OVERCONFIDENCE AND TRADING VOLUME: EVIDENCE FROM AN EMERGENT MARKET

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ABSTRACT:It has been a challenge for financial economists to explain some stylized facts observed in securities markets, among them, high levels of trading volume. The most prominent explanation of excess volume is overconfidence. High market returns make investors overconfident and as a consequence, these investors trade more subsequently and make some transactions more aggressively. The aim of our paper is to study the impact of the phenomenon of overconfidence on the trading volume and its role in the formation of the excess volume on the Tunisian stock market. Based on the work of Statman, Thorley and Vorkink (2006) and by using VAR models and impulse response functions, we find a little evidence of the overconfidence hypothesis when we use volume (shares traded) as proxy of trading volume.

Keywords: overconfidence, disposition effect, trading volume, emergent market

JEL Codes: G11; G12

1. Introduction

Some puzzles found on the financial markets, which previously could not be solved using the standard economic theory, we accounted for once overconfidence of investors was assumed. These issues include excessive trading volume. Several studies consider the proposition that investor overconfidence generate the high trading volume observed in financial markets[1] (De Bondt and Thaler, 1995), Odean (1998a, 1998b, 1999), Gervais and Odean (2001), Barberies and Thaler (2003) and Statman, Thorley and Vorkink (2006). These models predict that overconfident investors trade more than rational investors. De Bondt and Thaler (1995) ague that "the key behavioural factor needed to understand the trading puzzle is overconfidence". Overconfident investors overestimate the precision of their own valuation abilities, in the sense that they overestimate the precision of their private information signals (Daniel, Hiershleifer and Subrahmanyam (1998, 2004), Gervais and Odean (2001)).

Researches develop theory and testable implications under two assumptions. First, that investors are overly overconfident about the precision of their private information, and second, that biased self attribution causes the degree of overconfidence to vary with realised market outcomes.

There is no obvious ideal way to measure overconfidence (Deaves, Luders and Luo, 2008). According to Glaser and Weber (2007), overconfidence can manifest in four facets: miscalibration (Lichtenstein and al., 1982; Yate (1990), Keren (1991), and Mcclelland and Bolger (1994), better than average (Svenson (1981) and Taylor and Brown (1988)), illusion of control (Langer (1975) and Presson and Benassi (1998) and unrealistic optimism (Weinstein, 1980). The calibration technique is the one that most closely conforms to the new overconfidence models (Deaves, Luders

[1] Contrary to that, Varian (1989) finds that trading volume is entirely driven by differences of opinions.

and Luo, 2008). Statman, Thorley and Vorkink (2006) reports that there is a little difference in the trading patterns implications between the miscalibration[2] version of overconfidence and the better than average one (the idea that most investors simply believe their investment skills are better than average). In our study, the tests we conduct do not distinguish between them and we refer to previews voluminous studies that model overconfidence as the idea that investors often overestimate their private information.

Statman, Thorley and Vorkink (2006) argue that investor overconfidence is a driver of the disposition effect[3] (the tendency to sell winners too early and ride losers too long), because overconfidence encourages investors to trade asymmetrically between gains and losses. Overconfidence differs from the disposition effect in two ways. First, the disposition effect refers to an investor's attitude towards a specific stock in the portfolio (Odean (1998b), Ranguelova (2001) and Dhar and Zhu (2002). However, overconfidence affects the stock market in general. Second, the disposition effect explains the motivation for only one side of a trade. In contrast, overconfidence can explain both sides of a given transaction.

Many studies predict a link between current volume and lagged returns in the developed markets (Statman, Thorley and Vorkink (2006), Chuang and Lee (2006), Glaser and Weber (2007)), but, we find a little evidence in emergent market (Griffin, Nardi and Stulz (2007). Furthermore, compared to developed markets, emerging markets are considerably smaller and less liquid. This death of liquidity can play an important role in determining the relationship between stock returns and trading volume; it can potentially alter the previous findings of the developed markets (Pisedtasalasai and Gunasekarage, 2006).

The goal of our paper is to study to what extend overconfidence correlate with trading volume in the Tunisian market. Empirically, we use monthly data in order to correlate past market returns with market trading activity. Through the use of a threshold VAR, we find little evidence indicating that past market returns affect trading activity of individual investors (as measured by volume). Thus, overconfident investors trade more than the others. The rest of the paper is organised as follows. *Section 2* describes our data set and the methodology we employ. *Section 3* reports the results. *Section 4* discusses the results and concludes.

2. Data and methodology

Our database consists of monthly observations of Tunisian common stocks[4] from January 2000 to December 2006[5]. We focus on monthly observations under the perspective that changes in investor overconfidence occur over monthly or annual horizons (Odean, 1998; Gervais and Odean, 2001; Statman, Thorley and Vorkink, 2006).

Following Lo and Wang (2000) and Statman, Thorley and Vorkink (2006), we use a value-weighted rather than equal-weighted basis.

Figure 1 and 2 present trading volume approximated respectively by volume (shares traded) from January 2000 to December 2006.

[2] Individuals are asked to construct 90% confidence intervals for currently (or soon) knowable magnitudes, a percentage of individuals usually markedly below 90% produce intervals that bracket the true answer.

[3] See Shefrin and Statman (1985) and Weber and Camarer (1998) for further empirical and experimental evidence on the disposition effect.

[4] We consider a sample of 20 firms (the more liquid ones) from the Tunisian market which is composed in 2000 of 50 firms.

[5] We use monthly observations for trading volume and returns, but our estimate of volatility is constrained by the availability of daily returns.

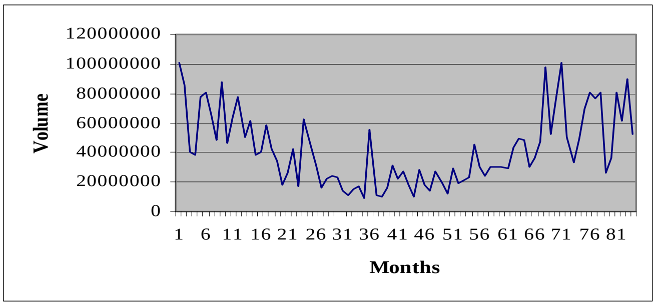

Fig. no. 1 - Monthly volume for Tunindex market

Figure 1 presents Tunindex volume from January 2000 to December 2006. An examination of long-term Tunisian trading volume indicates that the volume has increased over the last two years. The increase of transactions can be explained by the existence of noise traders. In fact, Black (1986) first argued that noise traders offer an exit from no-trading equilibrium of perfectly rational models of security markets. Odean (1998) and Gervais and Odean (2001) explained that overconfidence of noise traders increases trading volume as they attribute high returns in bull markets to their trading skills.

2.1 Definition of variables

- mret : the monthly stock market return
- mtrading : the monthly volume (shares traded).
- msig : the monthly temporal volatility of market return based on daily market returns within the month, correcting for realized autocorrelation, as specified in French, Schwert and Stambaugh (1987)[6].

This volatility control variable is based on Karpoff's (1987) survey of research on contemporaneous volume-volatility relationship, as is similar to the mean absolute deviation (MAD) measure in the trading volume study of Bessembinder, Chan and Seguin (1996).

According to French, Schwert and Stambaugh (1987), non synchronous trading of securities causes daily portfolio returns to be autocorrelated, particularly at lag one[7]. However, the negative sign of variance in the case of some individual securities leads us to use the approximation of Duffe (1995)[8]. In fact, French, Schwert and Stambaugh (1987) approximation results in a negative variance estimate if the first-order autocorrelation of daily returns in a given month is less than -0.5.

- Disp: cross-sectional standard deviation of returns for all stocks in month t.

We note:

w_i : the weight of stock i in the market portfolio

σ_{it} : the standard deviation of the return of stock i in month t.

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[6] The volatility according to French, Schwert and Stambaugh (1987) is calculated as follow: $Msig^2 = \sum_{t=1}^{T} r_t^2 + 2\sum_{t=1}^{T} r_t r_{t-1}$, where r_t is day t's return and T is the number of trading days in month t; and this in order to adjust the first order autocorrelation of returns.

[7] See Fisher (1966), and Scholes and William (1977).

[8] $Msig^2 = \sum_{t=1}^{T} r_t^2$.

$$Disp = \sum_{i=1}^{20} w_i \sigma_{it}$$

According to Statman, Vorkink and Thorley (2006), return dispersion is included as a control variable to account for potential trading activity associated with portfolio rebalancing. For example, large spreads between the individual stock returns might lead to trading activity among investors seeking to maintain fixed portfolio weights.

2.2 Summary statistics

The table 1 provides summary statistics on monthly market return and market trading as well as two market-wide based control variables: volatility and dispersion, during the period 2000-2006.

Table no.1

Market descriptive statistics

	Return (mret)	Volume	Detrended log volume (mtrading)	Volatility (msig)	Dispersion (Disp)
Mean	0.0004	2.81 E+08	3.84 E-14	0.0235	0.0042
Std Dev	0.0016	1.08 E+09	0.4032	0.0139	0.0029
Min	-0.0034	8682751	-0.9077	0.0051	0.0014
Max	0.0060	6150000000	0.9808	0.0714	0.0171
Skewness	0.7717	4.3837	-0.0799	1.2744	2.1866
Kurtosis	4.8985	20.6944	2.7361	4.3859	8.0665
Jarque-Bera	20.9536	1364.869	0.3332	29.4627	156.7879
Prob	0.00002	0.0000	0.8465	0.0000	0.0000

This table gives descriptive statistics on market-wide variables, where Return is defined as the monthly value-weighted market return, , Volume is the monthly volume (shares traded), Detrended log volume is the Hodrick-Prescott (1997) detrended natural log of market volume, Market volatility (Msig) is the French, Schwert and Stambaugh (1987) monthly volatility measure based on daily return standard deviation and Dispersion (Disp) is the monthly cross-sectional standard deviation of security returns.

To test for unit root, we employ the ADF and Phillips-Peron (PP test) for all variables. The test results[9] indicate that the null hypothesis that the variables are non stationary is strongly rejected except for the variable volume. We employ the Hodrick-Prescott (1997)[10] algorithm (HP) for detrending the trading variable[11]. In fact, the use of non stationary series can lead to bias in the coefficient standard errors of vector autoregressive we employ in this study.

Hodrick-Prescott (HP) algorithm is a two sided linear filter that computes the smoothed series S of y by minimizing the variance of y around S, subject to a penalty that constrains the second difference of S. Specifically, The HP filter chooses S_t to minimize:

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[9] For brevity tests of stationary are not reported.

[10] Previous studies report strong evidence of both linear and non-linear time trend in trading volume series (Gallant and al. (1992) and Chen and al. (2001)). However, these linear time trend detrending methodologies appear not flexible enough for time series (Statman and al. (2006)).

[11] We use the natural log transformation before detrending the series. According to Statman and al. (2006) this can help eliminating the correlation between the level of the trend and volatility around the trend.

$$\sum_{t=1}^{T}\left(y_t - S_t\right)^2 + \lambda\sum_{t=2}^{T-1}\left[\left(S_{t+1} - S_t\right) - \left(S_t - S_{t-1}\right)\right]^2 \tag{1}$$

The penalty parameter λ, controls the smoothness of the series S_t. The larger the λ, the smoother the S_t. As λ[12] $\rightarrow \infty$, S_t approaches a linear trend. Our motivation for detrending is to extract a stationary time-series, not to predict the trend[13].

To test the normality of returns, we refer to Skewness and Kurtosis statistics. For market return, the Skewness is $\neq 0$ (0.77) and the Kurtosis is $\neq 3$ (4.89). This implies the non-normality of the distribution of returns.

2.3 Empirical methodology

Following Statman and al. (2006), we use a vector autoregressive (VAR) and impulse response functions in order to study the interaction between market returns and trading proxies (volume). We use the following form of the VAR model:

$$Y_t = a + \sum_{k=1}^{K} A_k Y_{t-K} + \sum_{l=0}^{L} B_l X_{t-l} + e_t \tag{2}$$

Where,

- Y_t: a (nx1) vector of endogenous variables (return and trading proxy : turnover and volume).
- X_t : a (nx1) vector of exogenous variables : dispersion and volatility.
- e_t : a (nx1) residual vector. It captures the contemporaneous correlation between endogenous variables.
- A_k : the matrix that measures how trading proxy and returns react to their lags.
- B_l : the matrix that measure how trading proxy and returns react to month (t-1) realizations of exogenous variables.
- K et L: numbers of endogenous and exogenous observations. K and L are chosen based on the Akaike (1974) (AIC) and Schwartz (SC) information criteria[14]. In our case, the SIC leads to k = 5[15] and L = 2.

Glaser and Weber (2007) note that overconfidence models are not very precise on how we should specify the lag length in empirical studies. Statman, Thorley and Vorkink (2006) find that returns that are lagged more than 6 months do not significantly affect trading activity anymore.

In order to provide more insight into the finding of the VAR model, we employ impulse response functions to aggregate over coefficient estimates and illustrate how the endogenous variables relate to each other over time (Hamilton, 1994). Impulse response functions trace the effect of a one standard deviation shock in one residual to current and future values of the endogenous variables through the dynamic structure of the VAR.

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[12] We follow the common practice of setting λ =14,400 for monthly observations.
[13] The detrended time series used in this study is the monthly difference between log trading and its trend.
[14] Our choice is based on the Schwartz information criterion (SIC) (we choose the number of lags which minimize the SIC).
[15] Chuang and Lee (2006) chose also 5 lags for their model.

Equation (3) contains two endogenous variables (market turnover or market volume) and two exogenous variables (volatility and dispersion):

$$\begin{bmatrix} \text{mtrading}_t \\ \text{mret}_t \end{bmatrix} = \begin{bmatrix} \alpha_{\text{mtrading}} \\ \alpha_{\text{mret}} \end{bmatrix} + \sum_{k=1}^{5} A_k \begin{bmatrix} mtrading_{t-k} \\ mret_{t-k} \end{bmatrix} + \sum_{l=0}^{2} B_l \begin{bmatrix} \text{msig}_{t-1} \\ \text{disp}_{t-1} \end{bmatrix} + \begin{bmatrix} e_{\text{mtrading},t} \\ e_{\text{mret},t} \end{bmatrix} \quad (3)$$

Changes in one residual, say $e_{\text{mtrading},t}$, will immediately change the current value of mtrading, but will also affect the coefficient matrix of future values of mtrading and mret since lagged values of mtrading appear in both equations through the coefficient matrix A_k

To test the overconfidence, we shock the market return by one sample standard deviation and we track how market trading activity responds over time to the market return residual.

3. Market VAR estimation and test results

3.1 Market vector autoregression

Table (2) provides the results of equation (3). The variable mtrading in table (2) represent volume. The table is organised by rows for each endogenous variable (mret and mtrading) and by columns for lagged endogenous variables and exogenous variables.
For each coefficient, we report the estimated value, t statistic and the standard errors.

Table no.2

Market VAR estimation

	$mtrading_{t-1}$	**$mtrading_{t-2}$**	**$mtrading_{t-3}$**	**$mtrading_{t-4}$**	**$mtrading_{t-5}$**
$mtrading_t$	0.162807 (0.12369) [1.31628]	0.035738 (0.12347) [0.28945]	0.028013 (0.12169) [0.23020]	-0.074074 (0.12971) [-0.57106]	0.002777 (0.12940) [0.02146]
$mret_t$	-0.000313 (0.00049) [-0.64031]	-8.85 E -05 (0.00049) [-0.18123]	-0.000106 (0.00048) [-0.22060]	0.000163 (0.00051) [0.31777]	2.03 E -05 (0.00051) [0.039601]

( ): Standard errors; [ ]: t stat; *: coefficient significant at the level of 5 %

	$mret_{t-1}$	**$mret_{t-2}$**	**$mret_{t-3}$**	**$mret_{t-4}$**	**$mret_{t-5}$**
$mtrading_t$	15.67898 (31.8742) [0.49190]	2.703257 (31.8685) [0.08483]	14.81631 (32.1965) [0.46018]	-33.12995 (32.3617) [-1.02374]	**68.58366** **(32.2488)** **[2.12671]***
$mret_t$	0.122507 (0.12613) [0.97129]	0.069077 (0.12611) [0.5477]	0.028561 (0.12740) [0.22418]	0.142152 (0.12806) [1.11007]	0.131071 (0.12761) [1.02712]

( ): Standard errors; [ ]: t stat; *: coefficient significant at the level of 5 %

	constante	**$msig_t$**	**$msig_{t-1}$**	**$msig_{t-2}$**	**$disp_t$**	**$disp_{t-1}$**	**$disp_{t-2}$**
$mtrading_t$	0.040303 (0.17226) [0.23396]	**7.999411** **(3.97861)** **[2.01060]***	-4.665465 (4.10699) [-1.13598]	-1.667678 (3.83590) [-0.43476]	-27.58485 (18.0826) [-1.52549]	0.352951 (18.6282) [0.01895]	3.417001 (17.7277) [0.19275]
$mret_t$	-0.000568 (0.00068) [-0.83371]	0.026479 (0.01574) [1.68191]	-0.006500 (0.01625) [-0.39994]	-0.007345 (0.01518) [-0.48392]	-0.000514 (0.07155) [-0.00718]	-0.007350 (0.07371) [-0.09971]	0.124796 (0.07015) [0.54777]

( ): Standard errors; [ ]: t stat; *: coefficient significant at the level of 5 %

From the first part of table (2), we document that market trading is not autocorrelated, with non significant 5 lag coefficients. Lagged observations of trading volume are also not correlated to market return.

The second part of table (2) present the association between market trading and lagged market returns. We remark that market trading is positively related to lag market returns with only one significant coefficient (the fifth lag). This result is consistent with previous empirical studies of overconfidence hypothesis (Statman and al. (2006), Griffin, Nardi and Stulz (2007), Chuang and Lee (2006) and Glaser and Weber (2007)). According to Glaser and Weber (2007) and Deaves, Luders and Schroders (2007), high market returns make the investors overconfident in the sense that they underestimate the variance of stock returns. However, Hilary and Menzelt (2006) attribute this finding to the self attribution bias. In fact, investors think that their predictions are better than the others.

The third part of table (2) presents the relation between endogenous and exogenous variables (msig and disp). Results show a positive and significant contemporaneous association between volume and volatility. Our finding is consistent with Karpoff (1987) and Statman and al. (2006)[16].

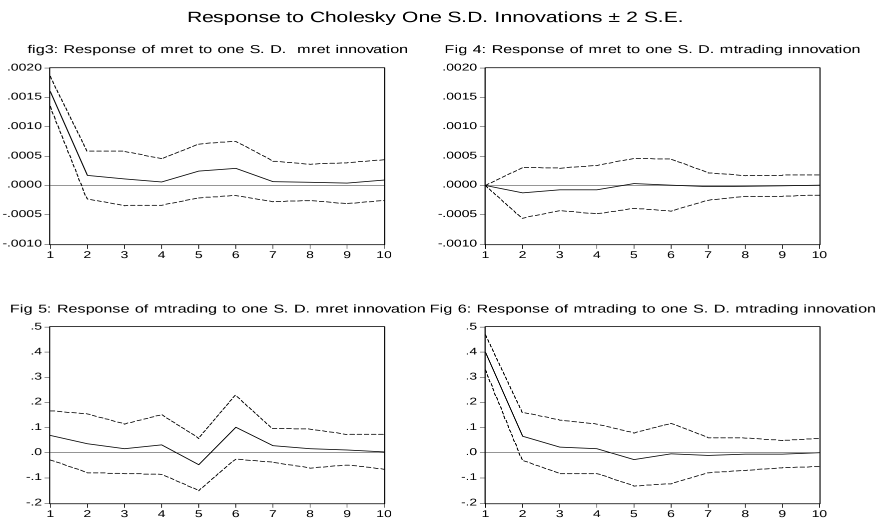
Dispersion does not affect market trading. In fact, the association between disp and trading volume is non significant. This result is inconsistent with the result of Statman and al. (2006) who find a high positive contemporaneous association between market turnover (proxy of trading volume) and dispersion.

3.2 Market impulse response functions

Individual VAR coefficient estimates do not capture the full impact of an exogenous variable observation. An impulse response functions use all the VAR coefficient estimates to trace the full impact of a residual shock that is one sample standard deviation from zero.

Figures 3, 4, 5 and 6 contain all four possible impulse response function graphs using the bivariate VAR estimation shown in table (2) and (3). The vertical axis measure the percentage increase in mtrading

mtrading = volume



We note that impulse response functions are forced to zero over time because mtrading proxy is detrended.

[16] Individual coefficients on lagged msig must be interpreted with caution because of autocorrelation in volatility (Gallant, Rossi and Tauchen (1992) and Chen, Firth and Rui (2001)).

Figure 3 and 4 represent responses of mret to one standard deviation of mret and mtrading along with confidence bands spaced out at two standard errors. In figure 3, the impulse response function indicates that impact of mret shock is positive and persistent for about 5 months. Figure 4 indicates that a one standard deviation shock to mtrading increases slightly, but, in general, the impulse response function coefficients are not significantly different from zero.

Figure 5 and 6 represents responses of mtrading to one standard deviation of mret and mtrading along with confidence bands spaced out at two standard errors. Figure 5, indicates a positive response in mtrading to mret shock; the key finding of this study[17]. However, this impact is weakly remarkable. Figure 6 indicates a large and persistent response in mtrading to an mtrading shock.

4. Conclusion

In this study, we analyse the overconfidence hypothesis in the Tunisian market using vector autoregressive (VAR) and associated impulse response functions.

We find a little evidence for this hypothesis. In fact, past market returns affect trading activity when the trading proxy used is volume over some months.

Finally, we find a contemporaneous significant positive relation between volume and volatility. The predictability of security returns based on lagged volume has been documented by many financial economists as a possible violation of strict market efficiency.

As future research, it would be interesting to use daily data (Chorida, Huh and Subrahmanyam, 2006) or weekly ones (Griffin, Nardari and Stulz, 2007). It would be also important to see which past returns affect trading volume (past market returns or past portfolio returns (Glaser and Weber, 2007). Finally, future empirical research can also distinguish between individual and institutional investors (Cho and Kyoosung, 2006).

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