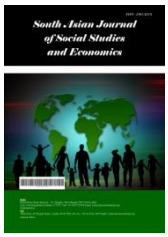

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Excess Volatility in the Tunisian Stock Market: Explanation by Behavioral Finance

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Author's contribution

The sole author designed, analyzed, interpreted and prepared the manuscript.

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ABSTRACT

In this paper, we tried to show the existence of excess volatility of stock prices in the Tunisian stock exchange during the period 2000 - 2017, by applying the variance bounds of Shiller. We used data on daily closing prices and the transaction volume of 22 companies listed on Tunisian Financial market during the period 2016/2017 to identify the relationship between over confidence bias and the Excess Volatility via the Granger causality test. Based on Chuang and Lee's approach, we studied the effect of the excess confidence component on volatility by the E-GARCH Model (1.1). Our results show that high market volatility resulted from overconfident investors.

Keywords: International portfolio investment; international diversification; gravity model; information asymmetry; the E-GARCH model; causality tests.

1. INTRODUCTION

Stock prices frequently undergo large changes that do not coincide with the publication of new information, changes in profits or potential dividends [1]. The most famous episode occurred on October 19, 1987, when stock prices fell around the world in the absence of new information (- 22% in the United States). Such events seem to contradict financial theory. In this sense, several academic researchers have demonstrated that the stock prices show an

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excessive volatility relative to that of fundamental value [2].

The COVID-19 pandemic has presented overwhelming economic effects on international financial markets. During the period between February and March 2020, these markets experienced excessive volatility. The risk levels of all the countries have increased substantially, from an average of 0.0071 in February 2020 to 0.0196 in March 2020 [3].

Broadstock and Zhang [4] have shown that sentiment investor extracted from social-media (Twitter), has pricing power towards American stock market volatility. Likewise, [5] found that the common sentiment and expectations of Chinese investors has an impact on the excessive volatility of the Chinese financial market caused by the coronavirus epidemic in 2020.

The notion of excessive volatility was first addressed by Shiller [6] LeRoy [2] and LeRoy and Porter [7]. These articles, written independently and approximately contemporarily, have established the existence of limits to the volatility of prices and returns and have proved the existence of excessive volatility.

The work of Shiller [6] and LeRoy and Porter [7] have shown that the volatility of stock prices greatly exceeds the volatility of dividends and ex-post profits. Although these conclusions were originally interpreted as a failure of the modern theory of rational expectations, Kleidon's (1986) critique has shown that such results do not contradict this model of rational expectations if dividends or gains are correlated and not stationary.

Since the studies of Shiller [6] and LeRoy and Porter [7] it has been recognized that the price volatility observed is much higher than the prices determined with the theoretical pricing models, taking into account the available evidence of volatility and non-stationarity of dividends.

Cuthbertson and Hyde [8] analyzed whether the French and German stock markets can be classified as efficient or if they exhibit excessive volatility. Applying the VAR methodology of Campbell and Shiller [9] on monthly stock market data during the period, the authors prove that both stock markets exhibit excessive volatility.

Heaney [10] has studied excessive volatility in the Australian stock market using annual data for more than 100 years and found that stock prices are strongly correlated with dividend changes.

Several interpretations have been made by the literature to explain the excessive volatility of the financial markets. Nevertheless, the most frequent interpretations are those which consider excessive volatility as a consequence of the variation of the fundamental determinants, notably the variable discount rate of dividends and the presence of rational bubbles [11].

Bubbles are usually associated with dramatic increases in asset prices followed by a collapse. They represent a persistent gap between the intrinsic value and the observed value of a financial asset [12].

Gürkaynak [13] indicates that bubbles are rational if investors are willing to pay for assets that are more expensive than their fundamental value if they hope to sell the asset at an even higher price.

Historically, we note that psychologists focus on the over-confidence bias and believe that overconfident investors overestimate their forecasting capabilities and face considerable losses.

Zia et al. [14] show that confident investors tend to react excessively and frequently to the stock market with poor performance. concluded that people tend to believe that they are better than they actually are.

According to Fabre and François-Heude [15] overconfidence occurs when investors exaggerate their predictive skills and ignore the impact of chance or external environmental factors that can cause stocks to underestimate. In other words, overconfidence is a psychological bias affecting the behavior of individuals. People who are affected by overconfidence tend to overestimate their abilities and personal knowledge.

Glaser and Weber [16] distinguish three aspects of overconfidence in finance, namely i) subjective probability greater than the real probability, ii) above-average effect, tendency to think that someone has above-average ability, and iii) unrealistic optimism: a belief that people have more ability to predict outcomes when they have high involvement.

Carpena et al. [17] show that confident investors tend to react excessively to the stock market with

poor performance. They concluded that people tend to believe that they are better than they actually are.

Studies by Benos [18] and Odean [19] argue that over confident investors negotiate more and that this behavior increases the volume of future transactions. They also associate over-confidence with overweighting the accuracy of their own information. Daniel et al [20] and Grinblatt and Keloharju [21] study the relationship between over-confidence and delayed performance. They find that these characteristics, in addition to other behavioral attributes, contribute to the increase in transaction volumes.

Graham et al. [22] find that an investor's trading volume is affected by the level of overconfidence. Bertella et al. [23] studied the over-confidence bias by analyzing stock market movements and their rates of return in an artificial stock market. Their study revealed that investors affected by overconfidence generate more variation in stock prices than normal investors.

This article focuses on the excessive volatility of the Tunisian financial market and tries to provide explanations by behavioral finance and particularly the bias of over confidence.

Our article is organized as follows; the second section presents a description of the data. In the third section, we will study the existence of a possible excessive volatility of stock prices on the Tunisian market during the period 2000-2017, using the test based on variance bounds of Shiller [6]. In the fourth section, we will try to provide empirical explanations of the phenomenon of increased volatility of prices, to attest that investors operating on the Tunis Stock Exchange are too confident. We will therefore study the impact of the delayed returns of 22 companies on the volume of transactions during the 2016/2017 period, via the test of causality in Granger's sense [22]. Based on Chuang and Lee [23] we will then identify the effect of the excess confidence component on volatility by the E-GARCH Model (1.1). The conclusion, which is the subject of the fifth section, will take up the main lessons learned from the empirical study carried out in this paper.

2. METHODS AND MATERIALS

2.1 Data Description

The data are extracted from the Tunisian securities exchange and the Central Bank of Tunis to obtain two samples. The first, used to test the findings of the Excess Volatility, includes 18 companies listed on the Tunisian Stock Exchange, observed over the period from 2000 to 2017.

Our first sample is well diversified, it brings several sectors of the Tunisian economy, four financial services companies (leasing and insurance), three banks, four companies operating in the service sector, two consumer goods companies, two buildings, two basic materials companies and a telecommunications company. Furthermore, the sample is based on annual observations as our volatility tests require the use of dividends that are distributed annually.

The second sample allows studying some aspects of behavioral finance. For this purpose, we used daily observations about closing prices, transaction volume and returns of 22 companies listed on the Tunisian Stock Exchange during the period between January 2016 and December 2017. We included in our sample only firms that have available information on stock price, trading volume, and market capitalization.

2.2 Detection of the Excess Volatility of Share Prices on the Tunisian Stock Market

2.2.1 Variance Bound Test of Shiller [6]: First Generation Test

To study the existence of excessive volatility of prices on the Tunisian stock market, we used Shiller's test [6] benchmark of variances, which consists of checking the presence of a gap between the observed price and the rational ex-post price. Shiller [6] proposes the following regression:

$$P_t = E_t\,(P^*_t/I_t) \qquad (1)$$

Where,
P_t: The expectation price conditional on the set of information available at time t;
p^*_t : The ex-post rational price;
I_t : All the information available.

The objective of the test is to bring the ex-post rational price closer to that of the observed price. So if the market is efficient, both prices should show the same dynamics.

$$P^*_t = P_t + \mu_t \qquad (2)$$

Where,
μ_t : The forecast error.

This equation leads to three crucial implications proposed by Shiller [6]:

(1) Given investors' rational expectations, there is no correlation between the forecast error term μ_t and the available information:

$$\text{cov}(P_t, \mu_t) = 0 \quad (3)$$

(2) In addition, the forecasts are not correlated with the forecast error, which gives a lower bound to the variance:

$$\text{var}(P^*_t) = \text{var}(P_t) + \text{var}(\mu_t) \quad (4)$$

(3) Given that variance can only be positive, the observed price variance P_t must not exceed the variance of ex-post rational prices P^*_t:

$$\text{Var}(P^*_t) \leq \text{var}(P_t) \quad (5)$$

In order to study the behavior and the dynamics of the price we will follow the methodology of Shiller [6], we compare the variance of the ex-post-rational price index with that of the observed price index in order to verify the existence of a possible excessive volatility on the Tunisian stock market. The market price index for the year (t) is as follows:

$$P_t = \sum_{1=1}^{1} w_{it} P_{it} \quad (6)$$

Where,
P_t : The price index of the year (t);
I : The number of companies; i=1,2,……18;
t : The number of years; t =2000, 2001,…, 2017;
P_{it} : The closing price of the company i on date (t);
w_{it} : Market Capitalization Coefficient or the weight of share (i) in the market on date (t).

After calculating the price indices, it is necessary to proceed to the calculation of the dividend indices that will be used to calculate ex-post rational prices. Similarly for the index of observed dividends:

$$D_t = \sum_{1=1}^{I} w_{it} D_{it} \quad (7)$$

Where,
D_t : Dividend index observed at date t;
D_{it} : Dividend distributed by action i, at time t.

Once the two indices are constructed, the last step is to calculate the ex-post rational price indices using the two indices already determined. Formally, it is to apply the following formula:

$$P_t^* = \frac{P_{t+1}^* + D_t}{1+R} \quad (8)$$

Where,
P_t^* : The ex-post rational price index at date t;
P_{t+1}^* : The ex-post rational price index at date t + 1;
D_t : The dividend index observed during the period t;
R: The average rate of return.

2.2.2 The Results of the Variance Bound Test

We have studied the evolution of observed prices and ex-post prices during the period 2000 - 2016. The results of the variance bound test (Table 1) show that the inequality of the variance bounding test is clearly violated, because the observed price variance exceeds the ex post rational price variance (18,366> 9,210). Our results indicate the existence of excessive volatility in the Tunisian stock market.

3. DETECTION OF OVERCONFIDENCE ON THE TUNISIAN STOCK MARKET

Previous empirical studies have shown that excessive volatility is a direct reaction to excessive trading by over-confident investors. Overconfidence is a psychological, cognitive and congenital bias that most investors suffer from. These can largely affect the decisions of agents and slow down the functioning of stock markets.

3.1 Detection of Overconfidence

Several empirical studies have shown that the confidence assumption provides for the verification of the positive relationship between the volume of transactions (measured with the turnover rate) and the lagged stock market returns. The objective is then to check whether the investors operating on the TSE exhibit an excess of confidence in their behavior.

Table 1. Variation Calculation of the Two Indices (Observed Prices, Ex-post Rational Prices)

	P_t	D_t	P^*_t
2000	14,893	,759	6,795
2001	12,583	,751	6,971
2002	12,365	,789	7,177
2003	11,486	1,114	7,374
2004	10,626	,795	7,274
2005	10,488	,748	7,479
2006	12,297	,787	7,759
2007	12,489	,810	8,039
2008	12,510	,526	8,333
2009	15,766	1,084	8,952
2010	21,001	,637	9,099
2011	22,334	,602	9,712
2012	25,080	,431	10,445
2013	19,595	,478	11,450
2014	16,821	,492	12,545
2015	16,885	,485	13,776
2016	12,176	,474	15,185
2017	16,256	,542	16,798
	$Var(P_t)$ = 8,366		$Var(P^*_t)$= 9,210

We will try to empirically validate this relationship based on Granger causality tests [24]. These tests make it possible to study the Co-variations between the two proxies and to examine the impact of the excess of confidence on the volatility of the financial markets. To perform our tests, we used daily data on the closing prices, traded quantities and outstanding securities of 22 listed companies during the period 2016-2017.

3.1.1 Measure of return rates and transaction volume

To calculate the performance of the Tunisian financial market we used the following formula:

$$R_t = \frac{\sum_{i=1}^{k} R_{it}}{k} \quad (9)$$

Where,

R_t : Daily market yield;

k : Number of shares on the market;

R_{it} : The daily return of the share i.

To calculate the transaction volume of the Tunisian financial market, we will use the daily turnover rate of 22 companies:

$$V_t = \frac{\sum_{i=1}^{k} V_{it}}{k} \quad (10)$$

Where,

V_t : The daily turnover rate of the market;

V_{it} : The daily turnover rate of the action i, defined by:

$$V_{it} = \frac{n_{it}}{N_{it}} \quad (11)$$

Where,

n_{it} : The number of securities exchanged daily for the share i;

N_{it} : The daily number of outstanding securities of the share i.

3.1.2 Stationarity Tests of Yields and Volume of Daily Market Transaction series

In a first step, we will test the unit root hypothesis on the yields and the volume of level transactions, in order to evaluate the stationary character of the two series. The test procedure followed is that of ADF (1981) with:

H_0: The series has a unit root
H_1: The series doesn't have a unit root; the series is stationary

3.1.2.1 Stationarity tests of the daily market yields

The trend of the series of returns (model 3) is significant since it presents a p-value of 1% less

than 5% (Table 2). The constant is also significant because it is equal to 0%. It turns out that the appropriate model for testing the stationarity of the daily yield series is that with a constant trend. Note also that the series is stationary because the ADF statistic of (-7.571238) is much lower than (-3.977619). As a result, our series of returns is stationary in level with trend and constant.

3.1.2.2 Stationarity tests of the daily market transaction volume series

From Table 2, we can see that the trend of the series of transaction volume (model 3) is not significant. Then, it is necessary to go to the second step. Model 2 shows a significant constant. In addition, the series is stationary because the ADF statistic equal to (-19.27383) is lower than the critical value of 1%. It turns out that the model with constant seems to be the most relevant for testing the stationarity of the series.

3.1.3 Tests between the Trading Volume and the Delayed Yield Series

To better specify the nature of the short-run dynamics and (Uni or bidirectional) causalities of yield and trading volume series, we used Granger causality tests [22][1]**.** These tests make it possible to specify the direction of causality between the two study variables. In accordance with the methodology followed by Chuang and Lee [25] we propose the equations representative of a bi-varied causality test in the sense of granger:

$$R_t = \alpha_0 + \sum_{j=1}^{p} \alpha_i R_{t-j} + \sum_{j=1}^{p} \delta_i V_{t-j} + \varepsilon_{Rt} \qquad (12)$$

$$V_t = \beta_0 + \sum_{j=1}^{p} \beta_i V_{t-j} + \sum_{j=1}^{p} \gamma_i R_{t-j} + \varepsilon_{Vt} \qquad (13)$$

Where,

V_t : The market trading volume of the day (t);

V_{t-j} : The volume of market daily transactions delayed;

R_t : The market yield of the day (t);

R_{t-j} : Delayed daily yield of the market;

p : The number of predetermined delays using the Akaike and Schwartz criteria.

The optimal number of delays is the one that minimizes the criteria of Akaike (AIC) and Schwartz (SC), it corresponds to (Lag=2). The results of the Granger causality tests for yield and trading volume series are reproduced in Table 3.

The causality tests in the sense of Granger show the presence of unidirectional causality relations of delayed yield towards the transaction volume at a level of significance equal to 1%. Nevertheless, the absence of causality of the volume of transactions towards the delayed yield attests the absence of a possible effect of positive feedback on the Tunisian stock market. The results are consistent with previous empirical studies by Chuang and Lee [25]; Chen, Firth and Rui [26]; and Wang et al [27] and confirm our basic assumption that the investors operating in the TSE exhibit excessive confidence in their behavior.

Table 2. Stationarity Tests of Return and Transaction Series

	Coefficient	Return	Transaction Volume
Model 3 with constant and trend (in level)	Intercept	.015 .000	.0288 .0000
	Trend	4.89E-06 .010	3.30E-06 .728
Model 2 with constant (in level)	Intercept	- 	.0295 .0000
	t-Statistic Probability	-7.571 .000	-19.273 .000
Critical Values	1% level 5% level 10% level	-3.977 -3.419 -3.132	-3.443 -2.867 -2.569

Table 3. Results of Granger Causality Tests for Series

	F-Statistic	Probability
R_t doesn't Granger Cause V_t	.480	.618
V_t doesn't Granger Cause R_t	9.172	.0001*

**: 1% significance level*

3.2 Detection of the Overconfidence Effect on the Conditional Volatility of Stock Market Returns

3.2.1 Decomposition of transaction volume

According to Chuang and Lee [23] we provide a trading volume decomposition that allows us to identify whether the Excess Volatility observed in the Tunisian stock market is the result of excessive trading by over confident investors or other operational factors (macro and micro economic).

We start with the following regression to break down the transaction volume into two components:

$$V_t = \alpha + \sum_{j=1}^{p} b_j R_{t-j} + \varepsilon_t \quad (14)$$

$$V_t = \left(\sum_{j=1}^{p} b_j R_{t-j} \right) + (\alpha + \varepsilon_t) \quad (15)$$

$$V_t = OVER_t + NONOVER_t \quad (16)$$

Where,

α : Intercept;

V : Transaction volume;

R : Market return;

b_j : Coefficient of delayed return;

p : Optimal number of lags;

ε_t : Error term.

The two components of the transaction volume are:

$NONOVER_t$ **:** The constant and the residual term: a component related to factors other than the over confidence of investors.

$OVER_t$ **:** A component associated with the behavior of over confident investors presented through the incidence of delayed return on the transaction volume

3.2.2 Modelling the conditional expectation of market returns

In order to model the Conditional expectation of the returns, we will follow the methodology of Box and Jenkins[2], for an average Autoregressive Moving Average Model ARMA (p, q):

$$R_t = \phi_0 + \sum_{i=1}^{p} \phi_i R_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t \quad (17)$$

Where,

ϕ_0 : Intercept;

ϕ_i and θ_j : real parameters;

ε_t : Error term.

In order to study the relationship between the overconfidence component "OVER" and return, we will focus on the identification of the order (p, q) of the ARMA Model. The two orders (p, q) are determined from the graph of the Autocorrelation Function (ACF) and that of the Partial Autocorrelation Function (PACF). The second step is to estimate the coefficients of the model that we have already identified. The choice of the ARMA specification is made from the information criteria. We will therefore retain the delay (p) which minimizes the Akaike (AIC) and Schwartz (SC) criteria and maximizes the Log Likelihood value. Finally, we determine if the error terms are white noise.

It is clear that the appropriate process is ARMA (1,1)[3] because the term that composes it has a significant coefficient at the 1% threshold.

3.2.3 Test of the impact of overconfidence on conditional volatility

Conditional volatility in the EGARCH model is modelled to capture the asymmetry effect of volatility. This asymmetry is estimated by the volatility parameter k . When k is significantly

different from zero, the response of the volatility is asymmetrical. If k <0, then negative shocks (bad news) have a greater effect on volatility than positive shocks (positive news). Thus, negative equity returns tend to increase more intensively than positive returns.

According to Chung and Lee [23] the next step is to identify the effect of overconfidence on conditional volatility. For this purpose, it is necessary to determine the impact of the transaction volume component associated with the excessive investor confidence "OVER" on conditional volatility. We integrate the two components of equation (15) in the conditional volatility model based on EGARCH (1,1), which is formally expressed as:

$$R_t = \mu_t + \eta_t \quad (18)$$

$$\frac{\eta_t}{V_t, \eta_{t-1}, \eta_{t-2}, ..., R_{t-1}, R_{t-2}, ...} \rightarrow GED(0, h_t) \quad (19)$$

$$Ln\, h_t = w + f_1\left(\frac{|\eta_{t-1}| + k\eta_{t-1}}{\sqrt{\eta_{t-1}}}\right) + f_2 Lnh_{t-1} + f_3 OVER + f_4 NONOVER \quad (20)$$

Where,

$GED(0, h_t)$: Generalized Error Distribution;

R_t : The market yield at the date t;

μ_t : The mean of average R_t conditional on past information at the date;

h_t : The conditional volatility at the date t;

η_t : An error term;

k : The parameter capturing the asymmetry effect in the EGARCH process;

$OVER_t$: The transaction volume component related to investor overconfidence;

$NONOVER_t$: The part of the transaction volume motivated by factors other than overconfidence;

f_1 : A coefficient that assesses the volatility of the previous period given by the lagged residual squared;

f_2 : A coefficient that captures the relationship between the conditional volatility at the date (t) and that of the previous date (t-1);

f_3 : A coefficient that measures the effect of overconfidence "OVER" on conditional volatility;

f_4 : A coefficient capturing the effect of factors other than overconfidence "NONOVER" on conditional volatility.

Parameters f_3 and f_4 capture the effect of trading volume on the conditional variance of market returns. f_3 is the overconfidence component of investors although f_4 is the component that expresses the effect of other factors. In this sense and following the methodology of Chuang and Lee [23] two main constraints must be fulfilled; $f_3 > f_4 > 0$ with coefficient f_3 is positive and statistically significant.

Table 4. Estimation of the ARMA Process by the Ordinary Least Square Method

	AR(1)	**AR(2)**	**AR(3)**
p=1	-0.371 (.000)	-	-
p=2	.095 (0.038)	-0.108 (.351)	-
p=3	.105 (.024)	0.173 (.0002)	-0.134843 (.233)
	MA(1)	**MA(2)**	**MA(3)**
q=1	-0.877 (0.000)	-	-
q=2	0.097 (0.033)	-0.830 (0.000)	-
q=3	.078 (.093)	.163 (.050)	.148 (.537)

Table 5. Effect of Overconfidence on Conditional Volatility of Market Return

Variable	Coefficient	Std. Error	z-Statistic	Probability
w	-19.708	1.068	-18.453	.000
f_1	.0199	.059	.337	.735
k	.204810	.046	4.424	.000
f_2	-0.821	.111	-7.364	.000
f_3	40.501	7.972	5.080	.000*
f_4	2.582	1.436	1.797	.072*

** : Significance level 10%*

Table 5 indicates that both coefficients f_3 and f_4 are positive and statistically significant at 1% and 10% level, respectively. Thus our results respect the constraint imposed by Chuang and Lee [23] that $f_3 > f_4 > 0$. It is therefore concluded that the conditional volatility of daily returns is largely affected by over-confident investors. Since the parameter k of value (0.204810) is positive and statistically significant at 1%, and then the hypothesis of asymmetry[4] of the EGARCH process is verified. Our results appear to be consistent with earlier findings by Harris and Raviv [28] Kandel and Pearson [29] and Chuang and Lee [23]. These authors asserted the existence of a positive relationship between the transaction volume component related to overconfidence and conditional volatility.

4. CONCLUSION

In this paper, we tried to verify the existence of a possible Excess Volatility on the Tunisian financial market. Following Shiller's study [6] of the variance boundary based on the annual variance of 18 TSE-listed companies between 2000 and 2017, we found that stock prices display Excess Volatility because the variance of observed price indices exceed that of ex-post rational prices.

We studied the effect of the Tunisian investor confidence phenomenon on the daily volatility of 22 companies listed on the TSE during the 2016/2017 period. Granger's Causality tests [24] have demonstrated the nature of the relationship between transaction volume and delayed returns. Our results appear to be consistent with previous studies that confirm the existence of a Granger unidirectional relationship of past performance to transaction volume.

In the second part we carried out a study led by Chuang and Lee (2006) to identify the effect of the component linked to overconfidence on volatility by the E-GARCH model (1.1). Our results show that high market volatility resulted from excessive investor confidence.

NOTES

1. Causality means predictability, y_t cause x_t means it is possible to predict x_t by knowing y_t
2. The Box & Jenkins Methodology Determines the Appropriate ARIMA Model for Modeling a Time Series
3. According to the results of the Table 4, we retain p = 1 and q = 1
4. It is the assumption that the effect of a negative shock on market returns increases volatility more than a positive shock

COMPETING INTERESTS

Author has declared that no competing interests exist.

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