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A Generalized Autoregressive Conditional Heteroskedasticity Examination of the Relationship between Trading Volume and Conditional Volatility in the Tunisian Stock Market: Evidence for the Information Flow Paradigm

Fethi Belhaj[1]*, Ezzeddine Abaoub[2]

[1]Faculty of Economics and Management Sciences of Nabeul, Tunisia, [2]College of Administrative and Financial Studies, Taif University, Kingdom of Saudi Arabia. *Email Fethipremier@yahoo.fr

ABSTRACT

This paper empirically examines the relationship between trading volume and conditional volatility of returns in the Tunisian stock market within the framework of the mixture of distribution hypothesis (MDH) and the sequential information arrival hypothesis (SIAH). Through this study, we especially aim to test the volatility persistence degree without volume, with contemporaneous volume, and with lagged volume. Our empirical analysis is based on daily data related to the 43 most active and dynamic securities traded from January 2, 2008 to June 29, 2012. Our daily analysis reveals several results. Firstly, we confirm the strong positive relationship between trading volume and returns conditional volatility issued from generalized autoregressive conditional heteroskedasticity (GARCH (1,1)) model. Secondly, according to the theoretical predictions of the MDH, we show that including contemporaneous trading volume in the conditional variance equation significantly reduces volatility persistence. Thirdly, through the addition of the lagged volume in the conditional variance equation, we show that volatility persistence remains in the whole at a high level and close to that obtained from the GARCH (1,1) model without trading volume, and also at a higher level than that resulting from the addition of the contemporaneous volume. Our results thus do not support the implications of the SIAH.

Keywords: Trading Volume, Conditional Volatility, Mixture of Distribution Hypothesis, Sequential Information Arrival Hypothesis, Generalized Autoregressive Conditional Heteroskedasticity, Volatility Persistence, Information flow
JEL Classifications: C22, C58, G10, G12, G13, G14, G15, G17

1. INTRODUCTION

The volume-volatility relationship has attracted a great deal of attention from researchers during the past three decades. As argued by Karpoff (1987), there are many reasons to examine this relation. First, the theory of the volatility-volume relationship provides insight into the structure of financial markets. It predicts that this relationship depends upon the rate of information flow to the market, information dissemination, market size, and the existence of short sale constraints. Second, the volatility-volume relationship has important implications for event studies that use a combination of price and volume data. Third, the relationship has important implications for the empirical distribution of speculative prices. In particular, the findings of the volatility-volume relationship tests generally support the mixture of distributions hypothesis (MDH), which helps explain the observed kurtosis in empirical stock return distributions and the well-known autoregressive conditional heteroskedasticity (ARCH) process that volatility follows.

Since Karpoff's (1987) study, a large number of empirical studies have documented a strong positive relationship between return volatility and trading volume (Jones et al., 1994; Lee and Rui, 2002; Alsubaie and Najand, 2009; Mahajan and Singh, 2009; Kumar et al., 2009; Giot et al., 2010; Kao and Fung, 2012; Chuang et al., 2012; Wang and Huang, 2012; Celik, 2013; Davidsson, 2014; Shahzad et al. 2014,…). Several theories have been developed to explain the relationship between volume and volatility. The main theoretical foundation is related to the information flow paradigm.

This paradigm is represented by the MDH introduced by Clark (1973) and the sequential information arrival hypothesis (SIAH) developed by Copeland (1976).

Developed by Clark (1973), Epps and Epps (1976), Tauchen and Pitts (1983), Lamoureux and Lastrapes (1990), Andersen (1996), Bollerslev and Jubinski (1999), Abanto-Valle et al. (2014), the MDH remains always at the basis of all researches that address the relationship between trading volume and price or returns volatility. This hypothesis assumes that volatiliy is highly influenced by information arrival whose trading volume is a proxy, and predicts the existence of a strong contemporaneous positive relationship between volume and volatility mainly due to their joint dependence on a common underlying directing variable (mixing variable) that measures the daily rate of information flow to the market.

According to the MDH, the time-varying conditional volatility could be generated by the serial correlation in the information arrival process whose volume is a proxy. This autocorrelation of information flow leads to temporal dependencies of the conditional volatility that could be modeled through a generalized autoregressive conditional heteroskedasticity (GARCH) process. This process deals with trading volume and price volatility as jointly driven by exogenous information shocks. Proponents of this hypothesis assume that information dissemination is contemporaneous and therefore, adding current trading volume into the conditional variance equation of a GARCH model, leads to a significant reduction in volatility persistence, and results in a strong positive contemporaneous volume-volatility relationship (Clark, 1973; Epps and Epps, 1976; Tauchen and Pitts, 1983; Lamoureux and Lastrapes, 1990). Empirically this assumption leads to our first hypothesis:

H1: The persistence of conditional volatility is substantially absorbed by the effect of the contemporaneous trading volume due to their joint dependence to information flow whose dissemination on the market is contemporaneous.

In contradiction with the MDH, SIAH (Copeland, 1976; Morse, 1980; Jennings et al., 1981; Jennings and Barry, 1983; Darrat et al., 2003) supposes that the new information is disseminated sequentially to traders, and traders not yet informed cannot perfectly infer the presence of informed trading. Under this assumption, the sequential reaction of investors to the information disseminated on the market results in a positive dynamic relation between volume and volatility where lagged values of trading volume may be used to forecast the current price volatility. Empirically, this implies that the addition of the lagged volume in the conditional variance equation of a GARCH model as a proxy for the arrival rate of information induces a great reduction in volatility persistence. This intuition leads to our second hypothesis:

H2: The persistence of conditional volatility is substantially absorbed by the effect of the lagged volume due to the sequential reaction of traders to information flow whose dissemination on the market is gradual.

In the previous literature, numerous empirical studies investigate the volatility-volume relationship within the framework of MDH and SIAH by using a GARCH model. The results of these investigations are mixed concerning the validity of these two hypotheses. Lamoureux and Lastrapes (1990) were the first to use a GARCH (1,1) model in order to investigate the volatility-volume relationship within the framework of MDH. They suppose that the autocorrelation hypothesis of information flow associated with the MDH leads to model the conditional variance of daily returns through a GARCH model, and also that the time-varying conditional volatility could be generated by the serial correlation in the information arrival process. This process is considered among theoretical models dealing with volume and volatility as jointly driven by exogenous shocks of information. Empirically, this implies that the addition of a proxy for information flow in the conditional variance equation of a GARCH (1,1) model significantly reduces the volatility persistence. Lamoureux and Lastrapes (1990) argue that daily trading volume can be used as a proxy for information arrival. Applying this approach for 20 American stocks, they find that trading volume is positively related to conditional volatility and that its addition in the conditional variance equation of GARCH (1,1) model results in a significant reduction in volatility persistence. This result confirms the hypothesis stating that GARCH behavior of conditional volatility is a manifestation of the autocorrelation in the time-varying rate of information arrival whose volume is a proxy, and thus provides an empirical support to MDH.

Bohl and Henke (2003) confirm the result obtained by Lamoureux and Lastrapes (1990) when examining the relationship between volume and returns volatility for 20 individual Polish stocks from 1999 to 2000. They show that volatility persistence tends to disappear when volume is included in the conditional variance equation of GARCH model. Galati (2000) shows that volume and volatility are positively correlated and both variables respond to information arrival as predicted by the MHD.

Darrat et al., (2003) test the relationship between trading volume and return volatility for all Dow Jones industrial average (DJIA) stocks using intraday data from April 1, 1998 to June 30, 1998. Using the EGARCH method, they find that contemporaneous correlations between trading volume and volatility are positive and statistically significant in only three of the 30 DJIA stocks. The other 27 DJIA stocks exhibit no significant positive correlation between trading volumes and return volatility. However, they also find that trading volume and return volatility follow a clear lead-lag pattern in a large number of the DJIA stocks. They conclude that their results do not support the MDH, but do support the SIAH.

Mahajan and Singh (2009) test the assumption proposed by Lamoureux and Lastrapes (1990) stating that the conditional heteroskedasticity in return series could be explained by taking into account trading volume as proxy for information arrival and therefore as mixing variable. Through using GARCH (1,1) model, they show that a strong and positive relationship exists between volume and volatility. However, contrary to what was found by several previous studies, the addition of the trading volume in the conditional variance equation of this model leads only to a small reduction in the persistence of conditional volatility and that ARCH and GARCH effects remain significant, results in contradiction with MDH.

Kumar et al., (2009) examine the trading volume contribution to the explanation of conditional volatility, of its persistence and the ARCH effects by using a GARCH (1,1) model applied to data related to 50 traded individual stocks on the Indian financial market from 2000 to 2008. They show that, for 80% of the considered stocks, the trading volume is significantly related to the conditional volatility, and that for 70% to 80% of stocks, taking volume into account in such analysis results in a significant reduction in volatility persistence and in ARCH effects which confirms the MDH.

Alsubaie and Najand (2009) study the volume-volatility relationship on the Saudi financial market using a GARCH (1,1) model, applied to market index, to five industries indices and to 15 individual enterprises during the 1993-2005 period. They find that the contemporaneous volume is positively related to conditional volatility of returns and that its addition in the conditional variance equation of this model results in a significant reduction in volatility persistence which confirms the MDH predicting that information dissemination is contemporaneous and consequently, the persistence of the conditional heteroskedasticity is largely absorbed by the volume effect, measuring the information arrival rate. Moreover, they find, by replacing the contemporaneous volume with a lagged one, that the lagged volume do not reduce volatility persistence as contemporaneous volume does. This result does not support the SIAH, which implies that lagged volume should be significant in reducing the volatility persistence.

Aggarwal and Mougoué (2011) investigate the volume-volatility relationship in the foreign exchange market using data for three major currency futures denominated in US dollar, namely the British pound, the Canadian dollar and the Japanese yen. They found that trading volume and return volatility, are negatively correlated, implying a lack of support for the MDH which predicts a contemporaneous positive relationship between the two variables. This result is confirmed by the linear and non-linear Granger causality tests that prove the existence of a significant lead-lag causality relationship between trading volume and returns volatility which is in accordance with the SIAH.

Celik (2013) empirically study the relationship between trading volume and volatility on the Turkish stock market from February 2005 to April 2010, in order to provide an empirical support to either the MHD or the SIAH. Two sub-periods have been used to consider the effect of Global crisis that began from 2008. Supporting the MDH, obtained results show the existence of a positive contemporaneous volume-volatility relationship in the pre-crisis period. However, the evidence is mixed in crisis period. Although they reject the MDH in crisis period, they cannot strongly reject the SIAH.

Our study is related to the empirical works mentioned above. It aims to empirically test the relation between the trading volume and the conditional volatility of returns with the purpose of offering an empirical support to either the MDH or the SIAH.

Despite the obvious importance of volatility-volume relationship, there is a paucity of research on this topic in emerging markets. Several empirical studies investigated the return volatility on these markets, but only some of them concentrated on the relationship between trading volume and volatility. We attempt to partially fill this gap by investigating volatility-volume relationship in the one of the emerging stock markets, namely the Tunisian Stock Market. For this reason, we utilize the GARCH (1,1) model to test the persistence of return volatility without volume, with contemporaneous volume, and with lagged volume. Trading volume is measured as the number of shares traded. Our empirical tests are applied on daily data related to a sample of 43 individual Tunisian stocks for the period from January 2, 2008 to June 29, 2012. Our findings confirm the strong positive relationship between trading volume and conditional volatility of returns. Moreover, In accordance with the MDH, including volume in the conditional variance of stock returns significantly reduces the persistence of conditional volatility. Overall our results provide an empirical support to MDH but do not support the SIAH.

The remainder of this paper is organized as follows: Section 2 presents the methodology employed in this study. The data and the preliminary results are presented in Section 3. Section 4 discusses the empirical findings and the last section concludes.

2. METHODOLOGY

The relationship between trading volume and the unconditional volatility of price or returns (measured by either absolute returns or squared returns) is generally studied within the framework of a standard linear regression where the residual term ε_t is supposed to have a zero mean and a constant variance. However, several studies have shown that variance's constancy hypothesis is not empirically verified and that returns time series are characterized by the presence of conditional heteroskedasticity. Therefore, a family of autoregressive models has been proposed to allow conditional variance to vary over time. These models take into account volatility persistence effect. GARCH specification that has been developed by Bollerslev (1986) is the most used to model volatility. In order to empirically study the relationship between trading volume and conditional volatility of returns, on the Tunisian Stock Market, we utilize a similar methodology to the one used by Mestel et al., (2003), Floros and Vougas (2007), Mahajan and Singh (2009), Alsubaie and Najand (2009), Louhichi (2011), that have been inspired by the work of Bollerslev (1986) and Lamoureux and Lastrapes (1990). In a first step, we estimate the following GARCH (1,1) model:

$$R_t = \mu + \sum_{i=1}^{p} \varphi_i r_{t-i} + \varepsilon_t + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} \quad [1] \tag{1}$$

$$\varepsilon_t \mid I_{t-1} \sim \mathrm{N}(0, \sigma_t^2) \quad [2]$$

1 Orders p and q of the conditional mean equation will be determined according to Box and Jenkins (1976) methodology.

2 Residues are supposed to follow a normal distribution. Gourieroux (1992) and Lardic and Mignon (2002) assume that the Gaussian density can be used to calculate the estimators of GARCH models even if the real density is not normal, specifying that most of hazards related to financial series do not follow a normal distribution. Instead, Nelson (1991) assumes that the Generalized Error Distribution (GED) has more chances to capture fatter tails of returns series in case of non normality.

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

Where R_t and I_{t-1} respectively represent the return in t (day t), and the informational set corresponding to all available information at t-1. For each stock, the daily return is calculated as follows: $R_t = \ln(\frac{P_t}{P_{t-1}})$. Returns are computed from closing prices, P_t, and are adjusted to stock splits. ε_t, is the conditionally Gaussian residual. α and β are respectively ARCH and GARCH coefficients. The sum $\alpha+\beta$ measures the persistence degree of the conditional volatility. The more this sum is high and close to 1, the more persistent will be the shock effect on volatility during the future time[3].

In order to investigate the contemporaneous relationship between trading volume and conditional volatility of returns issued from GARCH (1,1) model and to empirically test the MDH, we include the contemporaneous trading volume (V_t) in the conditional variance equation (equation 2) as a proxy for information arrival:

$$\sigma_t^2 = \omega + \alpha\,\varepsilon_{t-1}^2 + \beta\,\sigma_{t-1}^2 + \lambda V_t \quad (3)$$

Trading volume is measured by the number of traded shares.

The significance of λ would indicate the evidence of the contemporaneous relationship between conditional volatility of returns and trading volume. If MDH is validated[4], we expect that trading volume significantly influences the conditional volatility and reduces substantially its persistence In other words, coefficients λ should be significantly positive, and the sum $\alpha+\beta$ should decrease after including volume in the conditional volatility equation.

Some theoretical studies assume that the lagged volume could be a more relevant proxy for information flow than the contemporaneous volume since the information arrival to the market is sequential as expected by the SIAH, thus, their impacts on prices volatility are delayed in time and not contemporaneous. To analyze the relationship between lagged volume and conditional volatility of returns and consequently test the SIAH, we include the lagged volume into the conditional variance equation instead of the contemporaneous volume as follows:

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

When the coefficients λ are statistically significant, we can conclude that the lagged volume has an impact on the current volatility of returns. Moreover, if the lagged volume is a real proxy for information flows, we expect that λ will be significantly positive and the sum $\alpha+\beta$ will be considerably lower than if the Model (4) is estimated without a lagged volume.

3 This phenomenon is well known in finance under volatility clusters where there is a tendency to clustering when recording extreme values (high or low). Highest returns (positive or negative) tend to be followed by high returns of the same sign; also low returns tend to be produced in clusters.

4 This means that the contemporaneous volume is a real proxy for information flow and that it is driven by the same factors that generate the ARCH effects.

Before estimating the coefficients of the models presented above, we should first proceed to a preliminary analysis of series studied via the stationary test, the test of the normality hypothesis of return series and the test of the ARCH effect that priory requires the determination of the ARMA process followed by the daily returns series (determining the orders p and q of the equation 1 for each stock).

3. DATA AND PRELIMINARY RESULTS

The empirical study investigating the relationship between trading activity and returns' conditional volatility of returns is based on daily data related to the 43 most active and dynamic stocks on the Tunisian Stock Market running from January 2, 2008 to June 29, 2012. For the listed stocks after January 2, 2008, data are taken in account from their first listing day until June 29, 2012. Table A from the appendix presents the list of these 43 enterprises specifying for each enterprise its activity sector, the horizon of data period and the number of the observations.

For each stock of our sample, we consider the data related to transactions including daily closing prices and the number of shares traded (our measure of trading volume). These data have been provided by the Tunis stock exchange, excluding Saturdays, Sundays, public holidays in addition to days in which the considered stock is not exchanged.

In order to measure volatility via GARCH (1,1) model, it is necessary to first check the non-normal distribution of return series and conclude the presence of a potential heteroskedasticity (through testing ARCH effect) which is manifested by a leptokurtic distribution with fatter tails compared to the normal distribution.

Table 1 presents the descriptive statistics of the daily returns series for each of the 43 stocks of our sample during the study period. On average, 30 stocks among 43 have positive returns and only 13 stocks recorded average negative returns. The highest average returns are achieved by shareholders of SOTUVER (0.2105%) and MAGASIN GENERAL (0.1854%), whereas, the lower ones are generated by stocks of TUNISAIR (−0.0788%) and MODERN LEASING (−0.0736%). SIAME and GIF stocks, recorded the extreme values of the highest daily returns (a maximum of 23.3839% for SIAME stock and de 23.2154% for GIF stock). GIF stock has also an important minimum return of −22.3144%, which implies that its returns distribution extent is high; this result is approved by the relatively high standard deviation value (0.024727) considered as a volatility measure. Table 1 also shows that the lower extreme values of the daily returns were realized by shareholders of MONOPRIX (−40.0752%) and ATL (−32.1113%). In addition, price variability as measured by the standard deviation is less pronounced by stocks from TELNET (0.013004), SFBT (0.012890) and UIB (0.011833), and more pronounced by shares from SOPAT (0.025311), GIF (0.024727) and ELECTROSTAR (0.024633). It is likely for these stocks that returns distribution has fat tails compared to the normal distribution.

To test the normality of the series of the daily stock returns, we refer to Jarque–Bera test, based on the skewness and Kurtosis

Table A: List companies of the sample of study

Company name	Industry	Data period		Observations
		Début	Fin	
Amen Bank	Finance	2/1/2008	29/06/2012	1081
BT	Finance	2/1/2008	29/06/2012	1099
BIAT	Finance	2/1/2008	29/06/2012	1091
ATTIJARI Bank	Finance	2/1/2008	29/06/2012	1109
BH	Finance	2/1/2008	29/06/2012	1076
UIB	Finance	2/1/2008	29/06/2012	1100
STB	Finance	2/1/2008	29/06/2012	1102
ATB	Finance	2/1/2008	29/06/2012	1105
BNA	Finance	2/1/2008	29/06/2012	1100
Tunisie Leasing	Finance	2/1/2008	29/06/2012	1089
ATL	Finance	2/1/2008	29/06/2012	1095
CIL	Finance	2/1/2008	29/06/2012	1086
El WIFACK Leasing	Finance	2/1/2008	29/06/2012	1070
Modern Leasing	Finance	3/12/2010	29/06/2012	380
SPIDIT SICAF	Finance	2/1/2008	28/06/2012	1055
TUNINVEST SICAR	Finance	2/1/2008	29/06/2012	887
STAR	Finance	2/1/2008	29/06/2012	1087
ASSURANCES SALIM (SALIM)	Finance	5/4/2010	29/06/2012	493
TUNIS RE	Finance	19/05/2010	29/06/2012	511
SOTETEL	Telecommunications	2/1/2008	29/06/2012	1091
Magasin Genral (SMG)	Consumer services	2/1/2008	29/06/2012	1036
MONOPRIX	Consumer services	2/1/2008	29/06/2012	1095
ARTES	Consumer services	8/4/2008	29/06/2012	1039
ENNAKL Automobiles (ENNAKL)	Consumer services	16/07/2010	29/06/2012	471
SFBT	Consumer services	2/1/2008	29/06/2012	1107
TUNISAIR	Consumer services	2/1/2008	29/06/2012	1099
ADWYA	Health	2/1/2008	29/06/2012	1105
ASSAD	Consumer goods	2/1/2008	29/06/2012	1105
GIF-FILTER	Consumer goods	3/1/2008	29/06/2012	1050
SOPAT	Consumer goods	2/1/2008	29/06/2012	968
POULINA Group Holding (PGH)	Consumer goods	20/08/2008	29/06/2012	946
ELECTROSTAR	Consumer goods	2/1/2008	29/06/2012	1000
SOMOCER	Industry	2/1/2008	29/06/2012	1075
SIMPAR	Industry	2/1/2008	29/06/2012	981
SITS	Industry	2/1/2008	29/06/2012	1097
ESSOUKNA (SOKNA)	Industry	2/1/2008	29/06/2012	1004
Ciments de Bizerte (SCB)	Industry	21/10/2009	29/06/2012	649
Carthage CEMENT (CC)	Industry	23/06/2010	29/06/2012	490
SIAME	Industry	2/1/2008	29/06/2012	1074
SOTUVER	Industry	2/1/2008	29/06/2012	997
TPR	Basics materials	2/1/2008	29/06/2012	1109
SOTRAPIL	Oil and gas	2/1/2008	29/06/2012	1077
TELNET HOLDING (TELNET)	Technology	23/05/2011	29/06/2012	280

ALT: Arab Tunisian Lease

statistics. Table 2 provides the results of this test for each stock from the selected sample. Table 2 shows that skewness statistics are different from zero unlike the normal distribution, indicating that returns distributions are asymmetric. Moreover, Kurtosis statistics are >3 for all stocks which imply that distributions of the daily returns series present a leptokurtic aspect reflecting the presence of heteroskedasticity. Thus, normality hypothesis of these series is rejected for all stocks. This result is confirmed by Jarque–Bera significant statistics. Heteroskedasticity in return series priory supports our referring to GARCH model to measure price volatility.

In order to formally and clearly test the potential heteroskedasticity in the daily returns series, we implement the ARCH effect test developed by Engle (1982) that tests whether residual variances conditionally depend on the series' past or not. This test first requires the identification, the estimation and the validation of ARMA adequate processes modeling daily return series (determination the orders p and q of the equation 1 for each stock). For that, we referred to Box and Jenkins (1976) methodology. ARMA processes finally selected for each of our 43 sampled stocks are summarized in Table B of the appendix.

To test the presence of ARCH effects in the daily returns series, we apply the formal ARCH test indicated by the ARCH-LM test to justify using the GARCH model. The results of this test are presented in Table 2. Table 2 shows that the statistics of ARCH-LM test are significant for most of stocks of the selected sample, hence the rejection of the homoskedasticity null hypothesis in favor of the conditional heteroskedasticity alternative hypothesis in daily returns series. Thus, we accept the hypothesis supporting the presence of the ARCH effect in most of return series, which supports our use of GARCH

Table 1: Descriptive statistics of daily stock returns (02/01/2008 to 29/06/2012)

Stocks	Mean	Maximum	Minimum	Standard deviation	Observations
Amen Bank	0.000966	0.059112	−0.060093	0.014362	1.079
ATB	8.27 E-06	0.067951	−0.146603	0.014408	1.104
ATTIJARI Bank	0.000729	0.059020	−0.062418	0.014583	1.108
BH	−0.000340	0.095745	−0.072510	0.014634	1.075
BIAT	0.000560	0.087865	−0.061875	0.013977	1.090
BNA	0.000235	0.097540	−0.112997	0.016264	1.099
BT	0.000534	0.129005	−0.094336	0.014329	1.096
STB	−0.000172	0.092075	−0.090058	0.016391	1.101
UIB	0.000274	0.059009	0.075729	0.011833	1.099
ATL	0.000351	0.058269	−0.321113	0.018729	1.094
CIL	0.000430	0.111226	−0.195901	0.017359	1.084
Modern leasing	−0.000736	0.058926	−0.091619	0.018016	0.379
SPIDIT SICAF	5.27 E-05	0.061875	−0.091160	0.015423	1.054
Tunisie leasing	0.000499	0.068113	−0.078177	0.015339	1.088
Tuninvest SICAR	−0.000187	0.085634	−0.288741	0.023205	0.886
El WIFACK leasing	0.001020	0.059089	−0.060219	0.013356	1.069
SALIM	0.000663	0.058817	−0.091647	0.016242	492
STAR	0.001407	0.101633	−0.196106	0.019477	1.086
TUNIS RE	−0.000242	0.102095	−0.059807	0.018988	510
SOTETEL	−0.000301	0.108951	−0.207803	0.023080	1.089
ARTES	−6.20 E-05	0.100340	−0.077583	0.015087	1.038
ENNAKL	−0.000993	0.059049	−0.137561	0.018377	0.470
MONOPRIX	0.000516	0.069886	−0.400752	0.020808	1.093
SFBT	0.000159	0.059855	−0.140660	0.012890	1.106
SMG	0.001854	0.102194	−0.125601	0.018601	1.034
TUNISAIR	−0.000788	0.105361	−0.135438	0.019123	1.098
ADWYA	0.000967	0.070269	−0.062048	0.016294	1.104
ASSAD	0.000798	0.086849	−0.218126	0.017859	1.104
ELECTROSTAR	0.000602	0.129261	−0.132598	0.024633	999
GIF	0.000196	0.232154	−0.223144	0.024727	1.048
PGH	−5.15 E-05	0.058118	−0.061961	0.014309	0.945
SOPAT	0.000685	0.102499	−0.181302	0.025311	0.966
SOMOCER	−0.000161	0.128891	−0.135305	0.023529	1.074
SIMPAR	0.000853	0.131995	−0.131192	0.020378	0.980
SITS	0.000447	0.114839	−0.089705	0.018011	1.096
SOKNA	0.000836	0.080852	−0.102441	0.018830	1.003
SCB	−0.000506	0.185924	−0.137407	0.019955	0.648
CC	0.000835	0.058269	−0.105688	0.019824	0.489
SIAME	0.000752	0.233839	−0.091249	0.019373	1.073
SOTUVER	0.002105	0.097285	−0.062831	0.022451	0.995
TPR	0.000176	0.059034	−0.166897	0.016170	1.108
SOTRAPIL	−0.000216	0.116713	−0.099031	0.020537	1.076
TELNET	0.001109	0.057943	−0.056863	0.013004	0.279

model to model returns volatility and consequently study the volume-volatility relationship.

We also test the stationary of the daily return and volume series. To test the return and volume for unit roots, we use the augmented Dickey–Fuller and Phillips–Peron tests. The results[5] show that all return and volume series are stationary at the levels for all stocks.

4. EMPIRICAL RESULTS

In order to empirically study the relationship between trading volume and returns conditional volatility, we first estimate GARCH (1,1) model without volume (equations 1 and 2). Results obtained from parameters estimations of this model are presented in Table 3. Then, the relationship between the volume and the conditional volatility in addition to the MDH are tested modifying the conditional variance equation by adding contemporaneous trading volume as a proxy for information flow (equation 3). Estimations results of GARCH (1,1) model with contemporaneous volume are available in Table 4. MDH assumes that volume coefficient should be significantly positive and that volatility persistence should substantially reduce after including contemporaneous volume in the conditional variance equation.

Table 3 recapitulates estimations results of GARCH (1,1) model without trading volume aiming to model the conditional volatility's dynamic. These results show that ARCH coefficients α and GARCH coefficients β are statistically significant at a 1% significance level for all stocks. This implies the time-varying of conditional volatility of returns in fact that conditional variance is strongly explained by two lagged series one on the past squared residuals capturing the effect of a shock on volatility (measured by α), and the other on the past conditional variances (measured

5 For brevity, statistics for unit roots test are not reported here.

Table 2: Results of the normality and ARCH LM tests of the daily stock returns

Stocks	Skewness	Kurtosis	Jarque-Bera (JB)	LM test statistics
Amen Bank	0.5498	5.3252	297.454*	52.257*
ATB	−0.7639	16.8830	8973.326*	16.448*
ATTIJARI Bank	0.3440	6.9313	735.387*	188.428*
BH	0.3452	7.4960	927.928*	88.041*
BIAT	0.4268	7.8478	1100.449*	139.839*
BNA	0.1883	9.1035	1712.385*	70.372*
BT	0.4777	14.6502	6239.968*	58.986*
STB	0.2989	7.1194	794.911*	74.899*
UIB	0.2531	8.0077	1160.097*	17.120*
ATL	−4.3676	82.3810	290715.100*	0.101
CIL	−1.1924	22.5509	17521.320*	5.438**
Modern leasing	−0.2602	2.5858	109.876*	60.501*
SPIDIT SICAF	−0.1569	6.6214	580.303*	21.419*
Tunisie leasing	0.1244	5.4064	265.321*	120.770*
Tuninvest SICAR	−2.1935	30.8716	29388.360*	0.311
El WIFACK leasing	0.6125	6.4521	597.664*	119.408*
SALIM	−0.2819	6.9126	320.343*	108.121*
STAR	−0.7129	14.8169	6410.763*	6.003**
TUNIS RE	0.6483	6.0362	231.625*	21.705*
SOTETEL	−0.0674	9.8985	2160.192*	5.922**
ARTES	0.1829	8.4325	1282.189*	59.849*
ENNAKL	−1.2901	13.4207	2256.988*	31.773*
MONOPRIX	−7.0202	135.0092	802606.500*	0.114
SFBT	−1.1332	19.4351	12685.640*	5.296**
SMG	0.2698	7.6246	933.972*	94.981*
TUNISAIR	0.2236	8.3286	1308.197*	24.570*
ADWYA	0.4827	5.9910	454.406*	135.881*
ASSAD	−1.7576	26.9211	26890.700*	7.509**
ELECTROSTAR	0.2872	5.4348	260.526*	59.859*
GIF	0.2895	19.5965	12042.370*	31.147*
PGH	−0.1255	6.4011	457.964*	97.995*
SOPAT	−0.1946	7.0350	661.427*	8.352*
SOMOCER	0.4105	6.5803	603.802*	185.438*
SIMPAR	−0.0380	8.3894	1186.300*	18.812*
SITS	0.5188	6.1226	494.463*	53.492*
SOKNA	0.2064	4.5109	102.532*	59.740*
SCB	1.1504	20.2194	8 148.687*	38.241*
CC	−0.0521	6.2766	218.975*	49.515*
SIAME	2.9014	34.0084	44493.670*	194.662*
SOTUVER	0.3936	3.6597	43.745*	108.144*
TPR	−1.6726	22.4494	17980.490*	1.805
SOTRAPIL	0.3797	5.4671	598.756*	48.070*
TELNET	0.7853	7.1631	230.160*	40.986*

*Significant at 1% significance level. **Significant at 5% significance level. Table 2 presents the results of the normality and the ARCH effect (ARCH LM) tests of the daily returns series. To test the null hypothesis that there is no ARCH effect in the residuals resulting from the estimate of ARMA processes finally selected, the following regression is carried out on the squared residuals for each stock of our sample: $\hat{\varepsilon}_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \hat{\varepsilon}_{t-i}^2$, p is different from a stock to another (number of lags corresponding to p first terms significantly different from 0 of the graph of the partial autocorrelations)

by β) representing long term influences and translating the autocorrelation of information flow supposed to have an influence on volatility.

These results also show that the sum α+β is generally high and close to 1 for the most of stocks thus leading to strong conditional volatility persistence. This sum is >0.9 for 23 stocks and >0.8 for 37 stocks among 43, and recorded a minimum of 0.7329 indicating a high degree of volatility persistence. This strong

Table B: Processes ARMA representative of the series of daily stock returns

Stocks	ARMA (p, q) model	Stocks	ARMA (p, q) model
Amen Bank	ARMA (0,0)	MONOPRIX	ARMA (0,0)
ATB	MA (1)	SFBT	ARMA (0,0)
ATTIJARI Bank	AR (1)	SMG	ARMA (2,1)
BH	ARMA (1,1)	TUNISAIR	AR (3)
BIAT	ARMA (0,0)	ADWYA	MA (1)
BNA	MA (1)	ASSAD	MA (1)
BT	MA (1)	ELECTROSTAR	ARMA (3,3)
STB	MA (2)	GIF	MA (1)
UIB	ARMA (0,0)	PGH	ARMA (2,1)
ATL	MA (1)	SOPAT	AR (1)
CIL	ARMA (0,0)	SOMOCER	MA (1)
Modern leasing	AR (1)	SIMPAR	AR (1)
SPIDIT SICAF	ARMA (0,0)	SITS	AR (1)
Tunisie leasing	ARMA (0,0)	SOKNA	ARMA (0,0)
Tuninvest SICAR	ARMA (0,0)	SCB	MA (1)
El WIFACK Leas	AR (1)	CC	MA (1)
SALIM	MA (1)	SIAME	MA (2)
STAR	MA (2)	SOTUVER	AR (1)
TUNIS RE	MA (1)	TPR	AR (1)
SOTETEL	AR (1)	SOTRAPIL	MA (1)
ARTES	ARMA (0,0)	TELNET	ARMA (0,0)
ENNAKL	AR (1)		

Table B presents the results of application of the methodology of Box and Jenkins (1976) aiming at finding the ARMA (p, q) adequate specification which describes the evolution of the series of the daily returns for each stock of our sample according to the following representation: $R_t = \alpha + \sum_{i=1}^{p} \varphi_i R_{t-i} + \varepsilon_t + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j}$, where ε_t is a white noise with zero mean, constant variance and not auto-correlated ($\varepsilon_t \sim BB(0, \sigma_\varepsilon^2)$).

volatility persistence, on the Tunisian stock market, reflects the presence of volatility cluster phenomenon where high returns tend to be followed by high returns with same sign, and the lower returns also tend to be produced in clusters. Conditional volatility persistence and its time-varying are mainly the result of serial correlation in the information arrival process whose volume is a proxy as suggested by the MDH. To test this hypothesis, we add contemporaneous trading volume in the conditional variance equation of GRACH (1,1) model as a proxy for the information arrival rate (equation 4). This approach allows us to also test the contemporaneous relationship between trading volume and returns conditional volatility. Estimations results of GARCH (1,1) model with contemporaneous trading volume are summarized in Table 4.

Table 4 shows that the coefficients λ are positive and statistically significant at 1% level for all stocks, which implies that there is a strong positive contemporaneous relationship between trading volume and returns conditional volatility. This contemporaneous relationship is thus a result of the joint dependence of the volume and the volatility to an unobservable directing variable representing the daily rate of information flow as assumed by the MDH which supposes that the new information dissemination is contemporaneous and that the instantaneous reaction of different traders on its arrival on the market leads to a positive contemporaneous volume-volatility relationship. Moreover, Table 4 shows that for 38 stocks among 43, the addition of contemporaneous trading volume into the conditional volatility equation significantly reduces the volatility persistence as measured by the sum α+β. Volatility persistence is thus largely absorbed by the trading volume effect, indicating that the serially correlated

Table 3: The estimation results of the ARMA-GARCH (1,1) model without trading volume

Stocks	α		β		α+β
Amen Bank	0.2097*	(6.349)	0.5949*	(12.824)	0.8046
ATB	0.2415*	(5.608)	0.6451*	(12.129)	0.8566
ATTIJARI Bank	0.4303*	(10.094)	0.5569*	(18.513)	0.9872
BH	0.3462*	(9.051)	0.5782*	(17.455)	0.9244
BIAT	0.2818*	(12.117)	0.6471*	(35.458)	0.9289
BNA	0.4943*	(3.672)	0.4994*	(7.812)	0.9937
BT	0.3633*	(13.673)	0.6269*	(48.319)	0.9902
STB	0.4140*	(9.752)	0.4812*	(12.505)	0.8952
UIB	0.2342*	(8.612)	0.7221*	(34.791)	0.9563
ATL	0.2450*	(4.752)	0.6142*	(8.982)	0.8592
CIL	0.4515*	(22.442)	0.5417*	(24.665)	0.9932
Modern leasing	0.2985*	(4.251)	0.5541*	(5.493)	0.8526
SPIDIT SICAF	0.2665*	(8.489)	0.4752*	(9.827)	0.7417
Tunisie leasing	0.1731*	(5.551)	0.6572*	(12.910)	0.8303
Tuninvest SICAR	0.3439*	(3.701)	0.4564*	(4.579)	0.8003
El WIFACK leasing	0.2639*	(8.456)	0.5999*	(16.787)	0.8638
SALIM	0.2266*	(5.166)	0.5555*	(8.192)	0.7821
STAR	0.3691*	(9.986)	0.6182*	(18.931)	0.9873
TUNIS RE	0.0310*	(4.078)	0.9596*	(15.760)	0.9906
SOTETEL	0.3529*	(9.062)	0.4687*	(10.051)	0.8216
ARTES	0.2498*	(8.977)	0.6895*	(28.815)	0.9393
ENNAKL	0.6197*	(7.112)	0.3344*	(4.870)	0.9541
MONOPRIX	0.3399*	(5.681)	0.5008*	(7.748)	0.8407
SFBT	0.2646*	(6.367)	0.4878*	(12.232)	0.7524
SMG	0.4672*	(10.857)	0.4342*	(11.569)	0.9014
TUNISAIR	0.5161*	(5.060)	0.4536*	(6.301)	0.9697
ADWYA	0.2099*	(8.929)	0.7572*	(37.815)	0.9671
ASSAD	0.5493*	(4.977)	0.4432*	(8.722)	0.9925
ELECTROSTAR	0.2285*	(7.156)	0.6447*	(12.213)	0.8732
GIF	0.5666*	(16.128)	0.4249*	(18.277)	0.9915
PGH	0.1282*	(4.438)	0.8488*	(54.301)	0.9770
SOPAT	0.3152*	(7.375)	0.6010*	(14.821)	0.9162
SOMOCER	0.2886*	(4.315)	0.5466*	(6.856)	0.8352
SIMPAR	0.1676*	(5.685)	0.6762*	(12.261)	0.8438
SITS	0.3122*	(8.422)	0.6012*	(16.586)	0.9134
SOKNA	0.2470*	(7.274)	0.5524*	(8.499)	0.7994
SCB	0.5001*	(7.746)	0.3563*	(5.605)	0.8564
CC	0.5034*	(3.875)	0.4928*	(5.222)	0.9962
SIAME	0.4014*	(11.487)	0.5515*	(21.292)	0.9529
SOTUVER	0.1463*	(5.435)	0.8009*	(23.433)	0.9472
TPR	0.2167*	(9.501)	0.5162*	(20.161)	0.7329
SOTRAPIL	0.2419*	(6.965)	0.5534*	(9.512)	0.7953
TELNET	0.3367*	(4.253)	0.5519*	(9.694)	0.8886

*Significant at 1% significance level. Table 3 presents the estimation results of the GARCH (1, 1) model without volume for each stock of our sample: R_t~ARMA (p, q) where $\varepsilon_t \mid I_{t-1} \sim N(0,\sigma_t^2)$ and $\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2$. R_t is the return in t (day t). σ_t^2 is the conditional variance of the error process ε_t. $\alpha+\beta$ measures the persistence of the conditional volatility. The t-statistics are given in parenthesis

arrival information process proxied by the current volume, could be a significant source of conditional heteroskedasticity in return series in the Tunisian stock market. These results are consistent with Lamoureux and Lastrapes (1990), Bohl and Henke (2003), Mestel et al., (2003), Floros and Vougas (2007) Mahajan and Singh (2009), Alsubaie and Najand (2009), Kumar et al., (2009), Louhichi (2011), Celik (2013).

For ATTIJARI BANK, BT, UIB, PGH and SOPAT stocks, although trading volume coefficient is positive and statistically significant at 1%, the sum α+β is not reduced after including the contemporaneous volume in the conditional variance equation reflecting thus the non-reduction of volatility persistence. This result could be explained by volume inability to properly measure the informative content of the trading activity and therefore constitute a better proxy for information arrival rate on the market.

According to Table 4, we also notice that adding the contemporaneous trading volume into variance equation, ARCH α coefficients remain statistically significant for all stocks and GARCH β coefficients remain significant for 35 stocks among 43, indicating the existence possibility of other variable in addition to trading volume, that can contribute the conditional heteroskedasticity in return series on the Tunisian financial market.

Overall the evidence of positive contemporaneous volume-volatility relationship added to the significant reduction in volatility persistence resulting from the inclusion of the contemporaneous trading volume into the conditional variance equation, confirm our hypothesis H1 and empirically support the MDH stating that information dissemination is contemporaneous and therefore the persistence of conditional heteroskedasticity is largely absorbed by current volume that measures the arrival information rate.

Based on the suggestions of the SIAH assuming that information dissemination is sequential and that different traders react gradually to its arrival on the market which can delay over time its impact on price volatility, we empirically investigate the relationship between lagged trading volume and conditional volatility of returns through replacing the contemporaneous volume by the lagged one in the conditional variance equation of GARCH (1,1) model. If the SIAH is validated, we expect that lagged volume will significantly and positively influence conditional volatility and substantially reduce its persistence more than contemporaneous volume. Estimations results of GARCH (1,1) model with lagged volume are presented in Table 5.

Table 5 shows that unlike contemporaneous volume coefficients, λ coefficients are statistically significant only for 33 stocks among 43 (76% of all stocks faced to 100% for contemporaneous volume). Moreover, after including lagged volume in the conditional variance equation as a proxy for information arrival rate, the sum α+β remains, for most of the stocks, high and close to the persistence level arising from GARCH (1,1) model without trading volume and also higher than persistence level when including contemporaneous volume. This sum remains >0.9 for 13 stocks and >0.8 for 21 stocks. Furthermore, ARCH α and GARCH β coefficients remain significant. Unlike contemporaneous volume, these results imply that lagged volume can neither absorb conditional volatility persistence through reducing it nor explain heteroskedasticity in return series and the ARCH and GARCH effects characterizing them. Thus, the lagged volume cannot be a relevant proxy for the information arrival rate when explaining conditional volatility persistence of returns. These results thus do not confirm our second hypothesis H2 and do not support the SIAH assuming that information dissemination is sequential and that the gradual reaction of traders to its arrival on the market leads to a positive dynamic volume-volatility relationship where the lagged values of volume could affect the contemporaneous volatility of price or returns because of their informative content

Table 4: The estimation results of the ARMA-GARCH (1,1) model with contemporaneous volume

Stocks	α		β		λ		$\alpha+\beta$
Amen Bank	0.1407*	(4.651)	0.0300	(0.931)	3.00 E-08*	(8.952)	0.1707
ATB	0.1855*	(5.844)	0.6210*	(12.871)	1.09 E-09*	(3.384)	0.8065
ATTIJARI Bank	0.4021*	(8.889)	0.5031*	(18.070)	4.12 E-09*	(6.114)	0.9052
BH	0.3344*	(7.962)	0.3701*	(9.192)	4.17 E-09*	(7.987)	0.7045
BIAT	0.3463*	(8.735)	0.4764*	(17.568)	5.17 E-09*	(7.290)	0.8227
BNA	0.4239*	(3.812)	0.1869*	(2.761)	6.53 E-09*	(4.008)	0.6108
BT	0.3963*	(13.191)	0.5849*	(32.007)	3.34 E-10*	(6.722)	0.9812
STB	0.2716*	(4.619)	0.1735*	(4.619)	4.46 E-09*	(8.303)	0.4451
UIB	0.3139*	(10.645)	0.6404*	(32.188)	7.13 E-10*	(8.409)	0.9543
ATL	0.3160*	(4.683)	0.2794*	(3.430)	3.96 E-09*	(4.640)	0.5954
CIL	0.5559*	(22.422)	0.2394*	(9.479)	1.64 E-08*	(6.759)	0.7953
Modern leasing	0.4195*	(4.619)	0.0204	(0.224)	1.75 E-08*	(3.492)	0.4399
SPIDIT SICAF	0.2911*	(9.763)	0.1057**	(2.101)	5.73 E-09*	(8.433)	0.3968
Tunisie leasing	0.1963*	(5.485)	0.4683*	(8.666)	5.38 E-09*	(6.851)	0.6646
Tuninvest SICAR	0.2735*	(3.699)	0.3647*	(3.866)	5.34 E-08*	(3.398)	0.6382
El WIFACK Leas	0.2616*	(5.625)	0.2876*	(5.706)	8.62 E-09*	(6.659)	0.5492
SALIM	0.2327*	(4.399)	0.1932***	(1.908)	1.17 E-08*	(4.332)	0.4259
STAR	0.3265*	(6.206)	0.4623*	(10.422)	2.61 E-08*	(7.030)	0.7888
TUNIS RE	0.1927*	(2.991)	0.2827*	(2.674)	5.18 E-09*	(6.957)	0.4754
SOTETEL	0.2303*	(5.402)	0.0291	(0.625)	2.76 E-08*	(13.491)	0.2594
ARTES	0.2008*	(6.346)	0.0269	(1.517)	7.39 E-09*	(75.490)	0.2277
ENNAKL	0.3177*	(3.800)	0.2426*	(3.821)	3.58 E-09*	(6.219)	0.5603
MONOPRIX	0.3453*	(6.566)	0.3765*	(7.539)	2.84 E-08*	(7.242)	0.7218
SFBT	0.2012*	(5.932)	0.0692**	(2.487)	3.14 E-08*	(26.884)	0.2704
SMG	0.4748*	(10.901)	0.2752*	(7.819)	6.26 E-08*	(9.426)	0.7500
TUNISAIR	0.3043*	(4.788)	0.1522**	(2.297)	4.45 E-09*	(6.149)	0.4565
ADWYA	0.3096*	(7.723)	0.3748*	(9.002)	2.75 E-09*	(8.808)	0.6844
ASSAD	0.4022*	(5.019)	0.0901**	(2.032)	1.49 E-08*	(6.451)	0.4923
ELECTROSTAR	0.1372*	(3.954)	0.0274	(0.427)	8.86 E-08*	(6.273)	0.1646
GIF	0.4181*	(10.116)	0.1465*	(4.758)	9.62 E-09*	(15.603)	0.5646
PGH	0.1997*	(7.596)	0.7405*	(31.716)	2.18 E-10*	(4.823)	0.9402
SOPAT	0.3122*	(6.765)	0.6019*	(13.465)	4.76 E-10**	(2.359)	0.9141
SOMOCER	0.1933*	(3.436)	0.0989	(1.340)	3.12 E-09*	(5.108)	0.2922
SIMPAR	0.1562*	(4.502)	0.6177*	(9.041)	1.93 E-08*	(4.218)	0.7739
SITS	0.2713*	(7.165)	0.4390*	(10.383)	2.22 E-09*	(6.370)	0.7103
SOKNA	0.2662*	(6.224)	0.2773*	(3.110)	1.28 E-08*	(4.198)	0.5432
SCB	0.2502*	(4.511)	0.1545***	(1.935)	1.45 E-08*	(7.155)	0.4047
CC	0.3712*	(3.601)	0.2135**	(2.305)	4.02 E-10*	(4.198)	0.5847
SIAME	0.3851*	(8.746)	0.4730*	(13.244)	1.05 E-09*	(5.470)	0.8581
SOTUVER	0.3108*	(4.673)	0.1714***	(1.928)	3.41 E-09*	(5.452)	0.4822
TPR	0.2355*	(8.530)	0.2070*	(4.234)	3.12 E-09*	(10.559)	0.4425
SOTRAPIL	0.1527*	(3.612)	0.1290	(1.455)	5.37 E-08*	(6.585)	0.2817
TELNET	0.2235**	(2.569)	0.0394	(0.666)	3.60 E-09*	(4.748)	0.2629

*Significant at 1% level, **Significant at 5% level, ***Significant at 10% level. Table 4 presents the estimation results of the GARCH (1, 1) model with contemporaneous volume for each stock of our sample: R_t~ARMA (p, q) where $\varepsilon_t | I_{t-1} \sim N(0,\sigma_t^2)$ and $\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \lambda V_{t-1}$. R_t and V_t are respectively the return and the trading volume in t (day t). The significance of λ would indicate the evidence of the contemporaneous volume-volatility relationship. σ_t^2 is the conditional variance of the error process ε_t . $\alpha + \beta$ measures the persistence of the conditional volatility. The t-statistics are given in parenthesis

so that conditional volatility persistence will be substantially absorbed by the lagged volume effect.

Overall our results empirically support the MDH but not the SIAH.

5. CONCLUSION

This paper aims to test the relationship between trading volume and conditional volatility of returns in order to provide an empirical support to either the MDH or the SIAH. We utilize the GARCH (1,1) model to test the persistence of return volatility without volume, with contemporaneous volume, and with lagged volume. Our empirical analysis is based on daily data related to the 43 most active and dynamic securities traded from January 2, 2008 to June 29, 2012. The results show the existence of a strong positive relationship between trading volume and conditional volatility of returns. Moreover, adding the contemporaneous volume into the conditional variance equation significantly reduces the volatility persistence, according to the theoretical predictions of the MDH supposing that the persistence of conditional heteroskedasticity is largely absorbed by current volume effect measuring the information arrival rate. Through replacing contemporaneous volume by the lagged volume in conditional variance equation, we find that volatility persistence remains in the whole high and close to the persistence level arising from GARCH (1,1) model without trading volume and also at a higher level than the one resulting from the addition of contemporaneous volume, which implies that lagged volume cannot constitute a good proxy for the information arrival rate when explaining conditional volatility persistence of returns. Our results thus do not support the implications of

Table 5: The estimation results of the ARMA-GARCH (1,1) model with lagged volume

Stocks	α		β		λ		$\alpha+\beta$
Amen Bank	0.2051*	(5.816)	0.5697*	(11.282)	1.39 E-09**	(2.134)	0.7748
ATB	0.2357*	(5.923)	0.6208*	(12.429)	3.28 E-10	(1.464)	0.8565
ATTIJARI Bank	0.4143*	(9.580)	0.5519*	(18.002)	1.49 E-09*	(3.116)	0.9662
BH	0.3372*	(9.420)	0.5639*	(17.235)	7.23 E-09*	(5.715)	0.9011
BIAT	0.2734*	(12.033)	0.6467*	(35.489)	5.21 E-10	(0.034)	0.9201
BNA	0.5121*	(3.177)	0.4781*	(7.142)	5.87 E-10	(1.139)	0.9902
BT	0.5506*	(5.086)	0.4402*	(7.787)	2.36 E-10	(1.375)	0.9908
STB	0.3669*	(7.391)	0.1901*	(3.783)	1.66 E-09*	(7.686)	0.5570
UIB	0.3113*	(9.807)	0.6612*	(12.096)	7.57 E-10	(0.688)	0.9725
ATL	0.2347*	(4.797)	0.5563*	(8.346)	9.57 E-10*	(2.896)	0.7910
CIL	0.4630*	(20.095)	0.5207*	(21.345)	1.34 E-09	(1.524)	0.9837
Modern leasing	0.3174*	(3.795)	0.4068*	(3.375)	4.65 E-09***	(1.652)	0.7242
SPIDIT SICAF	0.2889*	(8.917)	0.4288*	(10.877)	4.03 E-09*	(5.023)	0.7177
Tunisie leasing	0.2045*	(5.674)	0.5514*	(11.444)	2.68 E-09*	(4.491)	0.7559
Tuninvest SICAR	0.2294*	(3.233)	0.4498*	(4.380)	2.53 E-08*	(2.866)	0.6792
El WIFACK Leas	0.2411*	(6.897)	0.5355*	(11.053)	2.29 E-09*	(3.598)	0.7766
SALIM	0.2035*	(4.839)	0.5642*	(9.038)	2.19 E-09	(1.540)	0.7677
STAR	0.3654*	(7.739)	0.5620*	(13.716)	1.04 E-08*	(3.995)	0.9274
TUNIS RE	0.1667*	(2.655)	0.8122*	(16.641)	6.17 E-10	(1.051)	0.9789
SOTETEL	0.3141*	(6.751)	0.0194	(0.359)	1.90 E-08*	(5.982)	0.3335
ARTES	0.2183*	(7.546)	0.6548	(22.543)	7.99 E-10*	(4.050)	0.8731
ENNAKL	0.4926*	(4.694)	0.1694*	(2.751)	3.72 E-09*	(5.407)	0.6620
MONOPRIX	0.3339*	(6.168)	0.4145*	(6.653)	1.27 E-08*	(5.326)	0.7484
SFBT	0.2150*	(5.376)	0.2282*	(3.593)	1.69 E-08*	(6.475)	0.4432
SMG	0.4657*	(9.875)	0.3298*	(8.093)	4.11 E-08*	(6.590)	0.7955
TUNISAIR	0.4456*	(4.759)	0.3286*	(3.969)	1.88 E-09*	(3.263)	0.7742
ADWYA	0.2446*	(8.245)	0.6613*	(28.514)	7.95 E-10*	(4.944)	0.9059
ASSAD	0.5287*	(4.371)	0.3309*	(5.577)	6.55 E-09*	(3.765)	0.8596
ELECTROSTAR	0.1841*	(5.186)	0.5962*	(7.723)	1.20 E-08*	(3.039)	0.7803
GIF	0.5957*	(13.923)	0.2305*	(8.762)	8.20 E-09*	(13.176)	0.8262
PGH	0.1685*	(6.616)	0.7941*	(30.316)	7.98 E-08*	(2.864)	0.9626
SOPAT	0.3150*	(7.153)	0.6017*	(13.955)	1.76 E-11	(0.087)	0.9167
SOMOCER	0.2656*	(3.819)	0.2632*	(2.741)	1.83 E-09*	(4.264)	0.5288
SIMPAR	0.1585*	(4.847)	0.6563*	(11.112)	1.02 E-08*	(2.811)	0.8148
SITS	0.2909*	(8.214)	0.5325*	(14.636)	1.36 E-09*	(5.632)	0.8234
SOKNA	0.2503*	(6.969)	0.4407*	(5.953)	5.79 E-09**	(2.310)	0.6910
SCB	0.3142*	(4.565)	0.0770	(1.080)	1.49 E-08*	(7.317)	0.3912
CC	0.4601*	(3.441)	0.4555*	(4.881)	1.50 E-10*	(3.025)	0.9156
SIAME	0.3940*	(9.402)	0.4963*	(15.519)	8.27 E-10*	(5.885)	0.8903
SOTUVER	0.2952*	(4.422)	0.3349*	(3.576)	1.51 E-09*	(3.691)	0.6301
TPR	0.3008*	(4.472)	0.3859*	(6.070)	8.60 E-09*	(4.884)	0.6867
SOTRAPIL	0.1481*	(3.349)	0.2257**	(2.318)	3.47 E-08*	(5.047)	0.3738
TELNET	0.2496**	(2.353)	0.0139	(0.139)	3.42 E-09*	(4.608)	0.2635

*Significant at 1% level, **Significant at 5% level, ***Significant at 10% level. Table 5 presents the estimation results of the GARCH (1, 1) model with lagged volume for each stock of our sample: R_t~ARMA (p, q) where $\varepsilon_t | I_{t-1} \sim N(0,\sigma_t^2)$ and $\sigma_t^2=\omega+\alpha\varepsilon_{t-1}^2+\beta\sigma_{t-1}^2+\lambda V_{t-1}$. R_t and V_{t-1} are respectively the daily return in t and the trading volume in t-1. The significance of λ would indicate the effect of lagged volume on return conditional volatility. σ_t^2 is the conditional variance of the error process ε_t . $\alpha+\beta$ measures the persistence of the conditional volatility. The t-statistics are given in parenthesis

the SIAH assuming that information dissemination is sequential and that the gradual reaction of traders to its arrival makes lagged volume informative and therefore, conditional volatility persistence is substantially absorbed by the volume effect.

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