Investor’s overconfidence and trading volume in the Tunisian market

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Abstract: A sample of 35 Tunisian companies is designed to study the relationship between investors’ overconfidence and trading volume by distinguishing it from the disposition effect. We use VAR model in two versions. VAR market model shows a significant and positive correlation between past market return and current market turnover. This result validates overconfidence hypothesis and disposition effect. Therefore, we use a securities VAR model that shows a significant and positive correlation between past market return and current securities turnover in presence of securities returns for some companies. This result validates overconfidence hypothesis and not disposition effect. Other companies are characterised by a disposition effect and not by overconfidence since securities VAR model shows a significant and positive correlation between individual past returns and their current turnover in presence of past market returns. We conclude that the exchange activity is not a simple summation of disposition effect of individual securities.

Keywords: efficiency; behavioural finance; overconfidence; trading volume; disposition effect; Tunisia.

1 Introduction

The high trading volume is a puzzle which affected almost all markets worldwide. The theoretical and empirical studies have given various explanations of the puzzle of the high trading volume. The survey by Shiller (2003) from market operators confirms that psychology is essential for understanding price dynamics (Fama, 1998; Hirshleifer, 2001; Ritter, 2003). Behind the term ‘market psychology’, investors include influences inter temporal and psychological biases such as investor overconfidence.

In this article we will study investor overconfidence bias and his effect on the trading volume and we will distinguish it from disposition effect. Therefore we must answer the following questions:

1. High degree of investor overconfidence causes an excessive trading volume?
2. Exchange activity is not a simple summation of disposition effect?
3. Past market returns causes trading volume levels and not the reverse?

We will analyse these questions on the Tunisian market by linking past returns with trading volume. In the first time, we will use vector autoregressive (VAR) model in two versions. A first version ‘market VAR model’ links past market returns with current market trading. The positive relation between these two variables is in favour of overconfidence hypothesis and disposition effect too. Therefore, to distinguish overconfidence hypothesis from disposition effect as they are two explanations of trading volume puzzle we will use a second version of VAR model that is ‘individual VAR
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model’ which tests the correlation between market returns and individual trading volume in the presence of individual (security) returns. If this correlation is significantly positive we will confirm that investor overconfidence explains high trading level and not disposition effect. In the second time, we will use Granger causality test that studying relationship between past market returns and market trading volume to examine the direction of causality between these two variables. If Granger causality direction is only the returns to trading volume we will confirm that past market returns causes trading volume and not the reverse that is in favour of overconfidence hypothesis.

A sample of 35 firms from Tunisian market with daily, weekly and monthly data was designed to study our aim. We can summarise our results as follow: first, the market VAR model shows that overconfidence causes trading volume only for short periods (daily) then it has no effect on the Tunisian market for long periods. The same result is in favour of disposition effect. Then, we find that trading volume is explained by the excess of investor confidence in their abilities and their private information and this result for some Tunisian firms. The other Tunisian investors suffer from a disposition effect which explains the current volume of transactions in their securities. The rest of Tunisian companies in our sample do not suffer from overconfidence or a disposition effect. Finally and through testing Granger causality, we find on daily and weekly frequencies, that the past returns explain trading volumes and not the reverse. This result is in favour of the hypothesis of overconfidence and its relationship with self-attribution bias. While monthly, there is no relationship between these two variables.

The rest of this paper is structured as follow. In the next section, we present the related literature. Section 2 describes the methodology. Section 4 presents variable measures. Section 5 shows and analyses empirical results on Tunisian market and on security time series. Section 6 concludes the results and provides several suggestions for future research.

2 Related literature

According to several past and recent studies (Statman et al., 2004; Glaser et al., 2003; Sheikh and Riaz, 2012) trading volume observed in financial markets is high and may be higher that we can explain by models taken from the paradigm of rationality. De Bondt and Thaler (1995) note that the high volume of transactions observed in financial markets is perhaps the single most embarrassing evidence to the standard finance paradigm. The theoretical and empirical studies have given various explanations of the puzzle of the high trading volume. Several researchers are in agreement that the liquidity needs, information flows or the re-balancing of portfolios are insufficient explanations of the huge level of transactions. The survey by Shiller (2003) from market operators confirms that psychology is essential for understanding price dynamics. Behind the term ‘market psychology’, investors include influences inter temporal and psychological biases such as investor overconfidence.

The bias of overconfidence has been well studied for a long time in psychology through the results of interviews, surveys and experiments. In the psychological literature, overconfidence does not have a precise definition, but it manifests itself in four forms, namely: miscalibration, better than average effect, illusion of control and unrealistic optimism. Miscalibration is a psychological result that people tend to overestimate the accuracy of their forecasts of uncertain events. This form of
overconfidence has been explained by studies that analyse assessments of uncertain quantities and always find that the probability distributions of individuals are more strained (Gervais and Odean, 2001; Glaser et al., 2010). This result seems to be robust especially when people judge difficult spots (Soll and Klayman, 2003). Taylor and Brown (1988) in their investigation confirm that people, unrealistically, have positive views in themselves. This behaviour is named ‘better than average effect’ and it is another form of overconfidence. An important event is that people judge themselves as better than others by looking at their personal skills or positive attributions. The illusion of control (Presson and Benassi, 1996), and unrealistic optimism are also two other manifestations of overconfidence. Langer (1975) defines illusion of control as “the hope, that the probability of personal success inappropriately high in relation to the objective probability, will be guaranteed”. From this definition we can understand the relationship between the illusion of control and unrealistic optimism.

Whatever the form of overconfidence, this bias was explained by the presence of bias self-attribution. This represents the fact that people tend to attribute good results to their own qualities and bad outcomes to bad luck or other factors. The psychological foundation that self-attribution bias varies the degree of overconfidence is exploited by several financial models that use overconfidence as an explanation of certain anomalies in financial markets. Chuang and Lee (2006) show empirically that if the bias of self-attribution can make investors overconfident, they will exchange more frequently in response to market gains. In the same view, Glaser and Weber (2005, 2007), show that self-attribution create and increase the feeling of confidence among investors, and consequently create excessive trading of securities in financial markets (Barber and Odean, 2002). Grinblatt and Keloharju (2009) state that, along with overconfidence, sensation seeking is another psychological trait, which may cause investors to trade more (Glaser and Weber, 2007). Their finding is inconsistent compared to the model of overconfidence by Gervais and Odean (2001).

Several studies tend to answer the question why past returns of stock market affect trading volume. So the answer is explained by overconfidence and its strong relationship with self-attribution. Most of these studies show that overconfidence is the psychological explanation of the huge level of trading volume (Ifcher and Zarghamee, 2011; Odean, 1999). However disposition effect is a cognitive bias observed in financial markets also answering of this question and it reflects the disposal of investors to sell securities ‘winners’ too quickly and to keep in portfolio securities too long time ‘losers’ (Shefrin and Statman, 1985). Therefore, this behaviour led investors to suboptimal management of their portfolios. The disposition effect is generally recognised as an investor attitude towards specific stocks in its portfolio. While investor overconfidence is a behaviour towards the market as a whole, if investors overestimate their ability to increase wealth by the current transaction, they maintain that knowledge of the securities in general rather than specific stocks that are currently held.

3 Methodology

In our empirical study, we try to test the hypothesis that overconfidence explains trading volume on the Tunisian market. For this reason, we study the relation between returns and trading volume over a sample of 35 Tunisian firms. Our database consists of daily, weekly and monthly observations over a period from January 1999 until October 2006.
For each action, we need its courses, turnover rate (as a measure of its volume of transactions) and market capitalisation. Daily, weekly and monthly observations are constructed from daily data of the Securities Exchange of Tunisia (Tunis Stock Exchange).

The interaction between trading volume and returns to test overconfidence hypothesis will be studied through modelling VAR. The interest of the VAR model is that it allows describing relationships between a set of variables, without putting in any a priori assumption on the coefficients between these variables.

The general form of the VAR model is as follows:

\[ Y_t = a + \sum_{k=1}^{K} A_k Y_{t-k} + \sum_{i=0}^{L} B_i X_{t-i} + \varepsilon_t \]  

(1)

\( Y_t \) is the vector of dimension (nx1) observations of period \( t \) of endogenous variables [trading volume \( (V_t) \) and returns \( (R_t) \)], \( X_t \) is a vector of observations of period \( t \) of exogenous variables, and \( \varepsilon_t \) is a residual vector of dimension (nx1), \( A_k \) and \( B_k \) are the coefficients of regressions that estimate relationships between time series of endogenous and exogenous variables (\( K \) is the number of lags of endogenous observations and \( L \) is the number lags of exogenous observations).

The VAR model allows a covariance structure that exists in the residual vector, which captures the contemporaneous correlation between the endogenous variables. Formal theories of overconfidence do not specify a time to study the relationship between returns and trading volume. So before any treatment, it is necessary to determine the optimal number of late to be included. To do this, we begin by estimating VAR models all with a number of delays from 0 to \( k \) (\( k \) is the number of maximum lag, it can be chosen depending on the nature of the data, example 12 for monthly data). The number of delay that will retain is a two that minimises Akaike (AIC) and Schwarz (SC) criterion of each estimate.

It should be noted as appropriate to ensure the stationary of the variables studied to estimate the coefficients of the VAR process. A process \( X_t \) is stationary if all its moments are invariant to any change of time origin. Hence it should be checked before using the VAR model that all variables are stationary by means of a suitable Dickey and Fuller test (see Appendix).

Based on the VAR model, we use impulse response functions to illustrate how the endogenous variables are interrelated through time (Hamilton, 1994). The impulse response functions trace the effect of a shock unit at residues on current and future values of endogenous variables through the dynamic structure of the VAR model.

In this study, we work with two versions of the VAR model: a version on the market in general (VAR market model) and another on every stock in our sample (individual VAR model).

3.1 VAR market model

Market version of the VAR model contains two endogenous variables (trading volume and market return) and two exogenous variables (temporal volatility of returns \( |R_{mt}| \) and the cross-market average deviation \( MAD_t \)) and it is written as follows:

\[
\begin{bmatrix}
V_{mt} \\
R_{mt}
\end{bmatrix} = \begin{bmatrix}
\alpha_{V_{mt}} \\
\alpha_{R_{mt}}
\end{bmatrix} + \sum_{k=1}^{K} A_k \begin{bmatrix}
V_{m_{t-k}} \\
R_{m_{t-k}}
\end{bmatrix} + \sum_{i=0}^{L} B_i \begin{bmatrix}
|R_{mt}| \\
MAD_t
\end{bmatrix} + \begin{bmatrix}
\varepsilon_{V_{mt}} \\
\varepsilon_{R_{mt}}
\end{bmatrix}
\]

(2)
The interdependence between past market returns and market trading volume, studied by the version of the VAR market, not only can test the effect of overconfidence but also the disposition effect. Therefore a positive and significant relationship between current trading volume and past market return can also be interpreted on the side of the disposition effect. In this case, investor activity may be more aggressive response to high return market, not only because the level of investor confidence in the accuracy of their private information or their investment performance has increased, but this can be explained from the fact that investors sell certain securities from their portfolios (winners) as soon as possible for gains, that is the disposition effect. A distinguishing characteristic of two alternative explanations is that the hypothesis of overconfidence of Gervais and Odean (2001) connects the transaction in general, while the disposition effect of Shefrin and Statman (1985) is generally regarded as a description attitude of investors towards specific securities in their portfolios. To clarify these two theories and testing our second hypothesis we will examine the activity of individual securities transactions. For this reason, we use a second version of the VAR model on each stock in our sample (35 stocks).

### 3.2 Individual VAR model

It is a version of the VAR model on each stock. It contains three endogenous variables (individual trading volume, individual returns and market returns) and one exogenous variable (temporal volatility of returns \( |R_{mt}| \)). The individual VAR model can be written as follows:

\[
\begin{bmatrix}
V_t^i \\
R_t^i \\
R_{mt}
\end{bmatrix} =
\begin{bmatrix}
\alpha_{Vi} \\
\alpha_{Ri} \\
\alpha_{Rm}
\end{bmatrix} + \sum A_k \begin{bmatrix}
R_{t-k}^i \\
R_{mt-k}
\end{bmatrix} + \sum B_k \begin{bmatrix}
|R_{mt-k}| \\
|e_{Rm}|
\end{bmatrix} + \begin{bmatrix}
e_{Vi} \\
e_{Ri} \\
e_{Rm}
\end{bmatrix}
\]

\(V_t^i\) is the trading volume of stock \(i\) at time \(t\), \(R_t^i\) is the return of stock \(i\) at time \(t\), \(R_{mt}\) is the market return at time \(t\), and \(|R_{mt}|\) is the temporal volatility of returns at time \(t\).

If overconfidence and disposition effect play a role in explaining the volume of transactions, we must find positive coefficients in regressions of stocks turnover on the past market returns also on the past returns of stocks. Version of the individual VAR model allows us to distinguish between the two psychological biases (overconfidence and disposition effect) and thus ensure that the behaviour of the exchange activity is not simply a summation the disposition effect observed in individual stocks.

It is important to note that there are theories of trading volume but not all see any causal relationship between returns and trading volume. We find for example the model of sequential information arrival of Copeland (1976) suggests a positive causal relationship between the return values and trading volume in both directions (feedback relationship). To reconcile the difference between the autocorrelation properties of short and long term aggregate return values, De Long et al. (1990) developed a model of positive feedback trading, implying positive bidirectional causality between trading volumes and values of returns. Therefore we will use Granger causality tests to examine causality direction between values return and trading volumes (Granger, 1988).
3.3 Granger causality tests

Our empirical procedure is to test whether there is a positive relationship between the measured return and trading volumes, using the Granger causality tests (1969 and 1988). These tests are based on the idea that the future cannot cause the present or the past. Formally, if the prediction of trading volume \( (V_t) \), using past returns \( (R_t) \), is more accurate than the prediction without the use of these returns in terms of error variance \( \sigma^2 (V_t|\Omega_t - 1) < \sigma^2 (V_t|\Omega_t - 1 - R_t) \), where \( \Omega_t \) is the set of information available], as a result \( R_t \) cause \( V_t \) within the meaning of Granger.

Our empirical study allows us to distinguish between overconfidence hypothesis and the alternative hypothesis of trading volume. Bi-variant Granger causality can be written as follows:

\[
V_t = \alpha_{V1} + \beta_{V2} [R_t] + \beta_{V3} \text{MAD}_t + \sum_{j=1}^{p} a_j V_{t-j} + \sum_{j=1}^{p} b_j R_{t-j} + \epsilon_{Vt} \tag{4}
\]

\[
R_t = \alpha_{R1} + \beta_{R2} \text{MAD}_t + \sum_{i=1}^{b} c_j V_{t-j} + \sum_{i=1}^{b} d_j R_{t-j} + \epsilon_{Rt} \tag{5}
\]

\( V_t \) and \( R_t \) are endogenous variables. \( |R_t| \) and \( \text{MAD}_t \) are exogenous variables.

In tests of Granger causality, rejecting the null hypothesis that the values of past return does not cause trading volume (H0: \( b_j = 0 \) for all \( j \)) supports the hypothesis of excess confidence. The rejection of the null hypothesis that trading volume does not cause the values of return (Ho: \( c_j = 0 \) for all \( j \)) implies that the direction of causality is from volume to return. If set, the two coefficients \( b \) and \( c \) are significant we say there is a causal relationship in either direction. This feedback relationship between the values of returns and trading volume is evidence in favour of the assumption of sequential information arrival or the assumption of a positive feedback trading. It is important to specify that this test is done on the assumption that \( \epsilon \) asymptotically follow a Fisher distribution. This may be the case if \( \epsilon \) is white noise; what it amounts to saying that the series considered to be stationary series. Where applicable, it is necessary to transform the series considered to stationary series suitable to be submitted to the causality test.

4 Variable measures

Some researchers use in their empirical studies a turnover as a measure relative and not absolute of the exchange activity (Lo and Wang, 2000; Statman et al., 2004; Chuang and Lee, 2006). The turnover is a measure closest to reality of market transactions (Lo and Wang, 2000). Therefore we will use in our study individual turnover that is measured as following: \( T_{it} = \frac{\text{number of traded securities of stock } i}{\text{number of outstanding securities of stock } i} \).

We measure market turnover by weighted market turnover as following: \( T_{m} = \frac{\text{number of traded securities of stock } i}{\text{number of outstanding securities of stock } i} \). We note that in this paper, we use the weighted market turnover because our sample of 35 firms does not reflect the entire Tunisian market. So this measure helps us to find actual results. \( W_{it} = \frac{\text{CB}_i}{\text{CB}_T} \), \( \text{CB}_i \) is the market capitalisation of stock \( i \) and \( \text{CB}_T = \text{securities number of stock } i \times \text{price of stock } i \), \( \text{CB}_T \) is the total market capitalisation.
Concerning return measure we will work with the weighted market returns. This measure is calculated according to a method similar to the determination of the index Standard and Poor’s Composite 500. This is the return of the market portfolio that each asset listed on the BVMT enters in its composition to a proportion given by the ratio of its market capitalisation (number of existing title multiplied by the unit price) to the total market capitalisation. Therefore weighted market return is calculated as following: 

\[ R_{wt} = \left( \sum_{i=1}^{N} CB_{it} \times R_{it} \right) / CBT, \] 

and \( R_{it} \) is the return of stock \( i \).

For exogenous variables, we will use \(|R_{mt}|\) that is the temporal volatility of market return at time \( t \), and \( MAD_t \) that is the cross-market average deviation at time \( t \), 

\[ MAD_t = \sum_{i=1}^{N} W_t |R_{it} - R_{m}|. \]

We note \( N \) the total number of stocks in our sample (\( N = 35 \)), and \( P \) the number of lags was selected using (AIC) and (SC) criterions. The use of variables \(|R_t|\) and \( MAD_t \) as control variables was motivated by studies planned in the different objectives. For example, Karpoff (1987) reviews and discusses the empirical results of the positive relationship between contemporary trading volume and volatility values of return for a variety of theoretical perspectives. So it is right to add the absolute value of the return of period \( t \) to control this contemporary relationship. Based on the intuition of Ross (1989) that in a market friction characterised by an absence of arbitrage opportunities, the rate of information circulated is revealed by the degree of price volatility that Bessembinder et al. (1996) use the absolute value of return to reflect the information circulated and shared for \( MAD_t \), specific information circulated to firms in order to account for informational investors. The recent empirical study of Chuang and Lee (2006) confirms our use of \(|R_t|\) and \( MAD_t \) as control variables to test the causality in the Granger sense between trading volume and return values.

5 Analysis of the results

5.1 The results of VAR market and associated impulse response functions

It should first choose the number of optimal delay. We estimate the VAR models with a number of delays ranging from 1 to 4. Then we choose the number of delay that minimises both AIC and SC criterions. In our case, we must choose 1 as a number of delays to remember, but we work with two delays to compare the model results in different delays. Table 1 presents the VAR-market results. For daily results we observe that the relationship between current turnover rate and delayed market return at one level is significantly positive since the \( R_{wt} \) coefficient of the first delay has a t-student statistic (3.11) that exceeds the critical value (1.96). This observation shows that the delayed return at one level explains the volume of transactions. Alternatively, the higher market return causes the high trading volume. Also the coefficient of delayed return is statistically significant (0.009680 proxy = 0.01 with standard deviation = 0.00311). So there is a relationship between trading volume and market return, which confirms the hypothesis of overconfidence and its impact on the volume of transactions through the self-attribution bias. But if we focus on relation between current return and delayed turnover we find that the t-Student statistic of at levels 1 and 2 is less than 1.96(1.14 and 1.19 < 1.96). This result implies that there is no significant relationship between the current market return and the delayed market turnover rate. We can conclude that is the
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return that explains the volume of transactions and not the reverse. These results are against what is found with Statman et al. (2004).

A significant and positive contemporaneous relationship between the turnover rate and the transverse deviation of returns (MAD) as the t-Student statistic associated with the coefficient of MAD variable is greater than 1.96 (2.21 > 1.96), which is not the case for temporal volatility of returns (|Rmt|). This result is due to the impact of market information (Statman et al., 2004).

Using weekly data, we find that is no significant relationship between market turnover rate and market returns. This result is against overconfidence hypothesis but with market efficiency hypothesis. We observe for monthly data the same results as those found with the weekly data. In conclusion, if the horizon is large the model will be no significant. That is to say that the relationship between transaction volume and values of returns in the short term is more significant and more important than in the long term. We explain this result as follows: a positive market past return can be interpreted by investors as a result of their strong ability to choose the best investments and the accuracy of their information, creating a sense of overconfidence among investors and eventually they will exchange them aggressively, which explains the high level of transactions for a short period. But these investors will understand later failure to correct their interpretation and their thoughts and expectations through several factors such as learning. That is to say that in a short period (daily) the investor will react quickly without thinking of the consequences of his decision, whereas in a long time (weekly or monthly) it may take time to reflect and take the right decision without overconfidence. This is what explains the absence of overconfidence in long periods and the return to market efficiency.

The observed value of adjusted R squared is generally low and the constant C is statistically highly significant. These results imply that there are other explanations for market turnover rate. To distinguish the effect of investor overconfidence of the disposition effect we move to study a second version of the VAR model studying the relationship between the individual turnovers and market returns in presence of individual (securities) returns.

Table 1  VAR-market model

| Daily VAR-market | Endogenous variables | Exogenous variables | | |
|-----------------|---------------------|---------------------| | |
| Rmt(-1)         | 0.243511 (0.01972)**| 0.009680 (0.00311)**| C 0.003054 (0.00019)**| 0.00281 (3.0E-05)**|
| Tmt(-1)         | 0.009680 (0.00311)**| 0.009680 (0.00311)**| MADT -0.460314 (0.03126)**| 0.010918 (0.00493)**|
| Rmt(-2)         | 0.097104 (0.01975)**| 0.001580 (0.00312)**| 0.001580 (0.00312)**| 0.010918 (0.00493)**|
| Tmt(-1)         | 0.158947 (0.13868)*| 0.103549 (0.21828)**| | |
| Rmt(-2)         | 0.164978 (0.13845)*| 0.166482 (0.21828)**| | |
| R2              | 0.267839 0.056018 0 | 0.265674 0.053226 | |
| Adjusted R2     | 0.267839 0.056018 0 | 0.265674 0.053226 | |
| F-statistique   | 123.7081 20.06753 0 | | |

Notes: Standard errors ( ) with: ***1%, **5%, *10%, statistic-tests [ ]
Table 1  VAR-market model (continued)

<table>
<thead>
<tr>
<th>Weekly VAR-market</th>
<th>Endogenous variables</th>
<th>Exogenous variables</th>
<th>( R_{mt} )</th>
<th>( T_{mt} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( R_{mt}(-1) )</td>
<td>0.113350 (0.04623)**</td>
<td>C (0.00135)***</td>
<td>-0.006138 (0.01163)***</td>
<td></td>
</tr>
<tr>
<td>( R_{mt}(-2) )</td>
<td>0.060809 (0.04661)**</td>
<td>MADT (0.08174)*</td>
<td>-0.005416 (0.70639)*</td>
<td></td>
</tr>
<tr>
<td>( T_{mt}(-1) )</td>
<td>-0.002330 (0.00563)***</td>
<td></td>
<td>0.669365 (0.09975)*</td>
<td>0.490015 (0.86202)*</td>
</tr>
<tr>
<td>( T_{mt}(-2) )</td>
<td>5.45E-05 (0.00562)***</td>
<td></td>
<td>0.169366 (0.67024)***</td>
<td>0.232161 (0.56845)***</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Monthly VAR-market</th>
<th>Endogenous variables</th>
<th>Exogenous variables</th>
<th>( R_{mt} )</th>
<th>( T_{mt} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( R_{mt}(-1) )</td>
<td>0.095144 (0.11367)*</td>
<td>C (0.00401)***</td>
<td>-0.007201 (0.05408)***</td>
<td></td>
</tr>
<tr>
<td>( R_{mt}(-2) )</td>
<td>0.067041 (0.10270)*</td>
<td>MADT (0.00514)***</td>
<td>0.056519 (0.06930)*</td>
<td></td>
</tr>
<tr>
<td>( T_{mt}(-1) )</td>
<td>0.001301 (0.00795)***</td>
<td></td>
<td>0.000592 (0.00224)***</td>
<td>-0.017290 (0.03023)***</td>
</tr>
<tr>
<td>( T_{mt}(-2) )</td>
<td>-0.003459 (0.00782)***</td>
<td></td>
<td>0.035539 (0.26395)***</td>
<td>0.298629 (-0.57186)***</td>
</tr>
</tbody>
</table>

Notes: Standard errors ( ) with: ***1%, **5%, *10%, statistic-tests [ ]

Based on the VAR model, we will use impulse response functions to illustrate how endogenous variables (\( T_{mt} \) and \( R_{mt} \)) are linked together through time (Hamilton, 1994). The impulse response functions trace the effect of a single shock at residues on current and future values of the endogenous variables through the dynamic structure of the VAR model. To study the impulse response functions, we exploit the results of the VAR market for daily observations confirming the hypothesis of overconfidence and its effect on transaction volume. The impulse response functions give more detailed results using all the estimates of VAR coefficients to trace the full impact of a shock on the residue. Shock on the residue (\( e_{Rmt} \)) has an impact on current and future values of turnover rate and market return, which allows testing the hypothesis of overconfidence. And shock on \( e_{Tmt} \) has an impact on current and future values of turnover rate and market return.
Table 2

The results of individual VAR model (daily observations) for Amen Bank

<table>
<thead>
<tr>
<th>Endogenous variables</th>
<th>$T_{it}$</th>
<th>$R_{it}$</th>
<th>$R_{mt}$</th>
<th>Exogenous variables</th>
<th>$T_{it}$</th>
<th>$R_{it}$</th>
<th>$R_{mt}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$T_{id}(-1)$</td>
<td>0.49741</td>
<td>2.85815</td>
<td>0.49252</td>
<td>C</td>
<td>7.64E-05</td>
<td>-0.00490</td>
<td>0.001572</td>
</tr>
<tr>
<td>(0.02216)**</td>
<td>(0.70368)*</td>
<td>(0.31960)*</td>
<td></td>
<td>(1.0E-05)**</td>
<td>(0.00033)**</td>
<td></td>
<td>(0.0001)**</td>
</tr>
<tr>
<td>[6.75816]</td>
<td>[4.05980]</td>
<td>[1.54239]</td>
<td></td>
<td>[7.32384]</td>
<td>[-1.47856]</td>
<td></td>
<td>[10.4422]</td>
</tr>
<tr>
<td>$T_{i}(-2)$</td>
<td>0.067826</td>
<td>0.03162</td>
<td>-0.09266</td>
<td>$R_{mt}$</td>
<td>0.00387</td>
<td>0.087261</td>
<td>-0.437656</td>
</tr>
<tr>
<td>(0.02219)**</td>
<td>(0.70478)*</td>
<td>(0.32010)*</td>
<td></td>
<td>(0.00174)**</td>
<td>(0.05536)**</td>
<td></td>
<td>(0.02514)**</td>
</tr>
<tr>
<td>[3.05637]</td>
<td>[0.05557]</td>
<td>[-0.29340]</td>
<td></td>
<td>[2.00070]</td>
<td>[1.57636]</td>
<td></td>
<td>[-17.4074]</td>
</tr>
<tr>
<td>$R_{i}(-1)$</td>
<td>0.000945</td>
<td>-0.00358</td>
<td>0.01857</td>
<td>$R^2$</td>
<td>0.04020</td>
<td>0.016444</td>
<td>0.194816</td>
</tr>
<tr>
<td>(0.00071)**</td>
<td>(0.02242)**</td>
<td>(0.01018)**</td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>[1.33333]</td>
<td>[-0.17654]</td>
<td>[1.82421]</td>
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<tr>
<td>$R_{i}(-2)$</td>
<td>-3.79E-05</td>
<td>-0.00963</td>
<td>0.02852</td>
<td>$R^2$ ajusté</td>
<td>0.036937</td>
<td>0.013451</td>
<td>0.192037</td>
</tr>
<tr>
<td>(0.00070)**</td>
<td>(0.02255)**</td>
<td>(0.01015)**</td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>[-0.05389]</td>
<td>[-0.43123]</td>
<td>[2.80961]</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$R_{mt}(-1)$</td>
<td>0.002873</td>
<td>0.09139</td>
<td>0.24557</td>
<td>$F$-statistique</td>
<td>12.14995</td>
<td>4.963651</td>
<td>70.09714</td>
</tr>
<tr>
<td>(0.00145)**</td>
<td>(0.04593)**</td>
<td>(0.02086)**</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>[1.98661]</td>
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<td>[11.7712]</td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>$R_{mt}(-2)$</td>
<td>0.001314</td>
<td>0.09863</td>
<td>0.09235</td>
<td></td>
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<td></td>
</tr>
<tr>
<td>(0.00145)**</td>
<td>(0.04597)**</td>
<td>(0.02088)**</td>
<td></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>[0.99745]</td>
<td>[2.16727]</td>
<td>[4.42340]</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: Standard error ( ) with: ***1%, **5%, *10%, statistic-tests [ ]
Figure 1  The pulse response functions associated with VAR market model (see online version for colours)

Graph A show the responses of market turnover to a shock on $e_{Tmt}$ and on $e_{Rmt}$. In the first period, a positive shock on the market turnover rate gives an answer of increasing of 0.0008 (SD = 1.2E-05) in the daily turnover. This implies that the market turnover rates are correlated for the first four periods. A positive shock on the market return gives a positive and persistent response of turnover. This result confirms what is found by the VAR market model and it is interpreted as our first empirical validation that the market returns have an impact on investor overconfidence and trading activity on the future. This result confirms the empirical study of Statman et al. (2004). Graph A shows that the response of turnover to a shock on the turnover rate is larger than the shock on return.

For the response of market return following a shock on the return and on the rate turnover we observe in the graph B that a shock on the turnover rate results a null return response. This confirms the results of the VAR model that market returns explain the turnover rate and not the reverse. This result is in favour of the hypothesis of overconfidence in the first period. A positive autocorrelation of market returns is observed in graph B too.

The impulse response functions associated with the VAR market for weekly and monthly observations confirm the results found by the VAR model.

5.2 The results of individual VAR model

Our sample consists of 35 Tunisian companies. By applying the individual VAR model [equation (3)] connecting three variables: individual turnover rate ($T_i$), individual returns ($R_i$) and market return ($R_m$) we test our second hypothesis which predicts that exchange activity is not a simple summation of disposition effect. We find that some stocks have overconfidence, some others, disposition effect is their main cognitive bias explaining its trading volume, but several other actions in our sample are devoid of both bias and therefore they are under the assumption of market efficiency. More detailed, we note that only four companies in our sample are characterised by an excess of confidence and they are: Amen Bank (Aa), Housing Bank (Aa), General Lease (Aa) and Tunisia leasing. For Amen Bank (Aa) stock, the Rmt coefficient of the first delay is statistically significant (t-Student statistic is 1.98661 higher than the critical value 1.96). This implies that there is a significant positive relationship between market return and Amen Bank (Aa) turnover...
even when delayed returns of this action are included in the model. This result is in favour of the hypothesis of overconfidence. While there is no relationship between the Amen Bank (Aa) return and its turnover (t-Student of the coefficient of Rit for two delays are not significant). This result is against the hypothesis of disposition effect. We conclude that Amen Bank (Aa) turnover is explained by the market return, that is to say by overconfidence and not the disposition effect. 

Several other stocks (Al Mazraa, ATL, Bank of Tunisia, CIL (Aa), General Store, Simpar, Sotetel (Aa), SPDIT-SICAF, Tunisian Banks) in our sample are under the disposition effect. That is to say that their turnovers are explained by their returns. The results of the VAR model applied to ATL stock show that there is a positive and statistically significant relationship between ATL turnover and its return (t-Student (2.84394) is greater than the critical value 1.96). So the disposition effect explains trading volume of the ATL stock and not overconfidence. The same results are founded with Bank of Tunisia, CIL (Aa), Sotetel (Aa), General Store and Tunisian Banks stocks. The rest of stocks are beyond the effect of overconfidence and the disposition effect. That is to say, that their turnovers are not affected by one of two cognitive biases.

**Figure 2** Response to Cholesky one S.D. innovations ± 2 S.E. (see online version for colours)
Individual VAR model shows that exchange activity is not a simple summation of disposition effect and investor overconfidence bias is an important explanation for the huge level of trading volume in financial markets.

Taking the case of Amen Bank stock, the impulse response functions associated with individual VAR model show the results sets in Figure 2.

The last three graphs G, H, and I represent the responses of turnover of Amen Bank (Aa) following a positive shock on Amen Bank (Aa) return, on the market return and on the Amen Bank turnover. We observe a negligible response of Amen Bank turnover rate to shock on its return $R_{it}$. While a positive and significant response (1.87E-05) to a positive shock on the market return for the first period and continued during the first three periods. This result confirms the VAR model’s results and it is in favour of overconfidence hypothesis for Amen Bank stock. Similarly, a positive shock on $T_{it}$ gives a significant and positive response of Amen Bank’s turnover rate of 0.000359 for the first time and this response remains positive until the fourth period. This result is a confirmation of an autocorrelation of individual turnovers.

The first three graphs A, B, and C show the responses of Amen Bank (Aa) return to shocks on her past return, on the market return and on his turnover rate. And D, E, and F graphs show the responses of market return to a shock on Amen Bank return, on the market past return and on Amen Bank turnover. Positive responses of $R_{mt}$ to shocks on $T_{it}$ and even on Amen Bank return but no response to a shock on Amen Bank turnover $T_{it}$. This shows an autocorrelation of market returns and interdependence between market return and Amen Bank return.

5.3 The results of Granger causality tests

We present the results of Granger causality tests in Table 3. Using daily data, we find that the probability associated with the null hypothesis that the turnover rate does not cause return is 0.94126 tends to 1. This result allows accepting this hypothesis and hence the turnover rate does not explain the return. While the hypothesis that the return does not cause the turnover rate is rejected because the associated probability is very low and tends to 0 ($p = 0.00283$). Hence, the direction of causality between return and turnover rate is the return on turnover rate and not the reverse. This result is the first empirical validation for overconfidence hypothesis. Weekly tests show similar results. We note that the null hypothesis that the turnover rate does not cause returns is accepted as the associated probability equal to 0.92799 tends to 1. While we reject the null hypothesis that the return does not cause the turnover rate because the associated probability is 0.10532 tends to 0 but greater than that in the case of daily data. The same result as daily data, the return explains the turnover rate. Yet this result is in favour of the hypothesis of overconfidence. Unlike the results found with daily and weekly data, the test of Granger causality between turnover and return for monthly data shows that no relationship can exist between these two variables.

By comparing the results daily, weekly and monthly, we note that the probability associated with the null hypothesis that the return does not cause the turnover rate increases (0.00283, 0.10532, and 0.92773) and closes to 1 with increasing the study period. We therefore conclude that the hypothesis of overconfidence is verified over short periods and it rejects over long periods on the Tunisian market. In the rest of this article we will advance in the study of the relationship between excess of confidence and
Investor’s overconfidence and trading volume in the Tunisian market

transaction volume by applying the VAR model in two versions: VAR market and individual VAR.

Table 3  The results of Granger causality tests

<table>
<thead>
<tr>
<th></th>
<th>H0: $T_{mt}$ does not cause $R_{mt}$</th>
<th>F-Statistic</th>
<th>Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>H0: $T_{mt}$ does not cause $R_{mt}$</td>
<td>F-Statistic</td>
<td>Probability</td>
</tr>
<tr>
<td>Daily results</td>
<td></td>
<td>0.06054</td>
<td>0.94126</td>
</tr>
<tr>
<td></td>
<td></td>
<td>5.88336</td>
<td>0.00283</td>
</tr>
<tr>
<td>Weekly results</td>
<td></td>
<td>0.07474</td>
<td>0.92799</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2.26348</td>
<td>0.10532</td>
</tr>
<tr>
<td>Monthly results</td>
<td></td>
<td>0.31202</td>
<td>0.73279</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.07508</td>
<td>0.92773</td>
</tr>
</tbody>
</table>

6 Conclusions

The proposal, that investors are overconfident about their abilities and their assessment of transactions, may explain the high trading volume observed. And through self-attribution can cause the level of investor overconfidence to vary with market past returns. Indeed, investors distinguish between market growth and recession. More recently, empirical studies of overconfidence support the hypothesis that market past returns explain the current level of trading volume (Statman et al., 2004; Glaser and Weber, 2007; Kim and Nofsinger, 2003; Chuang and Lee, 2006).

The objective of this paper was to study overconfidence hypothesis and its impact on trading volume on the Tunisian market. To achieve this goal, we first used a VAR model under two versions. A first version (VAR market) studying the relationship between market turnover and market return to test overconfidence effect on the market as a whole. We found a positive effect of investor overconfidence on the market turnover. As a result investor overconfidence is an important explanation of high level of transaction volume. This effect is important for short horizons (for days) but it is negligible for long horizons (for weeks and months). This result is explained by the fact that in the period of market gain the investor assigns positive returns to their investment skills and become overconfident what explain their aggressive investment and high turnover level. A week later investor will correct your misevaluation and overconfidence effect will be negligible. The results of the VAR market are in favour of the overconfidence hypothesis and even in favour of the disposition effect. To clarify the explanation of trading volume, we compared these two cognitive biases and their impact on the level of transactions. For this reason, we studied a second version of the VAR model on each that connects three endogenous variables (individual turnover rates relative to each stock $i$, individual returns and market return). We found a significant positive relationship between current turnovers rates of action $i$ and market past returns during some days. This result confirms overconfidence hypothesis for certain Tunisian action. For some other actions we found a significant positive relationship between their current turnovers and their past returns. This result confirms disposition effect hypothesis. The remaining actions in our sample are beyond the effect of these two biases and therefore confirming market efficiency hypothesis. Our methodology shows that exchange activity is not a simple summation of
disposition effect and overconfidence hypothesis is an important explanation of high turnover level puzzle.

Finally we used the Granger causality relationship between turnovers and return values and we found a first empirical validation that it is returns which explain the volume of transactions and not the reverse. This result is in favour overconfidence hypothesis.

References


Investor’s overconfidence and trading volume in the Tunisian market


Notes
1 The idea is required to Chuang and Lee (2006).

Appendix

The Dickey and Fuller (DF) test for a model with constant shows that the variables $R_{mt}$, $T_{mt}$, $MAD_t$ and $|R_{mt}|$ are stationary because each value of the test statistic DF found for each series is larger in absolute value than critical values at the 1%, 5% and 10% levels. These results are confirmed even for a model with constant and trend at a time. Whereas for the stock return of 35 actions ($R_t$) and turnover rate of these actions ($T_o$), the DF test shows that these two variables are stationary for any action except for the TUNISAIR and UNION INTERNATIONAL BANK. Both actions have two daily turnover of high volatility which takes us to differentiate them once to make them stationary.
Table 4  Study of the stationary variables

<table>
<thead>
<tr>
<th>Variables</th>
<th>Daily study</th>
<th>Critical values*</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>DF test</td>
<td>1%</td>
</tr>
</tbody>
</table>
| T
\text{mt} | -16.66748  | -3.9679 | -3.4146 | -3.1291 |
| R
\text{mt} | -17.95120  | -3.4366 | -2.8634 | -2.5678 |
| | | | |
| \text{absolute value of} R
\text{mt}** | -15.86017 | -3.9679 | -3.4146 | -3.1291 |
| MAD*** | -15.51223 | -3.9679 | -3.4146 | -3.1291 |

Notes: *Critical values for rejection of unit root hypothesis; **absolute value of \( R_{\text{mt}} \); ***the standard deviation of returns cross

Turning to the weekly data, the DF test shows stationary of variables: \( |R_{\text{mt}}|, \text{MAD}_t, \text{e}_t, R_{\text{mt}} \) but the turnover rate weighted market \( T_{\text{mt}} \) is not stationary because the value of the test statistic in absolute values is less than critical values at the 1%, 5% and 10% levels. It is therefore necessary to make the \( T_{\text{mt}} \) series stationary by differentiate it once.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Weekly study</th>
<th>Critical values</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Statistic test of DF</td>
<td>1%</td>
</tr>
</tbody>
</table>
| T
\text{mt}* | -2.520755 | -3.4487 | -2.8689 | -2.5707 |
| \text{d}T
\text{mt}** | -12.47251 | -3.4487 | -2.8690 | -2.5707 |

Note: * \( T_{\text{mt}} \) before differentiation; ** \( \text{d}T_{\text{mt}} \) after differentiation of order 1

And finally, using monthly data and the DF test, we find that the variable \( R_{\text{mt}} \) is stationary. This is not the case for \( T_{\text{mt}}, \text{MAD}_t \) and \( |R_{\text{mt}}| \) series. We use the log difference transformation to order 1 for the following non-stationary series \( T_{\text{mt}}, \text{MAD}_t \) and \( |R_{\text{mt}}| \). We obtain \( T_{\text{mt}}, \text{MAD}_t \) and \( |R_{\text{mt}}| \) transformed series in first logarithmic difference and which are stationary. If we have verified that all the series, on which we will work, are stationary, we proceed to apply the test of Granger causality between transaction volume and values of returns and VAR modelling study.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Monthly study</th>
<th>Critical values</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Statistic test of DF</td>
<td>1%</td>
</tr>
</tbody>
</table>
| T
\text{mt}* | -1.913653 | -3.5047 | -2.8939 | -2.5838 |
| \text{d}T
\text{mt}** | -7.621794 | -3.5055 | -2.8943 | -2.5840 |
| MAD*** | -0.344484 | -3.5047 | -2.8939 | -2.5838 |
| IMAD**** | -4.622943 | -3.5055 | -2.8943 | -2.5840 |
| \text{absolute value of} R
\text{mt}***** | -1.680742 | -2.5891 | -1.9438 | -1.6176 |
| \text{d}R
\text{mt}***** | -6.855043 | -3.5055 | -2.8943 | -2.5840 |

Note: * \( T_{\text{mt}} \) before transformation; ** \( \text{d}T_{\text{mt}} \) after transformation into log difference of order 1