***	-22.55***
	Trend and Intercept	-27.43***	-22.54***
PP Test	Intercept	-27.78***	-216.88***
	Trend and Intercept	-27.71***	-217.43***

Note: 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%;

3.2. Methodology

The ARCH model of [12] and the GARCH model of [13] are the most popular tools to examine the effect of trading volume on returns and volatility [2,14]. The methodology adopted in this paper is based on the Generalized Autoregressive Conditional Heteroscedasticity model (GARCH). Following the work of [2,4,5], we study the GARCH effects in the observed data and examine the effect of trading volume on returns and volatility using the GARCH (1,1) model. Following [2], 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, we identify the variance of return on the stock exchange index simply explained by the lags in conditional and unconditional variance using the specification included in the equations (3)–(5).

$$r_t = \rho_{t-i} + \varepsilon_t \tag{3}$$

$$\varepsilon_t / \left(\Phi_{t-1}\right) \approx N\left(0, h_t\right) \tag{4}$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1} \tag{5}$$

$\left(r_t\right)$ is the daily TUNINDEX market return measure

$\left(\rho_{t-i}\right)$ is the AR (p) term in the mean equation in order to account for the time dependence in returns; according to [15] 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. [15] adds that the conditional mean is typically captured by AR or ARMA model.

$\left(h_t\right)$ represents the term for the conditional variance at time t,

$\left(\alpha_1\right)$ represents the new information coefficient for ARCH term,

$\left(\alpha_2\right)$ represents the volatility persistence coefficient related to GARCH term.

$\left(\Phi_{t-1}\right)$ represents the variables included in the set of available information.

Second, following the work of [2,4], we have included the total trading volume in the conditional variance equation in a second model.

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1} + \gamma V_t \tag{6}$$

$\left(V_t\right)$ is the daily volume.

As noted by [4] and [5] the sum $\left(\alpha_1 + \alpha_2\right)$ is a measure of the persistence of a shock to the variance of returns taking values between 0 and 1. As this sum approaches unity, the greater is the persistence of shocks to volatility. As noted by [16], if this sum equals one implying that shocks to the conditional variance persist over future horizons.

4. Empirical Results

The adequate conditional mean for the TUNINDEX return series was determined by comparing different lag lengths using Akaike Information Criteria. The conditional mean has been found to be AR (1) for each period. AR (1) has the lowest AIC criterion.

The empirical results are presented in Table 3, Table 4 and Table 5. Log-L is the maximum value of the log-likelihood function. Q(12) and Q^2 (12) are the Ljung-Box Q-statistics on standardized residuals and squared standardized residuals of order 12. LM is the Lagrange Multiplier test to testing white noise disturbances against GARCH disturbances.

The diagnostic tests results presented indicate that both Q(12) and the Q^2 (12) statistics are insignificant, the null hypothesis of no serial correlation in the residuals of the mean models cannot be rejected at 1% significance level. This indicates that the standardized residuals are linearly as well as non-linearly independent. ARCH-LM test results show the absence of ARCH effects in the standardized residuals.

Regarding volatility, the GARCH model parameters $\left(\alpha_1\right)$ and $\left(\alpha_2\right)$ are all positive and statistically significant at the 1% confidence level for all periods; which 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 stock indices.

The γ volume coefficient is positive and statistically significant for all three periods, indicating a positive impact of volume on volatility, which means that there is a positive contemporaneous relationship between volume and volatility

Pre-revolution period, January 2, 2006 to June 30, 2010

The results are presented in Table 3. The persistence in volatility as measured by the sum of $\left(\alpha_1 + \alpha_2\right)$ in model without volume is close to unity (0.8957). That indicates the persistence of past volatility in explaining current volatility. By including the contemporaneous value of volume into the conditional variance, the model with volume yields a positive and statistically significant relationship between volume and returns volatility. Moreover, the sums of $(\alpha_1+\alpha_2)$ is fairly close to unity (0.9170), compared to the model without the proxy variable.

Table 3. Volatility persistence on the pre-revolution period: Maximum likelihood estimation of GARCH (1,1) model assuming the hypothesis of Generalized Error Distribution.

	Pre-revolution :model without volume		Pre-revolution :model with volume	
	h_t	*P*-value	h_t	*P*-value
α_1	0.1865	0.0000	0.1605	0.0000
α_2	0.7092	0.0000	0.7565	0.0000
$\alpha_1+\alpha_2$	0.8957	-	0.9170	-
γ	-	-	0.0359	0.0067
Log L	-736.2473	-	-734.1930	-
LM(1)	12.9400	0.3003	19.9298	0.1000
Skewness	0.0266	-	0.00098	-
Kurtosis	5.0162	-	4.7317	-
Q(12)	27.119	0.404	26.071	0.606
$Q^2(12)$	16.077	0.188	24.203	0.119

Source: Compiled by author based on data from Tunisian Stock exchange annual reports.

During-revolution period, July 1, 2010 to June 30, 2011

The results are presented in Table 4. The sum of $(\alpha_1+\alpha_2)$ is fairly close to unity (0.9948). It indicates that the GARCH effect is consistent across return series during this period.

Table 4. Volatility persistence during the revolution period: Maximum likelihood estimation of GARCH (1,1) model assuming the hypothesis of Generalized Error Distribution.

	During -revolution :model without volume		During -revolution :model with volume	
	h_t	*P*-value	h_t	*P*-value
α_1	0.9229	0.0000	0.2844	0.0030
α_2	0.0719	0.0091	0.4517	0.0099
$\alpha_1+\alpha_2$	0.9948	-	0.7361	-
γ	-	-	0.3428	0.0018
Log L	-240.9211	-	-251.6793	-
LM(1)	1.0664	0.3008	4.3281	0.0384
Skewness	-0.4199	-	0.1278	-
Kurtosis	4.7452	-	6.6734	-
Q(12)	9.3107	0.593	10.690	0.470
$Q^2(12)$	5.1631	0.952	8.6075	0.736

Source: Compiled by author based on data from Tunisian Stock exchange annual reports.

In addition, the study shows a reduction 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 (0.7361). While these parameters are reduced they are still statistically significant; which implies that the GARCH effect is not eliminated.

This contradicts the findings of [4], who argue that GARCH effects disappear with the inclusion of volume in the conditional variance equation.

Post-revolution period, July 1, 2011 to December 31, 2015

The results are presented in Table 5. Similar results have been obtained, GARCH effects are consistently significant. There is a positive and statistically significant relationship between volume and returns volatility. It is observable that, this period has less volatility in prices than the previous periods. The reason could be due the improvement of the Tunisian stock exchange which experienced more stability during this period.

Consistent with results of [3] during the Pre- and Post Crisis on Kuala Lumpur Stock Exchange, our results show that the persistence in volatility remains in return series even after volume is included in the model as an explanatory variable. These results are in line with several studies using the same econometrics methodologies [2,5,7,8,9] and [6].

Table 5. Volatility persistence on the post-revolution period: Maximum likelihood estimation of GARCH (1,1) model assuming the hypothesis of Generalized Error Distribution.

	Post -revolution :model without volume		Post -revolution :model with volume	
	h_t	*P*-value	h_t	*P*-value
α_1	0.3095	0.0001	0.2921	0.0001
α_2	0.3536	0.0031	0.3976	0.0002
$\alpha_1+\alpha_2$	0.6631	-	0.6897	-
γ	-	-	0.0297	0.0074
Log L	-527.6298	-	-524.8395	-
LM(1)	0.0686	0.7932	0.0379	0.8454
Skewness	-1.2410	-	-1.2823	-
Kurtosis	14.5424	-	14.9705	-
Q(12)	32.460	0.301	31.408	0.101
$Q^2(12)$	1.8334	1.000	2.1146	0.999

Source: Compiled by author based on data from Tunisian Stock exchange annual reports.

5. Conclusion

This study presents an empirical analysis to determine whether a GARCH model can adequately represent return volatility in the Tunisian stock market exchange. We use GARCH model to analyze the empirical relationship between stock return, volatility and trading volume. Using daily data for the TUNINDEX closing price and trading volume from 2006 to 2015, we include the Tunisian revolution period. The analysis period is divided into three sub-periods: pre-revolution, during revolution and post-revolution. The volatility persistence on the GARCH effect for each period has been verified by including and excluding trading volume in the volatility model. Our results show that the persistence in volatility remains in return series even after volume is included in the model as an explanatory variable. This finding holds during the pre and post revolution period.

References

[1] Anthony Miloudi, Mondher Bouattour, Ramzi Benkraiem", Relationships between Trading Volume, Stock Returns and Volatility: Evidence from the French Stock Market ", *Bankers Markets & Investors: an academic & professional review, Groupe Banque,* 144, 44-58. 2016.

[2] Aragó, V., & Nieto, L. "Heteroskedasticity in the returns of the main world stock exchange indices: volume versus GARCH effects", *Journal of International Financial Markets, Institutions and Money*, 15(3), 271-284. 2005.

[3] Huson Joher Ali Ahmed, Ali Hassan and Annuar M.D Nasir, "The Relationship between Trading Volume, Volatility and Stock Market Returns: A test of Mixed Distribution Hypothesis for A Pre- and Post Crisis on Kuala Lumpur Stock Exchange", *Investment Management and Financial Innovations*, 2(3), 146-158. 2005.

[4] Lamourex, C. G., & Lastrapes, W. D, "Heteroskedasticity in Stock Return Data: Volume Versus GARCH Effects", *The Journal of Finance*, 45(1), 221-229. 1990.

[5] Sharma, J., L., Mougoue M., Kamath, R., "Heteroskedasticity in Stock Market Indicator Return Data: Volume versus GARCH Effects", *Applied Financial Economics*. 6, 337-342. 1996.

[6] Woroucoubou ALI Habibou, "Dynamics of the relationship between trading volume, return and volatility in African stock markets ". *Paripex-Indian Journal Of Research*, 5(3). 2016.

[7] Najand, M., and Yung, K, "A GARCH Examination of the Relationship Between Volume and Price Variability in Futures Markets", *Journal of Futures Markets*, 11: 613-621. 1991.

[8] Foster, A, "Volume-Volatility Relationships for Crude Oil Futures Markets", *Journal of Futures Markets*, 15, 929-951. 1995.

[9] Huang, B.N. & Yang, C.W, "An empirical investigation of trading volume and return volatility of the Taiwan Stock Market", *Global Finance Journal*, 12, 55-77. 2001.

[10] Adeel Mustafa, Maria Tariq, Sabra Noveen, and Rabia Najaf, "Investigation of relation between stock returns, trading volume, and return volatility", *International Journal of Research – Granthaalayah*, 4(7), 231-239. 2016.

[11] Choi, K. Z. Jiang, S. Kang and S. Yoon, "Relationship between Trading Volume and Asymmetric Volatility in the Korean Stock Market", *Modern Economy*, 3(5), 584-589. 2012.

[12] Engle, R. F, "Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of U.K. Inflation", *Econometrica*, 50, 987-1008. 1982.

[13] Bollerslev, T, "Generalized autoregressive conditional heteroskedasticity", *Journal of Econometrics*, 31, 307-327. 1986.

[14] Sabbaghi, O, "Asymmetric volatility and trading volume: The G5 evidence " *Global Finance Journal*, 22(2), 169-181. 2011.

[15] Rachev S, Mittnik S, Fabozzi F, Focardi S, Jasic T, *Financial Econometrics: From Basics To Advanced Modelling Techniques*, John Willey and Sons, Inc. 2007.

[16] Engle, R., and Bollerslev, T, "Modeling the Persistence of Conditional Variances ", *Econometric Reviews*, 5, 1-50. 1986.