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Abstract

The purpose of this paper is to provide that the explanation of excessive volatility can be only done through an attentive description of the psychological aspects of the investors. Our interest is carried in particular to the overconfidence bias. Our objective in this study is to identify whether the excessive volatility of observed stocks on the Tunisian Stock Market (TSE) results from the excessive trading of overconfident investors. The analysis of the obtained results, over the period January 1999 – October 2007, indicates quite clearly the importance of considering this bias in analysis of the specificities of Tunisian Stock Market (TSE). It appears that overconfidence admits a more pronounced effect on the volatility for daily time intervals compared to weekly and monthly intervals. The asymmetric nature of the dynamics of return volatility in response to positive and negative shocks is also checked.

Key words: Excessive volatility; overconfidence hypothesis; Market efficiency; Anomalies; Rationality; Behavioural finance; Psychological aspects; leverage Effect; GJR-GARCH model; Tunisian Stock Market

JEL classification: G10, G12, G14, C22.

Introduction

The idea conveyed by the efficiency theory is that stock prices are determined by the discounted current value of the future anticipated dividends according to the following model:

$$P_t^r = \sum_{i=1}^{\infty} \delta^i E_t(D_{t+i})$$

P_t^r : Anticipated rational Price. $\delta = \frac{1}{1+k}$: Which

k : the required return rate. D_t : Paid Dividend by stock at the date t . The stock prices are thus supposed to reflect the fundamentals of the company. In the context of an efficient market, the level of return volatility would have to evolve in reasonable margins. However, if we refer to various studies of Shiller (1981) and Shiller (1989), it appears that the stock prices exhibit an excessive volatility relatively to fundamentals. The excessive volatility of stock prices is a pathological phenomenon because, on the basis of rationality principle, it seems improbable to explain the level of volatility of the risked stocks based purely and only on the dynamic behaviour of fundamentals (e.g. Shiller, 1981 ; Shiller, 1989 ; Odean, 1999 ; Barberis and Thaler, 2003 ; Chuang and Lee, 2006 ; Glaser and Weber, 2007). A hypothesis always advanced by standard finance consists in viewing that the investor as an economic agent whom the decision-making processes as well as the anticipations is specified in rational way. Thus, the psychological and social characteristics of the individuals are excluded from the paradigm of the efficient markets theory. However the observation of the real financial markets delivers a very different message to us. By examining the economic history, it appears surprising the recurrence of the financial crises, the financial crashes and the speculative bubbles, followed by their bursting starting from the bubble of tulips to bubble Internet. These bubbles lead the financial community to bring renewed attention to the concept of volatility and revive interest in the issue of explanation.

Explanation of excessive volatility phenomenon on the financial markets

Various interpretations have been suggested to explain the excessive volatility of stocks

prices. The most frequently advanced explanation is to see volatility as a consequence of changes in interest rates. According to Shiller (1981), the return volatility appears too much high to be allotted to unspecified new information on the anticipated dividends. A finding that challenges the market efficiency hypothesis. A possible explanation of the excessive volatility of stocks prices is that the investors believe that the growth rate of dividends is more variable than it actually is. When they observe the increase of dividends, they believe quickly that the average growth rate of increased dividends. Their affluence pushes the price to increase compared to dividends which make increase the prices volatility. This mechanism is a direct application of the representative bias. It is the contribution of the behavioural finance through which eminent work explores the effect of the psychological mechanisms of investors on the price formation. The investigation of Shiller (1989) near the operators of market confirms that psychology is essential in order to understand the dynamics of prices. The investors include the overconfidence, the interpersonal influences, the mimicry and the contagion. These phenomena were often studied by several empirical studies (e.g. Kahneman, Solvic, and Tversky, 1982 ; Griffen and Tversky, 1992 ; Benos, 1998 ; Barber and Odean, 2000 ; Odean, 1999 ; Caballé and Sakovics, 2003 ; Biais et al., 2005 ; Statman, Thorley, and Vorkink, 2006) which offer two different and complementary explanations, on the one hand, the investors would not be " Bayesian " and on the other hand they would be in addition exaggeratedly confident in their judgment: First, the agents would not have a behaviour Bayesian, i.e. they would revise their opinions without taking account of all last information. Second, the investors would be exaggeratedly optimistic and would have a very great confidence in their judgment; in particular, the agents would tend to confuse their desires with the probability of occurrence of an event.

The loss aversion, house money effect and excessive volatility

An important experimental and empirical principle accumulated is obviously recommended for the idea that the

behaviour of an investor is affected by the found results and the changes of richness. However the direction of reaction to previous gains/losses is not yet well defined since various psychological theories propose different reactions. Thaler and Johnson (1990) study the way in which the risk taking is empirically affected by the previous profits and losses. They announce that the investors become less risk averse following the realisation of the profits. This aversion increases following the realisation of the losses. Thus the accumulation of past earnings weakens the psychological impact of the losses reducing the required return of stocks forcing the prices to increase more quickly than dividends. The return volatility is thus seen increasing. Hwang and Satchell (2010) confirm these findings. They show that investors in financial markets are more loss averse. The investors become far more loss averse during bull markets than during bear markets, indicating their more profound disutility for losses when others enjoy gains. The effect of «House money » results into a desire for greater risk in the presence of pre-gain. Barberis, Huang and Santos (2001) also show that the house money effect and the loss aversion can explain both the enigma of the risk premium and the predictability of returns at low frequencies. The authors use this effect to explain the extent of the risk taking as well as the excessive volatility on financial markets.

Limited arbitrage, mimicry and excessive volatility

Spiester (2000) considers that excessive volatility on the markets and their destabilising character is due primarily to the professionalisation of the asset management. Thus, this one is subjected to standards performance and a competition to divide the market combined with a shortening horizon of management relative to private investment. It is at these types of conditions that nestle the effects of two phenomena widely cited in the literature on the increase in volatility of stock prices: the limited arbitrage and mimicry. According to Camerer (1992), the rational arbitragists cannot entirely cancel the effect of "noisy trader" on the market if their size and their resources for the negotiation are limited. Being the mimicry, we distinguish two horizons, the short term and the long term.

From the perspective of short-term, the herd behaviour contribute to explain why change in market sentiment can lead to sudden rearrangements of the portfolio, amplify the variations of stocks prices and thus create distortions of price and higher volatility than the normal (Nofsinger and Sias, 1999). From the perspective of long-term, Calvo and Mendoza, (1998), Choe, Kho, and Stulz (1999) and Chari and Kehoe (2002) also retain that investors who engage in strategies of bandwagon effect and vicious circle can notably bring the prices away from their fundamental values and contribute substantially an excessive volatility in the markets they are accessing.

Buckle feedback and excessive volatility

The Buckle feedback refers to trading strategies maintaining the historical trend of stock prices. These buckles result from the movements of extrapolation and continuation based on previous signals. They suggest that good news lead to positive attitudes and bad news generates negative attitudes. This behaviour reinforces the historical trend of prices. This is the buying case when previous prices rise and sale case when these prices decrease.

De Long, Shleifer, Summers and Waldmann (1990b) consider that the presence of hunters trends on the market ("positive feedback traders": investors who follow the strategy of purchase in the case of increase of prices and sale in the case of decrease) creates overreactions of the prices which exclude the market value of its fundamental value. Cuthbertson (2000) shows that presence of irrational operators on the market, for which the request for stocks grows after the prices had increased, involves an overreaction of prices to fundamental, an excessive volatility as well as an autocorrelation between the returns.

Overconfidence of the investors and excessive volatility

The argument given by behavioural finance considers that the irrational actions of some investors mainly due to their overconfidence constitute the keystone of the building of excessive volatility. The behavioural authors consider well the thesis of overconfidence as the reason which resounds more in echo of

empirical and experimental reports consigned by several researchers. Odean (1998) ; Benos (1998) ; Daniel, Hirshleifer, and Subrahmanyam (2001) ; Hirshleifer and Luo(2001) ; Gervais and Odean (2001) , by using a GARCH (1,1) model, show that overconfidence is a systematic cognitive bias whose the majority of investors suffer and the effects can significantly affect the movements of stocks prices and thus get some parts of the puzzle of excessive volatility. They show that the daily trading volume is a good proxy to represent the information flow having a significant explanatory power regarding the daily return volatility for the individual firms under the conditions of the mixed hypothesis (e.g. Diebold, 1986; Stock, 1987; Stock, 1988).

Benos (1998) proposes a model in which the aggressive behaviour of overconfident traders, in the exploitation of their advantageous information in addition to the preserving trading strategies of the rational traders, brings the prices to be varied in an excessive way. Benos (1998) specifies that trading activity results from the conjugation of transactions of the rational traders, the overconfident traders, the needs liquidity traders and the market makers. Glaser and Weber (2009) find that both past market returns and past portfolio returns affect trading activity of individual investors (as measured by stock portfolio turnover, the number of trading stocks). These studies however did not specify which component of trading volume affects the volatility, i.e. which informative contents of the trading volume affect volatility. Recent works on behavioural finance examine the importance to consider the psychological factors in the analysis of financial decision-making. Thus, minority of financials were ventured today to deny the extent of the contribution of this new current research to explain the processes leading to an irrational behaviour. We think that the elucidation of excessive volatility can be only done through an attentive description of psychological aspects of the investors. Our interest is carried in particular to the overconfidence bias. The literature showed that it is about a systematic cognitive bias whose majority of investors suffers and of which the effects can affect appreciably the stock markets. The hypothesis that overconfidence increases.

The volatility represented the subject of several studies (e.g. Daniel, Hirshleifer, and Subrahmanyam, 1998 ; Odean, 1998 ; Wang, 1998 ; Gervais and Odean, 2001 ; Scheinkman and Xiong, 2003 ; Chuang and Lee, 2006). Since the overconfidence hypothesis provides that trading volume and volatility increase with the overconfidence of investors and owing to the fact that several studies showed the existence of synchronous relationship between trading volume and return volatility, it will be most appropriate to examine this issue directly by examining the relationship between trading volume and return volatility. Indeed, the presence of overconfidence bias is the most famous illustration in the verification of positive relationship between trading volumes of stocks and lagged stock returns. The trading volume resulting from this relationship will be used as a proxy for measuring investor overconfidence. We are interested throughout this study in the aggregate behaviour of the investors on the Tunisian Stock Market (TSE) next to the implications of overconfidence hypothesis. The remaining parts of the paper are structured as follows: The section 3 will be interested in the description of specificities of the Tunisian Stock Market (TSM) as well as data necessary for empirical testing. The analysis of the overconfidence effect on the no conditional return volatility of the market will be the subject of section 4. Further the examination of this effect on the conditional volatility will be presented at the last section.

Data and empirical specifications on the Tunisian Stock Market

The data

Our sample data contain monthly, weekly and daily returns and trading volume published by the Tunisian Stock Market (TSE). We chose the period from January 1, 1999 to October 27, 2007. The Tunisian Stock Market, compared with other emerging markets, has a relatively low value in terms of market capitalisation. It is very narrow since the number of listed companies is not more than 50. The table 1 reports the number of companies in Tunisian stock market.

Variables of study

Market returns

From the closing prices, Returns at time t of stocks are calculated with reinvestment of dividends as follows:

$$R_{it} = \frac{P_{it} + D_{it} - P_{it-1}}{P_{it-1}} \quad (1)$$

Where P_{it} and P_{it-1} is the closing price of stock i respectively at time t and t-1; D_{it} is the dividend used on stock i during period t; Note that the weekly returns are calculated on the basis of closing prices of Wednesday to

$$R_t^E = \frac{(\sum_{i=1}^K R_{it})}{K} \quad (2)$$

Where R_{it} : Return of stock i in period t adjusted for dividends. K: Number of stocks on the market. This return is taken as proxy for the market portfolio while giving the same importance for all stocks. This can be seen as relating the performance of portfolio of all stocks in equal proportions.

The weighted market return R^P

It is the return of the market portfolio where each quoted stock on the Tunisian Stock Market from its membership for a proportion given by the ratio of market capitalisation to the total market capitalisation.

$$R_t^P = \frac{[\sum_{i=1}^k CB_{it} * R_{it}]}{CB_{Mt}} \quad (3)$$

avoid the weekend effects or Monday effect. Note also that to overcome the problem of discontinuity of the data, we used the predecessors method of replacing the missing data by the last available ($\hat{P}_t = P_{t-1}$). We calculated two types of market returns (equi-weighted and weighted to correct the effect size), which take into account all data available on the market and are adjusted for dividends and changes in capital.

The equi-weighted market return R^E

This return is an arithmetic average return of all stocks in the market during the study period:

$$CB_{Mt} = \sum_{i=1}^k CB_{it} \quad (4)$$

$$CB_{it} = N_{it} * C_{it} \quad (5)$$

Where: CB_{it} : Market capitalisation of stock i during period t; CB_{Mt} : Total market capitalisation of the market during the period t. K: Number of shares on the market. C_{it} : Stock price i in period t. N_{it} : Number of stocks outstanding of stock i during period t. Both measures of returns have the characteristic whereby they exclude any of their composition of financial stocks available on the Tunisian Stock Market.

Table 1. Number of companies in Tunisian stock market

Period	1999	2000	2001	2002	2003	2004	2005	2006	2007
Number of companies	44	44	45	46	45	44	45	48	50

Thus in 2007, almost half (22) companies listed on the Tunisian Stock Market works in the financial sector (banks, (11) Insurance (3), leasing (5) and investment companies (3)). The other half (28) consists of companies operating in the chemical industry (5), food (3), distribution (3), travel and leisure (3), automobiles and equipment (6) and other (8)).

Trading activity

The weekly and monthly trading volumes are calculated as the sum of daily volumes that make up the period in question as recommended by Lo and Wang (2000). In literature, there are two aggregate measures of activity in equity markets.

The Volume: refers to the number of traded stocks for each of quoted stocks on the market. Information about the activity is usually translated in number of traded stocks. The volume is a concept that represents the information flow in the market. The agents generally use as an indicator of liquidity.

The turnover rate

Since the outstanding trading quantity of stocks on the market varies from year to year for most listed companies (due to changes in capital, stock split ...), an increase in trading volume defined by trading quantity may not reflect the increased activity in the market. Thus, the measurement generally used in trading activity is a relative and not absolute (e.g. Lo and Wang ,2000 ;Statman, Thorley, and Vorkink ,2006), the turnover rate of stock i in time t $V_{it} = \frac{n_{it}}{N_{it}}$

Where : n_{it} : Number of traded stocks of stock i during period t. N_{it} : Number of outstanding stocks of stock i during period t. From this definition, we can identify a single turnover rate for an individual stock, while for the market, two alternatives present themselves: weighted rate and equi-weighted rate to account for the size effect. This suggests the importance of studying the sensitivity of results to various measures of the trading volume of market.

The weighted turnover rate

$$V_t^P = \sum_{i=1}^k w_{it} * V_{it} \quad (6)$$

Where: K: Number of stocks on the market. w_{it} : Weight of the stock i on the market. w_{it} is defined by : $w_{it} = \frac{CB_{it}}{CB_{Mt}}$ where CB_{it} : The market capitalisation of stock i during the period t. CB_{Mt} : The market capitalisation of the market during the period t.The weighted-turnover rate of the market also accepts the following expression:

$$V_t^P = \frac{\sum_{i=1}^K n_{it} C_{it}}{CB_{Mt}} = \frac{\text{Total of trading volume at time t}}{\text{The market capitalisation during the period t}} \quad (7)$$

The equi-weighted turnover rate

The measurement of trading activity of the market that will be used in our study is the turnover rate of the market (weighted and equi-weighted).

$$V_t^E = \frac{\sum_{i=1}^K V_{it}}{K} \quad (8)$$

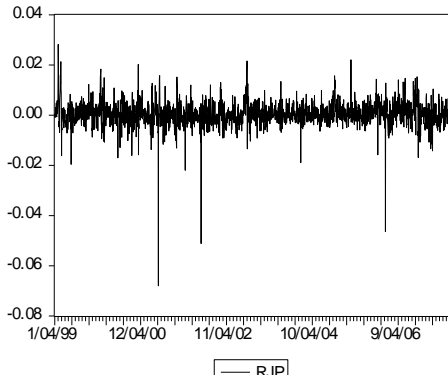
Preliminary analysis

The preliminary study of statistical properties of the various used series is important in order to apply numerous econometric tests. In this context, we search to analyze stationarity and normality of the distribution of return time series and trading volumes time series. A first intuition about the stationarity of the series is provided by the graphs in Figure 1 that trace the evolution over time of return and turnover rate. We can report that the series appear stationary because they converge to their average over the long term and are showing an instability that varies across time periods with more or less volatile. To better confirm the graphical analysis, two tests will be applied the augmented Dickey and Fuller (1979) test (ADF) and the Phillips and Perron (1988) test (PP). The empirical results of applying these unit root tests show that the null hypothesis of the existence of unit root is rejected for all series at a significance level of 1%. Thus, the series studied are governed by a stationary process; this is consistent with the observation of the graphs in Figure 1.

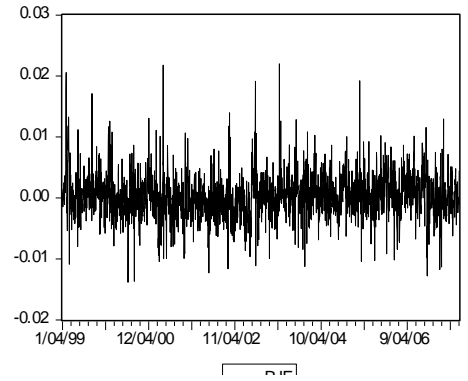
Tables 2 and 3 provide descriptive statistics of returns and trading volumes on the market. The distributions of both weighted and equi-weighted variables for the three frequencies are significantly different from the normal distribution at 1%. The empirical results show that the distribution of variables is asymmetric that a normal distribution. The positivity of the asymmetry coefficients indicates that the returns and trading volumes (except the weighted daily return market) had more positive shocks than negative shocks during the analysed period.

These results generally lead to the rejection of normality hypothesis of the series. This conclusion is reinforced by the formal test of Jarque and Bera. From a theoretical point view, the normality of returns is questionable whether the information flow is not linearly in the market, or if investors do not respond linearly to its arrival. In both cases, a leptokurtic distribution of returns of the securities should

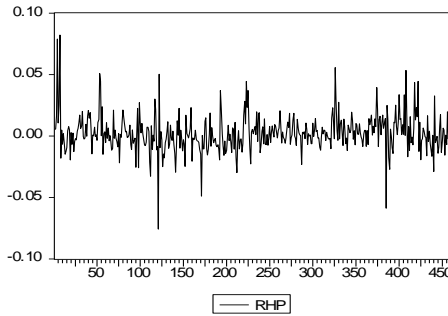
Figure 1. Pattern of weighted and equi-weighted market return and the weighted and equi-weighted turnover rate in Tunisian Stock Market.



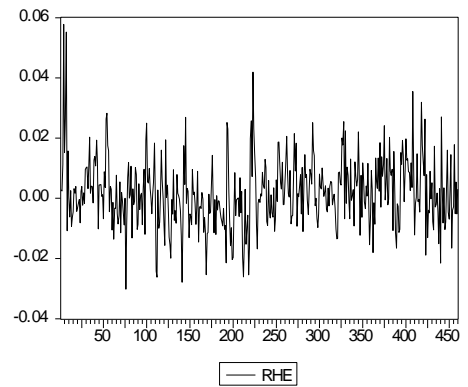
Daily weighted return



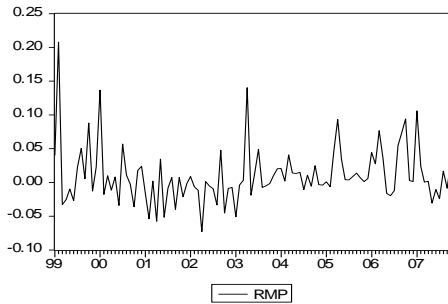
Daily equi-weighted return



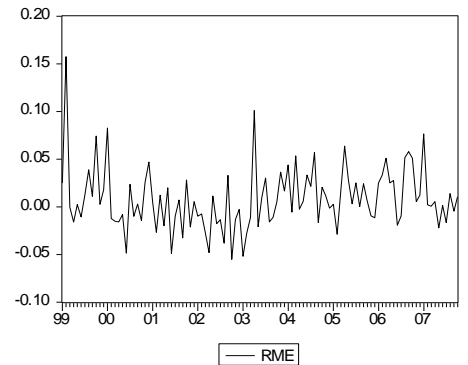
Weekly weighted return



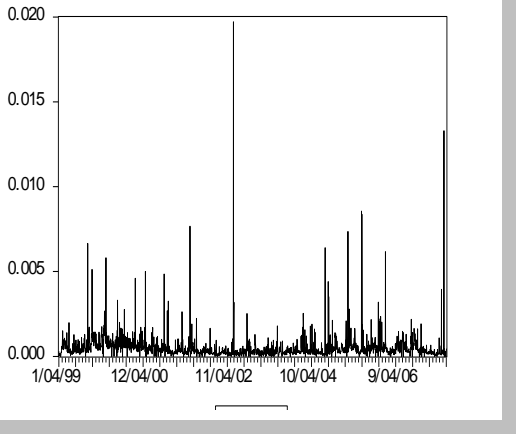
Weekly equi-weighted return



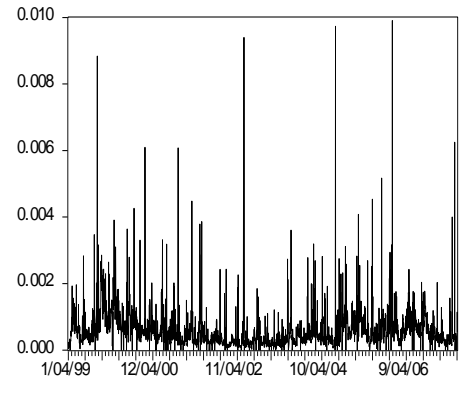
Monthly weighted return



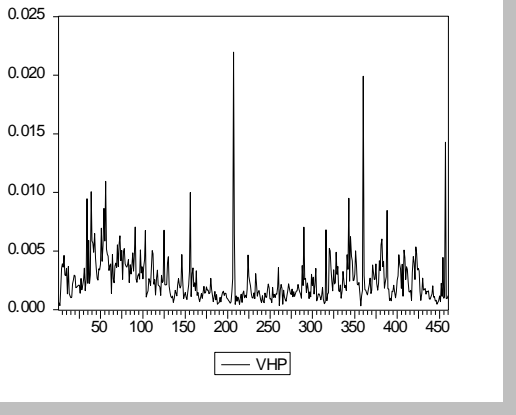
Monthly equi-weighted return



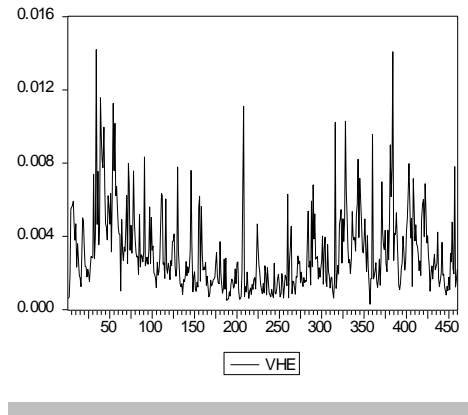
Daily weighted turnover rate



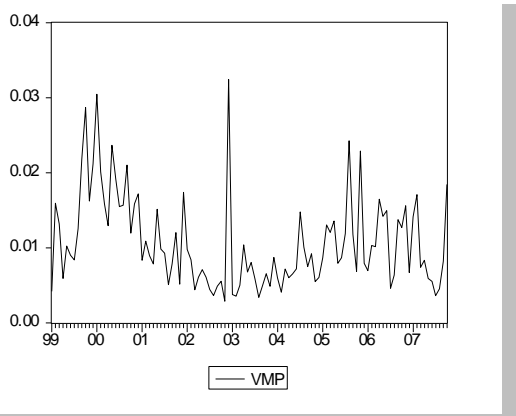
Daily equi-weighted turnover rate



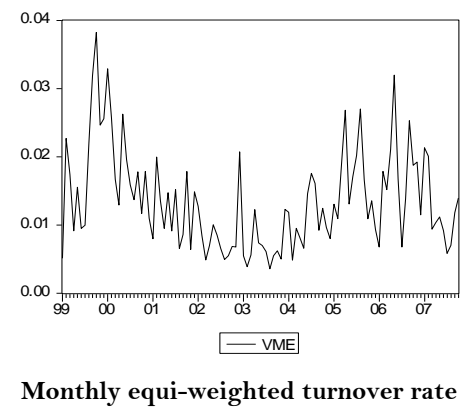
Weekly weighted turnover rate



Weekly equi-weighted turnover rate



Monthly weighted turnover rate



Monthly equi-weighted turnover rate

Table 2. Descriptive statistics of weighted and equi-weighted market returns.

	Frequency	Mean	Median	Stan dev	Max	Min	Skew	Kurt	Jarque-Bera (Prob)	Observations number
Weighted	Daily	0.0004	0.0001	0.0049	0.028	-	1.721	29.684	69464 (0.00)	2303
	Weekly	0.0023	0.0012	0.0149	0.082	-	0.605	8.842	682.37 (0.00)	460
	Montly	0.0103	0.0024	0.0416	0.207	-	1.689	7.980	160.00 (0.00)	106
Equi-weighted	Daily	0.0003	0.0001	0.0036	0.022	-	0.518	6.146	1053.2 (0.00)	2303
	Weekly	0.0017	0.0012	0.0113	0.057	-	0.620	5.178	120.44 (0.00)	460
	Montly	0.0083	0.0037	0.0327	0.157	-	1.193	6.355	74.90 (0.00)	106

Table 3. Descriptive statistics of weighted and equi-weighted turnover rate.

	Frequency	Mean	Median	Stan dev	Max	Min	Skew	Kurt	Jarque-Bera (Prob)	Observations number
Weighted	Daily	0.0005	0.0003	0.0007	0.019	0.000	11.57	219.82	4562671 (0.00)	2303
	Weekly	0.0025	0.0019	0.0021	0.021	0.000	3.863	28.344	13455. (0.00)	460
	Montly	0.0107	0.0087	0.0061	0.032	0.002	1.256	4.4596	37.28 (0.00)	106
Equi-weighted	Daily	0.0006	0.0004	0.0007	0.009	0.000	5.342	52.533	246395 (0.00)	2303
	Weekly	0.0031	0.0025	0.0021	0.014	0.000	1.673	6.631	467.46 (0.00)	460
	Montly	0.0135	0.0120	0.0072	0.038	0.003	1.014	3.769	20.80 (0.00)	106

be observed. The leptokurtic nature of returns has prompted the proliferation of ARCH models, which seek to incorporate the information in the tails of a distribution of returns in time series models.

Empirical evidence

The over confidence-unconditionnal return volatility relationship

Decomposition of trading volume

Like the Chuang and Lee (2006) study, we decompose the trading volume into two components. The first component is due to the excessive activity of investor overconfidence. The second component represents the effect of other factors. The proposed model is:

$$V_t = \alpha + \sum_{j=1}^p \beta_j R_{t-j} + \varepsilon_t \quad (9)$$

$$V_t = \left[\sum_{j=1}^p \beta_j R_{t-j} \right] + [\alpha + \varepsilon_t] \quad (10)$$

$$V_t = \text{Overconfidence}_t + \text{No overconfidence}_t \quad (11)$$

The component of trading volume associated with the behaviour of investor overconfidence is evidenced through the impact of past returns on trading volume. Thus, Odean (1998a) and Gervais and Odean (2001) develop models by showing that high earnings of market make the investors more confident about the accuracy of their private information and their ability to select stocks. Their trading activity becomes more aggressive in later periods. This means a positive causal relationship from returns to trading volume. A positive relationship between return and trading volume could find explanations other than those related to overconfidence. We cite three main reasons: First, The disposition effect describes the behaviour of investors more willing to realise their profits, but reluctant to hand over the stocks down because of loss aversion. The disposition effect is to hold losers stocks in the portfolio longer than winner’s stocks. Second, the sequential arrival of information model from Copeland (1976) and Jennings, Starks, and Fellingham (1981) suggests a positive feedback relationship between returns and trading volume. Indeed, due to the sequential flow of information, the trading volume could have a predictive power for current returns and past returns may also have an explanatory power of

the current trading volume. Third, De Long et al., (1990b) develop a trading model of positive feedback involving a positive and bidirectionnel causal relationship between trading volume and return. On the one side, the positive causal relationship from trading volume to returns is consistent with the hypothesis of the model that the trading strategies followed by the noise traders generate a variation of the price. On the other side, the positive causal relationship from return to trading volume is consistent with the positive feedback strategies of noise-traders why the decision to purchase or sale is conditioned by past movements in the prices stocks.

The constant and the residual term form the second component of the trading volume is not related to overconfidence. The number of lags (P) to be included will be determined using the Akaike criteria (AIC) and Schwartz criteria (SC). The selection procedure of the order is to estimate all models for an order from 0 to h. we retain the lags that minimise the AIC or SC and maximise the value of log-likelihood. The estimated model (1) will be applied to both weighted variables and the equi-weighted variables for the three types of horizons. Also the extraction of the component of trading volume due to overconfidence will be the subject of six regressions. Table No. 4 summarizes the main results.

It appears that the shifts are most relevant to four trading days in the case of daily data, from 3 weeks in the case of weekly data and one month for the monthly data and that for both sets (weighted and equi-weighted). This memory effect projected from returns to the past trading activity seems more present in the most frequent data. We can therefore conclude that it is the psychological aspect that may influence the way whose individuals see the past returns. The positive sign of all estimated parameters related to past returns is quite consistent with the suggestions of studies on overconfidence, a positive relationship between

past returns and trading volume. The high market return indicates that investors are more confident and probably ready to trade more aggressively in subsequent periods. The reverse case will be observed if the market return is

negative. The presence of excessive confidence of investors invited to examine the effect of this bias on the return volatility.

Table N°4. Decomposition of trading volume and extraction of the component related to overconfidence.

Frequency	Type	α	b_1	b_2	b_3	b_4	F-statistic
Daily	weighted	0,0005***	0,0130***	0,0029	0,0058*	0,0060*	8,23***
	Equi-weighted	0,0006***	0,0236***	0,0021	0,0136***	0,0137***	21,61***
Weekly	weighted	0,0024***	0,0182***	0,0133**	0,0139**		6,75***
	Equi-weighted	0,0029***	0,0418***	0,0164*	0,0348***		21,22***
Monthly	weighted	0,0105***	0,0272**				3,6421**
	Equi-weighted	0,0131***	0,0586***				8,0062***

Notes : ***, **, * : Significance levels respectively 1%, 5% and 10%.

Overconfidence and unconditional return volatility

In order to check whether the component of trading volume related to overconfidence has an explanatory power of the return volatility, we regress the four models:

$$|R_t| = \alpha + \beta \text{Overconfidence}_t + \varepsilon_t \quad (12)$$

$$R_t^2 = \alpha + \gamma \text{Overconfidence}_t + \varepsilon_t \quad (13)$$

$$|R_t| = \alpha + \beta |\text{Overconfidence}_t| + \varepsilon_t \quad (14)$$

$$R_t^2 = \alpha + \gamma \text{Overconfidence}_t^2 + \varepsilon_t \quad (15)$$

Where, $|R_t|$: Absolute value of the market return in period t; R_t^2 : Square of the market return for the same period; Overconfidence_t :

Trading Part motivated by a sense of overconfidence and outcome of model 1; $\text{Overconfidence}_t^2$: Square of Overconfidence

in period t. Models (2) and (3) refer to the effect of overconfidence on return volatility. Models (4) and (5) show the impact of temporal variability overconfidence on return volatility.

Two measures of unconditional volatility of market returns are used: the absolute value of the variable and its square. The square represents the variance if the mean is zero. This hypothesis is verified especially for daily and weekly frequency data. Furthermore, in order to justify the empirical relevance of the choice of long memory process in volatility of variation in stocks prices, we have inspired the same approach of Bollerslev and Mikkelsen (1996), we used the absolute variation of return series R_t as measure of volatility (Bollerslev and Mikkelsen, 1996, p. 155-156). We underline that the return volatility of the market may be due to effects related to potential trade associated with the operations of adjusting the portfolio composition. These adjustments, as result of large variations in stock prices, can induce the trading activity. Thus, the major implication will be high trading volume due to large increases and decreases of stock price, that is to say high returns positive and negative. In addition, the trading generated by adjusting the portfolio composition should normally immediately follow the price movements. The one-month periods or more invalidate the existence of such pattern of trading (Statman, Thorley, and Vorkink (2006). The adoption of time horizon of one month is used to control the possible effects of such trading motivations. Results from the four models are

shown in Tables 5 and 6. Several findings arise from consideration of these tables. The sensitivity coefficients obtained related to overconfidence are significant at the 1% and 5% for both daily data than for weekly data. If we consider the monthly horizon, it appears that the level of investor overconfidence and its

variability plays no role in the formation of the unconditional volatility of weighted and unweighted return market. An examination of signs of the coefficients associated with overconfidence shows that this factor contributes positively to market volatility in Tunisian Stock Market.

Table N°5. Effect of Overconfidence on the market returns volatility.

$$\text{Model(1) : } |R_t| = \alpha + \beta \text{Overconfidence}_t + \varepsilon_t$$

Frequency	Type	α	β	F-statistic
Daily	weighted	0,0032 ^{***}	4,4896 ^{***}	29,26 ^{***}
	Equi-weighted	0,0026 ^{***}	1,8328 ^{***}	21,82 ^{***}
weekly	weighted	0,0098 ^{***}	3,4672 ^{***}	8,98 ^{***}
	Equi-weighted	0,0084 ^{***}	1,0975 ^{**}	5,62 ^{**}
Monthly	weighted	0,0261 ^{***}	3,9967	1,98
	Equi-weighted	0,0238 ^{***}	0,2539	0,04

Notes : ^{***}, ^{**}, ^{*} : Significance levels respectively 1%, 5% and 10%.

$$\text{Model (2) : } R_t^2 = \alpha + \gamma \text{Overconfidence}_t + \varepsilon_t$$

Frequency	Type	α	γ	F-statistic
Daily	weighted	2,38E-05 ^{***}	0,042	2,11
	Equi-weighted	1,32E-05 ^{***}	0,0259 ^{***}	29,22 ^{***}
Weekly	weighted	0,0002 ^{***}	0,1970 ^{***}	8,67 ^{***}
	Equi-weighted	0,0001 ^{***}	0,0549 ^{***}	10,71 ^{***}
Monthly	weighted	0,0017 ^{***}	0,4660	1,09
	Equi-weighted	0,0011 ^{***}	0,0767	0,28

Notes : ^{***}, ^{**}, ^{*} : Significance levels respectively 1%, 5% and 10%.

Table N°6. Effect of overconfidence volatility on the market returns volatility.

$$\text{Model (1) : } |R_t| = \alpha + \beta |\text{Overconfidence}_t| + \varepsilon_t$$

Frequency	Type	α	β	F-statistic
Daily	Weighted	0,0023 ^{***}	14,8655 ^{***}	192,58 ^{***}
	Equi-weighted	0,0020 ^{***}	6,2864 ^{***}	123,44 ^{***}
Weekly	Weighted	0,0072 ^{***}	9,1898 ^{***}	34,61 ^{***}
	Equi-weighted	0,0063 ^{***}	3,8452 ^{***}	33,78 ^{***}
Monthly	Weighted	0,0264 ^{***}	1,1300	0,09
	Equi-weighted	0,0265 ^{***}	-1,8417	1,21

Notes : ^{***}, ^{**}, ^{*} : Significance levels respectively 1%, 5% and 10%.

$$\text{Model (2) : } R_t^2 = \alpha + \gamma \text{Overconfidence}_t^2 + \varepsilon_t$$

Frequency	Type	α	γ	F-statistic
Daily	Weighted	2,12E-05 ^{***}	367,8163 ^{***}	19,80 ^{***}
	Equi-weighted	1,02E-05 ^{***}	186,1497 ^{***}	134,45 ^{***}
Weekly	Weighted	0,0001 ^{***}	345,5645 ^{***}	28,7724 ^{***}
	Equi-weighted	8,86E-05 ^{***}	70,9306 ^{***}	45,29 ^{***}
Monthly	Weighted	0,0018 ^{***}	-34,1710	0,06
	Equi-weighted	0,0012 ^{***}	-21,7150	0,57

Notes: ^{***}, ^{**}, ^{*} : Significance levels respectively 1%, 5% and 10%.

All of these results confirm our idea. Indeed, considering the time horizon daily, it is clear that investors reason in the short term and are guided by their psychology that's the effect is more pronounced on daily frequency data. This observation is further confirmed by testing on weekly data for which the psychological phenomenon still preserves its explanatory power in contrast to the case of monthly. Presumably, the intensity of the impact of overconfidence on the daily market volatility depends on the time horizon of investment. More over this horizon widens, more this effect is diluted and finally disappears on a monthly perspective. The non-statistical invalidity of the constant, which allows absorbing any information not captured by the explanatory variable in the model, proves that in addition to overconfidence, other potential variables that may intervene in the explanation of variation returns of the market. The results presented above let us first take a favourable decision on the validation of initial hypothesis of our study. However an analysis more advanced should be conducted to ensure the suitability of the conclusions reached with the requirements of the theory.

The over confidence-conditionnal return volatility relationship

An examination of the dynamics of time serie returns shows three major characteristics for the leptokurtic distribution, the "clustering" phenomenon and stationarity. These three features called to consider the conditional mean and variance of the times series.

The modelation of conditional mean of market return

We have already verified the stationarity of weighted and unweighted return series for the different steps of estimate; we can therefore directly apply the Box-Jenkins method to modelling of the conditional mean. Recall that the ARMA models are representative of process generated by combination of past values and past errors. A stationary process ARMA of order (p, q) is defined by the following wording:

$$R_t = \phi_0 + \sum_{i=1}^p \phi_i R_{t-i} + n_t - \sum_{j=1}^q \theta_j n_{t-j} \quad (16)$$

Where ϕ_0 is a constant term, the ϕ_i and θ_j are real parameters and $(\eta_t, t \in \mathbb{Z})$ is a white noise with variance σ^2 . The identifying step of the most appropriate model is to determine the lags order p and q. We proceed to analyze the correlograms of autocorrelation coefficients and partial autocorrelation coefficients. In addition, we estimate the parameters of ARMA models using the least squares method (for the AR model) and the maximum likelihood method (for ARMA models because of the moving average component). The choice of ARMA specification is made from the comparison of the values of estimated variance of residuals, the coefficient of determination, and the information criteria of Akaike and Schwartz. The estimation of different specifications drove the following results in table 7 where all estimated parameters are statistically significant at 1%.

Table N°7. Estimation of diffrents ARMA models

Frequency	Type	$R_t = \phi_0 + \sum_{i=1}^p \phi_i R_{t-i} + n_t - \sum_{j=1}^q \theta_j n_{t-j}$	F-stat
Daily	Weighted	ARMA(2,0) : $R_t = 0,0004^{***} + 0,2897^{***} R_{t-1} + 0,0895^{***} R_{t-2} + \varepsilon_t$	139,74 ^{***}
	Equi-weighted	ARMA(2,0) : $R_t = 0,0003^{***} + 0,3184^{***} R_{t-1} + 0,1074^{***} R_{t-2} + \varepsilon_t$	182,91 ^{***}
Weekly	Weighted	ARMA(3,3) : $R_t = 0,0018^{***} + 0,3997^{***} R_{t-1} - 0,2730^{***} R_{t-2} + 0,4978^{***} R_{t-3} - 0,3360^{***} \varepsilon_{t-1} + 0,4031^{***} \varepsilon_{t-2} - 0,5033^{***} \varepsilon_{t-3} + \varepsilon_t$	10,31 ^{***}
	Equi-weighted	ARMA(2,2) : $R_t = 0,0014^{***} + 1,2494^{***} R_{t-1} - 0,4085^{***} R_{t-2} - 0,9994^{***} \varepsilon_{t-1} + 0,2436^{***} \varepsilon_{t-2} + \varepsilon_t$	17,85 ^{***}
Monthly	Weighted	ARMA(0,0) : $R_t = 0,0104^{***} + \varepsilon_t$ (White noise)	
	Equi-weighted	ARMA(0,0) : $R_t = 0,0083^{***} + \varepsilon_t$ (White noise)	

Notes : ***, **, * : Significance levels respectively 1%, 5% and 10%.

At this step, it is important to remember that overconfidence is generated by a memory effect related to past returns and that the existing analysis shows that this psychological bias disappears for the case of monthly horizon. In view of the results obtained at this level, it is possible to advance an explanation for the absence of the phenomenon of overconfidence in the monthly case by the idea that the market is efficient considering the horizon since the process followed by the market returns is white noise. Investor behaviour is thus consistent with the recommendations of the theory of efficient markets that if the investment horizon widens investors become more rational and psychological phenomena fade. These results are also consistent with the theory of "noise trading" which is based on the idea that investors whose investment horizon is short-term influence security prices than do the long-term investors.

Overconfidence-conditional return volatility relationship

Asymmetry of the dynamics of conditional variance

The asymmetric phenomenon resulting of conditional variance to shocks affecting the conditional mean also called the leverage effect (e.g. Black, 1976; French, Schwert and Stambaugh, 1987; Nelson, 1991; Schwert, 1990 and Kim and Kon, 1994) is defined by the relation whereby a negative shock of return increases volatility more than does a positive

shock. In the financial literature, this negative relationship between conditional returns and conditional variance is supported by several studies (e.g. Sentani, 1991; Campbell and Hentschel, 1992; Glosten, Jagannathan and Runkle, 1993; Whitelaw, 2000). One explanation for this phenomenon refers to the leverage effect whereby a decrease in the stock price (negative return) increases the debt / the company equity ratio knowing that most indebted company is more risky, so the volatility increases. Another possible explanation of this phenomenon is the concept of "volatility feedback" (e.g. Pindyck, 1984; French, Schwert and Stambaugh, 1987) suggesting that higher anticipated volatility increasing the required return by investors since the stock value will become more risky, this implies that the stock value decreases immediately all things being equal. A third possible explanation for the asymmetric variance could refer to the implications of the value function which describes the risk-taker behaviour, in space loss (negative shock) and risk-averse in the space of gains (positive shock). This asymmetric attitude vis-à-vis risk implies that investors driven by the aversion to loss choose riskier portfolios and conduct more speculative strategies contributing to the increased volatility in the market. The opposite behaviour is supposed to happen in a gain case. The GARCH (Generalised Autoregressive Conditional Heteroskedasticity) are stochastic processes that can model the time series whose immediate variance depends on the past values.

They are well adapted to the modelling of financial time series. However, the standard GARCH model does not allow the detection of the asymmetric effect of disturbances on the conditional variance. A method to detect the leverage effect is to apply the model EGARCH (Exponential GARCH) proposed by Nelson (1991). The asymmetric effect of positive and negative shocks can also be identified by the GJR-GARCH model of Glosten, Jagannathan and Runkle (1993) who proposes a threshold model specifying the asymmetry of conditional variance by a dummy variable equal to 1 if the residue of the previous period is negative and zero otherwise. The equation for the conditional standard deviation is a linear function by piece depending on the sign of the shock and on the conditional standard deviation of previous period. A version of this model known as the Threshold GARCH or TGARCH of Zakoian (1994) specifies the asymmetry of the conditional standard deviation and not the conditional variance.

GJR-GARCH (1,1) Specification

The exploration of the relationship between overconfidence and conditional volatility is to examine the effect of the component of trading volume due to the trading activity of investor overconfidence on the conditional volatility of market returns following an asymmetrical ARMA-GARCH. To do this, like the work of Lamoureux and Lastrapes (1990) and Chuang and Lee (2006) who used EGARCH (1, 1) and GJR-GARCH (1, 1), we choose to estimate the GJR-GARCH model (1.1) as follows:

$$R_t = u_t + n_t \quad (17)$$

$$n_t | [V_t, n_{t-1}, n_{t-2}, \dots, R_{t-1}, R_{t-2}, \dots] \sim [0, h_t]$$

$$h_t = w + f_1 [n_{t-1}^2] + f_2 h_{t-1} + \theta S_{t-1}^- [n_{t-1}^2] + f_3 EC_t + f_4 NEC_t \quad (18)$$

Where: R_t : Market return at time t ; u_t : Conditional mean of R_t at time t on the set of past information ; n_t : Residual from the equation of conditional mean at time t ; h_t : Conditional volatility at time t ; S_{t-1}^- : Dummy Variable; if $\eta_{t-1} < 0$ then $S_{t-1}^- = 1$, if not $S_{t-1}^- = 0$; EC_t : Trading part motivated by the sense of

overconfidence and outcome from model No. 1; NEC_t : Trading part not related to past market returns and outcome from model No. 1; θ : Volatility parameter ; f_1 : Parameter measuring the recurrence relationship between the conditional variance to the unconditional variance of the previous period; f_2 : Parameter measuring the recurrence relationship between the conditional variance to that of the previous period; f_3 : Parameter measuring the effect of the overconfidence on the conditional variance ; f_4 : Parameter measuring the effect of factors other than overconfidence on the conditional variance. The evolution of the conditional variance is explained by the importance of past error terms, the sign of these errors and lagged conditional variances. The effect of asymmetric GJR-GARCH model is highlighted by the parameter θ of volatility. The good news has an impact of f_1 while bad news has an impact of $f_1 + \theta$. Thus, when $\theta > 0$, the negative shock has a greater impact on conditional volatility compared to positive shock, and vice versa. If the hypothesis of the leverage effect is satisfied then we expect to find $\theta > 0$. If the conditional volatility can be explained by overconfidence induced by the trading activity of investors subject to this bias, then we expects that f_3 is significantly different from zero and persistent volatility measure ($f_1 + f_2$) is small and statistically insignificant. The positivity (negativity) of parameter f_3 implies that the conditional volatility increases (decreases) in synchronisation with trading volume related to the excessive confidence of market participants. Indeed, reading studies on the nature of the relationship between trading volume and volatility shows that this relationship is positive (e.g. Harris and Raviv, 1993; Shalen, 1993; Kandel and Pearson, 1995; Karpoff, 1987). And we expect that f_3 and f_4 are positive. The parameter f_3 captures the effect of overconfidence on volatility while f_4 reflects the effect of other potential factors. If overconfidence can explain the conditional volatility, then we expect that $f_3 > f_4 > 0$ with f_3 is statistically significant. The results of the estimation of the model (7) are provided in Tables 8 and 9 as follows:

Table 8. Overconfidence effect on the conditional volatility of market returns.

Frequency	Type	Model	W (t-Stud)	f ₁ (t-Stud)	f ₂ (t-Stud)	f ₃ (t-Stud)	f ₄ (t-Stud)	θ (t-Stud)	LLK	F-stat(Prob)
Daily	Weighted	AR(2)-GJR-GARCH(1,1)	2,61E-06 (7,5)***	0,2252 (6,92)***	0,5745 (19,89)**	-0,0043 (-1,37)	0,0022 (7,03)***	0,2062 (4,83)***	9269,0 4	32,52 (0,00)***
	Equi-weighted	AR(2)-GJR-GARCH(1,1)	6,35E-06 (11,97)***	0,1003 (3,52)***	0,0331 (0,59)	0,0061 (3,51)***	0,0060 (8,14)***	0,0452 (1,03)	9834,3 6	45,09 (0,00)***
Weekly	Weighted	ARMA(3,3)-GJR-GARCH(1,1)	8,96E-05 (4,34)***	0,0943 (0,99)	0,0958 (1,08)	0,0980 (4,38)***	0,0068 (1,13)	0,6186 (3,27)***	1323,0 9	2,97 (0,00)***
	Equi-weighted	ARMA(2,2)-GJR-GARCH(1,1)	1,68E-05 (1,55)	0,1145 (1,50)	0,5691 (4,54)***	-0,0048 (-0,57)	0,0054 (2,35)***	0,0351 (0,27)	1440,9 0	4,64 (0,00)***
Monthly	Weighted	ARMA(0,0)-GJR-GARCH(1,1)	9,34E-05 (0,25)	-0,0972 (-0,68)	0,7608 (5,24)***	0,0868 (0,17)	0,0294 (3,83E+99)***	0,1996 (0,43)	195,56	
	Equi-weighted	ARMA(0,0)-GJR-GARCH(1,1)	-7,69E-05 (-1,97)**	-0,1703 (-4,68)***	0,9264 (13,98)**	0,0932 (2,88)***	0,0090 (16,64)***	0,3838 (6,56)***	225,63	

Notes : ***, **, * : Significance levels respectively 1%, 5% and 10%.The model parameters are estimated using the algorithm of Berndt-Hall-Hall-Hausman.

Table 9. Results of the Wald test used to examine the null hypothesis that f3 = f4.

Frequency	Daily		Weekly		Monthly	
Type	Weighted	Equi-weighted	weighted	Equi-weighted	weighted	Equi-weighted
F-stat(Prob)	4,09(0,04)	0,00(0,98)	15,63(0,00)	1,21(0,27)	0,01(0,91)	6,62(0,01)

It is interesting to interpret some changes in the results due to the consideration of the conditional volatility of the market. If we consider the daily dimension, the equi-weighted return of the market seems more consistent with the implications of the overconfidence hypothesis. Indeed the statistical significance and the positivity of the coefficient f₃ indicate that the conditional volatility of daily equi-weighted returns of the market are subject to the influence of overconfidence behaviour of investors in the Tunisian Stock Market. This conclusion is mitigated by the statistical significance of f₄ on the presence of other factors that may influence the dynamics of market volatility that persists and appear insensitive to method of calculating the rate of return and the equal statistical between the two coefficients f₃ and f₄. The positive sign of the coefficient θ on the leverage effect and its statistical significance for the case of the weighted return of the market prove the asymmetric response of conditional volatility to shocks. If we consider the weekly and monthly dimension, it appears that the overconfidence

hypothesis is accepted in the case of weighted variables as well as in the equi-weighted variables where the high level of volatility is explained by the presence of overconfidence investor in the market. This finding is supported by the Wald test rejecting the equality hypothesis of both coefficients. The leverage effect is still checked for this type of data (θ is positive and statistically significant).

Conclusion

The basic question posed at the beginning of this work was attached to an attempt to explain the excessive volatility of market return from a behavioural aspect. The overconfidence has been put forward as the predominant explanation for this phenomenon. Indeed, when investors accumulate capital gains, their belief in their superior ability amplified through the attribution bias drives them to negotiate a lot the stock markets. We tried to link the component of trading activity of overconfidence investors to market volatility. We considered weighted and unweighted data

of Tunisian Stock Market for the period January 1999 - October 2007 for three temporal frequencies: daily, weekly and monthly. The operating results of all tests indicate quite clearly the importance of considering this bias in the analysis of the specificities of the Tunisian Stock Market. The observed volatility has been seen a consequence of trading activity of the investor overconfidence. The asymmetric nature of the dynamics of volatility in response to positive and negative shocks is also checked. An interesting aspect revealed by this study is that, at short term, investors are guided by their psychology than they do for longer time horizons. Indeed, overconfidence admits more pronounced influence on the unconditional volatility for daily time intervals compared to weekly and monthly intervals.

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