Business and Economic Research
ISSN 2162-4860
2016, Vol. 6, No. 2

The Reversal of Stock Market Trends as a Behavioral Bias: Evidence from Tunisian Stock Exchange

Hsini Mosbeh

Higher Institute of Commerce and Accountancy of Bizerte, Carthage University, Tunisia

E-mail: lahsinim@gmail.com

Kouki Mondher (Corresponding author)

Faculty of Economics and Management of Tunis, Tunis El Manar University, Tunisia

E-mail: koukimondher@yahoo.fr

Received: April 17, 2016 Accepted: May 2, 2016

doi:10.5296/ber.v6i2.9326 URL: http://dx.doi.org/10.5296/ber.v6i2.9326

Abstract

This paper examines the behavioral bias in Tunisia, a country with a small stock market in terms of capital, but surprisingly dynamic in comparison to other emerging markets. Our study is consistent with *Jegadeesh & Titman (1993)' approach as presented to* highlight an analysis of such reversal phenomena of portfolio returns, and provides explanatory factors to the so-called market trends reversal. The empirical investigation is based on a weekly database for a period from January 2002 to January 2013 related to stock prices and index values of market capitalization (TUNINDEX). The empirical test demonstrates the existence of winner-loser phenomenon in accordance with over-reaction hypothesis stating that portfolios with the worst past performance outperform, during the subsequent periods, those having produced best past performance and vice versa.

Keywords: Behavioral bias, Reversal, Stock market trend, Momentum effect

JEL Classification: G11, G12, G14, G15

1. Introduction

Financial market anomalies known as an empirical pattern in stock market that are not predicted by the standard equilibrium model (e.g, capital asset pricing model). Much of the earlier studies document that various anomalies remain without explanation; they seem to disappear, reverse or attenuate. *Jegadeesh and Titman (1993)* show that the winner assets during the three to twelve months are more likely to continue behaving winner through the three and twelve subsequent months, reporting consequently a momentum bias over the short period. *Fama (1998)* conclude that tendency not to react (under-reaction) to certain firms' news is also frequent as the tendency to overreact (over-reaction) to these news.

According to Lee et al. (1991) , Rowenhorst (1999), Shiller (2000b),George & Hwang (2004), Lowenstein & Willard (2006), Titman & Daniel (2008) , Gervais et al. (2011) Bertrand & Morse (2012), Buraschi et al. (2014), investors do not react properly to the information they receive. Indeed, they commit cognitive errors that can be profitably exploited by other operators. This incorrect reaction towards information includes under-reaction, over-reaction, momentum, bubbles and crashes.

The concept of momentum in stock markets is defined as the way the prices can fluctuate in the market. In this sense, when the market is in a phase of upward or downward acceleration, momentum increases and consequently the price trend persists. The zero crossing is representative of a reversal trend, and constitutes thus a signal to buy / sell [*Delong et al. (1990), De Bondt & Thaler (1985), Lee et al. (1991), Orlean (1994), Sherbina (2004), Ang et al. (2005) Gervais et al. (2011), Alti & Lock (2014)]*. Furthermore, other researchers mainly Barberis et al. (1998), Hong & Stein (1999), Jegadeesh & Titman (2001a, 2001b) have examined the hypothesis that the momentum effect is attributed to operators' slowness when reacting to good news. The idea underlying these stock market anomalies is that securities have performed well over the last twelve months tend to beat the market over the next twelve months. Evoking this behavioral bias fact reveal a phenomenon of persistence of winners, at least in the short term, synonymous securities with known abnormal returns during the six to twelve months tend to do better than average in the six to twelve months. *Baker & Wurgler (2006), Gervais et al. (2011), Bazak & Makarov (2014)* considered that even mutual funds and exchange-traded funds are characterized by a momentum effect. They postulate that the funds that have performed very well during the last year would tend to beat the index during the next twelve months. Conversely, securities against a known performance during the past twelve months have high propensities to repeat the poor performance during the next twelve months. Following Daniel et al. (1998) if there is a momentum effect of stock prices in the short term (one to two years), there is however a long term reversal effect (three to five years). This observation derives its essence from the fact that shares that made significant gains in the last three to five years tend to exhibit a reversal in yields and consequently to produce returns below average during the next three to five years.

The remainder of the paper is organized as follows. The next section provides framework of theoretical background and evidence according to the prior empirical tests. The third section presents the data and methodology. The empirical results are reported in section 4 and the least section concludes the paper.

2. Literature Review

2.1 The Momentum Effect Causes

Faced with an abnormality such as the momentum effect, many studies have analyzed this phenomenon and have therefore advanced the generating causes of this. *Rowenhorst (1998)* postulates that securities enjoying a momentum effect are not more risky and volatile than others. In addition, it is not the size of the companies or their book value compared to their market price that explains this stock bias. Moreover, momentum effect is relatively independent of risk, beta, size, and valorization multiples. Likewise, *Chan et al. (1996)* note that financial markets are not fully efficient while incorporating such a new public information in stock prices. Thus, it often takes more than a year before the firm recovery; the profitability improvement and its resumed earnings growth are eventually reflected in the share price.

Jegadeesh and Titman (1993) advanced the idea that investors are supposed to revise their beliefs according to Bayes' theorem. Moreover, the use of simple heuristics in certain situations led them to make bad decisions and they do not revise properly their opinions. This can be explained by the fact that investors tend to consider a small series of events as representative of the events series distribution. Such behavior is highlighted when a company announces for several years higher earnings than expected, then, investors have a tendency to extrapolate these good results in the following years and buy accordingly these considered securities. *De Bondt & Thaler (1985), Daniel et al. (1998)* argue that most operators are inclined to overestimate their ability to make good decisions. This is known as the overconfidence bias, which is reinforced by the fact that one attributes to himself more easily the positive consequences issuing such a decision, whereas negative consequences are rejected on external circumstances (self attribution bias). Thus, operators have the tendency to believe that not only their information is better than those of others operating over the market but also to overestimate their ability to make the right investments.

In the same context, the model of Barberis et al. (1998) is based on two assumptions that the investor would exercise such a conservatism excess when updating his models and his expectations (conservatism bias), Besides, investor cognitive functioning would lead him to do extrapolation based on the latest information at the expense of other relevant financial data (representative heuristic). The first assumption results in a short-term under-reaction that explains the profitability of momentum strategies, while the second hypothesis would support the theory of price mean reversion in a long-term. *Daniel et al. (2098), Lewellen (2002), Fong (2005) Gervais et al. (2011) Bazak & Makarov (2014)* note that when investors undertake costs when looking for information so they overestimate the quality of this information. Thus, when new information (earnings announcements) come to market, revising their expectations is not alike as it confirm or not their private information. *Kahneman & Tverky (1979)* postulate that when a security has good performances, then investors are less sensitive to future bad news. They consider therefore this asset as being less risky than before and update future flows at a lower rate, increasing their price earnings ratio(PER). Conversely, a security having yet bad performances let them more sensitive to future bad news. They consider therefore this asset as riskier and update future flows at a higher rate that decreases their PER. These discount rate changes let securities more volatile than cash flows. Investor behavior also shows that securities with high valuation ratios have significant returns than those with smaller ratios. While operators prove to be risk averse in a gain position, they can also become risk takers after a series of good performances. This behavior is known as the house money effect.

2.2 The Securities Past Performance And Investment Strategies

The momentum or relative continuity in stock returns corresponds to the tendency of these securities having witnessed a good (bad) performance in the past to achieve a good (bad) performance in the future. *Jegadeesh & Titman (1993)* postulate that investment strategies which involve the purchase of best performing securities during the previous three to twelve months(3-12months) and to sell short the worst performing ones during the same period, are profitable and generate accordingly a return of around 1% per month for the subsequent three to twelve months. Moreover, their investigation revealed the effect of buying past winner stocks and a sale of those behaving losers in the past, when referring to the series of returns

This result, corroborated by Fama & French (1996), Albert & Wang (1998), Chan et al. (1999), Jegadeesh &Titman (2001), Gervais et al. (2011) Bazak & Makarov (2014) for the United States, does also worth for developed markets namely Europe and Canada. A study of Bacmann & Dubois (1999) conducted on the Swiss market showed abnormally high profitability for mimetic strategies known as momentum, for medium term (six to eighteen months). It goes alike for contrarian strategies for recomposed portfolios in short term (conservation of such a position from one week to one month) or even in long term (three to five years). Both types of strategies differ only in the reference period used for calculating the past profitability as well as the portfolio definition.

Rowenhorst (1999) argued, for twelve European countries, the phenomenon of the momentum effect initially observed in the United States. In the same vein, Chan et al. (1996) confirmed these results. They argue that several possible reasons for the persistence of the phenomenon, especially the under-reaction to changes in earnings forecasts, the positive feedback trading, and under-reaction to announcements of benefits. George & Huang (2004), Leowenstein et al. (2005), Kogan et al. (2006), Zhang (2006) highlighted the danger of choosing equity funds, and particularly those who have done very well for five years. They assert that caution recommends betting including equity funds have generated excellent returns during the last twelve months, and keep them thereafter only one year. As for the funds that generated poor results, it is favourable to focus on funds whose horizon is a little longer, at least three years (Tversky & Kahneman (1982), Jegadeesh & Titman (1993), Zigler (2001), Durham et al. (2005)).

3. Data and Methodology

The momentum reflects the difference in price of a security for a given time interval. In this sense, the momentum known as the Relative Strength Index (RSI) measures prices' assessment for a given period. However, unlike the RSI, which is the ratio between prices' increases and fluctuations' set, momentum can analyze only prices' variations between the beginning and end of the study period. Thus, more this period is wide, the more the daily fluctuations tend to disappear. Similarly, when the momentum is above zero or its curve is rising, it indicates an upward trend. Furthermore, a buy signal is given as soon as the momentum exceeds zero, and vice versa when it drops below it triggers a sell signal (Rowenhorst (1998), Hong & Stein (1999)). Jegadeesh & Titman (1993) postulate that momentum is obtained by calculating day-by-day prices' difference of securities for a given time interval. The following formula shows how to calculate such a momentum of x days:

$$Mom_{(x\ days)} = C_t - C_{t-x} \quad (1)$$

Where C_t is the price of day t, C_{t-x} is the price x days before. Thus, since the momentum follows securities' prices, it is up to the latter therefore to fluctuate more than the former does. The period can range from one day for extremely volatile securities to 200 days for very long-term transactions. The most used values are over a period of 12 to 25 days. In fact, more the momentum is high, the more the security is overbought. Conversely, more the momentum is lower, the more the security is oversold. However, it is prudent to wait for a signal confirmation by the prices since such a security can remain overbought or oversold during a given time interval. Jegadeesh & Titman (1993) consider that a phenomenon long recognized in securities analysis is the cyclical nature of the increases and decreases. It is this cyclicality that momentum seeks to stand out. Thus, the momentum for 12 days is recognized as giving an enough cyclic result oscillating up and down regularly. Consequently, the trend can be anticipated to come from previous cycles.

The majority of studies developed on the international financial markets that deals with portfolios formation and classification to winner or loser portfolios by calculating abnormal returns are spread over a long period. Our empirical investigation consider a weekly database for the period ranging from January 2002 until January 2013. Returns for both securities and market are calculated for every Wednesday as a reference day. In the absence of such quotation that day, we take the correspondent price of Tuesday (the day before), if not, the price of the day after (Thursday). Once there is no trading or Tuesday or Thursday, then we resort to the adjustment by the simple moving average (order four) of the missing data:

$$P_t = (P_{t-4} + P_{t-3} + P_{t-2} + P_{t-1}) / 4. \quad (2)$$

Our sample is consisted of ten (10) companies over a period of eleven years (11years) related to their stock prices and the index values of Tunisian market capitalization (Tunindex).

$$R_{it} = \ln (C_t / C_{i,\ t-1}) \quad (3)$$

C_t is the closing price of stock i during the week t, $C_{i,\ t-1}$ is the closing price of stock i during the week(t-1) We consider that R_{mt} represents the weekly returns of the market index (Tunindex):

$$Rmt = In (I_{m,t} / I_{m,t-1}) \quad (4)$$

$I_{mt:}$ market index Tunindex week t, $I_{m,t-1:}$ market index Tunindex of the week t-1, Once determining the returns R_{it} of stock i and those of market R_{mt} and for the sake to form our portfolios, we proceed to calculate the Average Residuals (AR) and then their Cumulative Average Residuals (CAR). The Average Residual of each stock i represents the difference between its return and market one: Average Residual:

$$AR_t = R_{it} - R_{mt} \tag{5}$$

The cumulative average residual of each security i for each period of 36 weeks is the sum of AR in the first week until the 36th week: Cumulative Average Residual: CAR = cumulative average residuals

$$CAR = \sum_{t=1}^{t=36} AR_{i,t} \tag{6}$$

Note that the same procedure has to be redone fourteen times during the test period. It is important to point out in this framework that in order to state for the existence of a winner-loser phenomenon, we divided our study period into sub periods of 36 weeks and a portfolio is related to each sub period. To create winner and loser portfolios, it is important to mention that at the end of each period of 36 weeks (36, 72, ..., .360, 396), a CAR is obtained, and then we proceeded to sort descending the CAR .This ranking allows to arbitrate winner stocks of those losers which will form our fifteen portfolios relatively to the fifteen sub-periods. After forming the various portfolios that were determined at the end of the formation period of 36 weeks, we conduct several tests within what we call the test period. Formation and identification of winners and losers portfolios is done through stocks that had expressed extreme residual returns into the formation periods. Generally, losers and winners portfolios are formed from extreme stocks according to their past performances.

The number of securities composing a portfolio does vary from one author to another, for instance: 35 extreme stocks chosen by De Bondt and Thaler (1985) , 10 extreme stocks chosen by Alonso and Rubio (1990), 5extreme stocks chosen by Rodrigues and Fructaso (2000), 3 extreme stocks chosen in our investigation related to the Tunisian stock market. After ranking the CAR in a descending order, the winner portfolio consists of the three stocks with the highest performance, while the loser portfolio is formed by the three stocks having the worst CAR. The CAR of each portfolio (w) and (L) during each 36-weeks test period is:

$$CAR_S = \sum_{i=1}^{3} CAR_{s,i} \tag{7}$$

Where S is the nature of the portfolio winner (W) or loser (L)

4. Empirical Results

4.1 Examination of Loser-Winner Effect

The test period which follows the formation period consists of fourteen portfolios except the fifteenth portfolio corresponding to the initial formation period(table 1). During the second period (test period), we will test the evolution of CAR and this respectively winners and losers portfolios (PF1, PF15) determined during the first period

Table 1. Observation and detection of reversals winner & Loser portfolios

Portfolio	*Formation period CAR*		*Test period CAR*		*Transformation phenomenon*	*Detection*
PF1	W	0.289127	-0.0862115	L	WL	Exist
	L	0.1117926	0.08670031	L	LL	Do not exist
PF2	W	0.0874379	-0.478562	L	WL	Exist
	L	-0.20610108	-0.41600893	L	LL	Do not exist
PF3	W	-0.09674974	-0,02201333	W	WW	Do not exist
	L	-0.4516644	-0,1127013	W	LW	Exist
PF4	W	0.02258053	-0,42669362	L	WL	Exist
	L	-0.19913907	-0,50484224	L	LL	Do not exist
PF5	W	-0.2747831	-0,23267728	L	WL	Exist
	L	-0.53526904	-0,23077566	W	LW	Exist
PF6	W	-0.085002	-0,74032633	L	WL	Exist
	L	-0.327868	-0,83314204	L	LL	Do not exist
PF7	W	-0.553847	-0,7354081	L	WL	Exist
	L	-0.982282	-0,30807216	W	LW	Exist
PF8	W	-0.061891	-0,23401706	L	WL	Exist
	L	-0.7581589	-0,36733768	W	LW	Exist
PF9	W	-0.07573862	0,22709402	W	WW	Do not exist
	L	-0.55567895	-0,09811062	W	LW	Exist
PF10	W	0.198224506	-0,7517704	L	WL	Exist
	L	-0.1681864	-0.80271792	L	LL	Do not exist
PF11	W	-0,61661982	-0.62011479	L	WL	Exist
	L	-0.921167155	-0.77054482	W	LW	Exist
PF12	G	-0.50171003	0.27519405	W	WW	Do not exist
	L	-0.77054482	-0.00178617	W	LW	Exist
PF13	G	0.27519405	0.03805047	L	WL	Exist
	L	-0.00178617	-0.2096479	L	LL	Do not exist
PF14	G	0.03805047	0.25942842	W	WW	Do not exist
	L	-0.20967479	-0.31159883	L	LL	Do not exist
PF15	G	0.17798358	---------------	--	--------------	---------------
	L	-0.31159883	---------------	--	--------------	---------------

After detecting such phenomena of returns reversal, we calculated the percentages of each observed phenomenon (Table 2).

Table 2. Reversal phenomenon Detection

Total number of observations	28
Number of Winner-Loser phenomena	10
Number of Loser-Winner phenomena	07
Number of Loser-Loser phenomena	07
Number of Winner-Winner phenomena	04
Percentage	60.7%

Following the detection of up to 60,7% reversal phenomenon on the Tunis Stock market, we have to inquire about the generating causes of these irrational behaviors of financial assets such as: the risk effect; the size effect and the seasonal effect.

4.2 The Risk Effect

In this framework, we have to test whether the Winner-Winner phenomenon is explained by the difference in the risk level associated with the securities of each portfolio. The arbitrage portfolio is obtained according to the approach of Zaroin (1990) as follows:

$$R_{At} = R_{Lt} - R_{Wt} \tag{8}$$

R_{At} is arbitrage portfolio return for the week t, $R_{Lt:}$ losers' returns for the week t, $R_{wt:}$ performance for the winners for week t. We determined in a first step portfolios returns R_{at}, and in a second step, we determined the parameters of the following equation via Eviews8.0:

$$R_{At} = \delta_A + \beta_A (R_{mt} - R_{ft}) + \varepsilon_{At} \tag{9}$$

$$R_{at} = \gamma_a + \beta_a (R_{mt} - R_{ft}) + \psi_{at} \tag{9}$$

δ_A and β_A are the equation parameters, R_{mt} is the market performance for the week t , R_{ft} is the risk free rate (obtained from monetary market rates) , ε_{At} is the residual term. Our results are reported in the following table:

Table 3. Detection of a possible risk effect on stock returns

PF	δ_A	β_A	P-value (μ_2)	A	Constatation	Risque effect	Adjusted R-squared
PF1	-0.000623	-0.268641	0.0309	0,05	Significant	Présence	-0.000625
PF2	0.003616	0.133678	0.6274	0,05	Non Significant	Absence	-0.002809
PF3	-0.018807	-0.317129	0.4829	0,05	Non Significant	Absence	0.015980
PF4	-0.019286	-0.322791	0.0757	0,05	Non Significant	Absence	-0,001494
PF5	-0.069057	-1.328825	0.0599	0,05	Non Significant	Absence	0.024104
PF6	-0.025510	-0.394176	0.0824	0,05	Non Significant	Absence	0.017860
PF7	0.017251	0.319341	0.9570	0,05	Non Significant	Absence	0.048070

PF8	0.036938	0.855555	0.0732	0,05	Non Significant	Absence	0.023286
PF9	-0.018093	-0.214810	0.4030	0,05	Non Significant	Absence	0.029093
PF10	-0.016713	-0.309933	0.0508	0,05	Significant	Présence	0.012770
PF11	-0.045069	-0.909559	0.1582	0,05	Non Significant	Absence	0.043854
PF12	-0.018898	-0.224729	0.6435	0,5	Non Significant	Absence	0.036512
PF13	0.009123	0.074725	0.6707	0,5	Non Significant	Absence	0.028260
PF14	-0.009661	-0.246516	0.2250	0,5	Non Significant	Absence	0.009705

The adopted decision rule remains the same which involves:

If P-value $\leq \alpha$ there is rejection of Ho hypothesis and then a risk effect existence.

If P-value $\geq \alpha$ the null hypothesis is accepted, meaning an absence of risk effect.

Table 4. Risk effect presence on returns reversals

Total number of observations	14
Number of unfavorable observations	**2**
Number of favorable observations	12
Percentage	14,28%

This result allows considering the existence such a linkage between the winner-loser effect and the level of risk only to the extent of 14.28%. Consequently, this L- W phenomenon seems to be weakly generated by the risk of the securities composing portfolios, hence the need to look for other explanations for this phenomenon, such as the effect size.

4.3 The Size Effect

De Bondt and Thaler (1985) argue that there is a possible linkage relationship between the reversal phenomenon and the firm size since they observed that this phenomenon persists for small size firms. We follow the approach of Zaroin (1990) for the sake to test eventual size effect as follows: The firm size is determined from its capital value over the market that we calculated it using the following formula:

$$V_{mt} = N_t . C_{mt} \tag{10}$$

V_m: the value of capital market**,** N: number of securities issued on the market, C_t: the price observed at time t on the market**.** Once the market capitalization is calculated, we proceed to the classification of these values in descending order. Our results are expressed in the following table:

Table 5. Portfolios distribution according to firm size

Winner Portfolio	Market capitalization	Firm size	Loser Portfolio	Market capitalization	Firm size
W11	102.010092	Big	L7	81.460426	Big
W5	74.469660	Big	L1	38.846008	Big

W8	56.462875	Big	L13	37.373016	Big
W6	53.260941	Big	L12	20.324949	Big
W10	42.761588	Big	L10	16.585214	Big
W9	37.291744	Big	L6	15.450290	Big
W7	20.906924	Big	L8	11.795162	Big
W12	19.439445	Small	L5	9.072808	Small
W1	16.940619	Small	L2	7.666006	Small
W13	15.505738	Small	L9	6.569773	Small
W2	14.072411	Small	L4	6.126221	Small
W4	13.951523	Small	L11	3.350295	Small
W3	12.400523	Small	L3	1.408937	Small
W14	1.375275	Small	L14	0.232828	Small

Once determined the set of portfolios having small size, besides those with big one, we highlight solely the set of portfolios with a return reversal phenomenon and their respective sizes enabling to decide whether these return reversals concern only small size portfolio. The result of this comparison is shown in the following table:

Table 6. Detection of size effect on return reversals

Portfolio	W /L	Phenomenon	Respective size	Observation
PF1	W1	WL	Small	Favorable
	L1	LL	Big	Indecided
PF2	W2	WL	Small	Favorable
	L2	LL	Small	Indecided
PF3	W3	WW	Small	Indecided
	L3	LW	Small	Favorable
PF4	W4	WL	Small	Favorable
	L4	LL	Small	Indecided
PF5	W5	WW	Big	Indecided
	L5	LW	Small	Favorable
PF6	W6	WL	Big	Unfavorable
	L6	LL	Grande	Indecided
PF7	W7	WL	Grande	Unfavorable
	L7	LW	Big	Unfavorable
PF8	W8	WL	Big	Unfavorable
	L8	LW	Big	Undecided
PF9	W9	WL	Big	Favorable
	L9	LL	Small	Favorable
PF10	W10	WL	Big	Unfavorable
	L10	LL	Big	Undecided
PF11	W11	WL	Big	Unfavorable
	L11	LW	Small	Favorable
PF12	W12	WW	Small	Undecided

	L12	LW	Big	Unfavorable(8)
PF13	W13	WL	Small	Favorable (8)
	L13	LL	Big	Undecided
PF14	W14	WW	Petite	Undecided
	L14	LL	Petite	Undecided(12)

Table 7. Linkage relationship between size effect and return reversals

Total number of observations	28
Number of unfavorable observations	08
Number of favorable observations (Small)	08
Number undecided observations	12
Percentage	8/28= 28,57(%)

Owing to the findings displayed in table above, we consider that there is no a priori significant relationship tying Winner-Loser phenomenon and firm size since this phenomenon was detected for both small firms and large ones. Therefore, the firm size cannot explain this anomaly only in 28.57% of cases.

4.4 The Seasonality Effect

The existence of January effect hypothesis suggests that cumulative average residuals CAR of winner and loser portfolios during only this month appear to be higher than the generated CAR during the other months. In this context, we will take the portfolios that verify the existence of return reversal and do prove whether this anomaly is explained by January seasonality or not et ce by calculating the CAR average for the January month and then comparing it to those found during all other months together, using the Dummy variable (Dichotomous) which takes the value 1 in January and 0 if not.

Table 8. Detection of seasonality effect on return reversals

Portfolio	Phenomenon	Test period	January effect
PF1	WL	From 09/09/02 to 17/05 /03	Existence
	LL	From 09/09/02 to 17/05 03	Absence
PF2	WL	From 19/05/03 to 30/01/04	Existence
	LL	From 19/05/03to 30/01/04	Absence
PF3	WW	From 02/02/04 to 09/10/04	Existence
	LW	From 02/02/04 to 09/10/04	Absence
PF4	WL	From 11/10/04 to11/06/05	Existence
	LL	From 11/10/04 to11/06/05	Absence
PF5	WW	From 13/06/05 to18/02/06	Absence
	LW	From 13/06/05 to18/02/06	Existence
PF6	WL	From 20/02/06 to 28/10/06	Absence
	LL	From 20/02/06 to 28/10/06	Existence

TPF7	WL	From 30/10/06 to 07/06/07	Existence
	LW	From 30/10/06 to 07/06/07	Existence
PF8	WL	From 09/06/07 to15/03/08	Existence
	LW	From 09/06/07 to 15/03/08	Existence
PF9	WL	From 17/03/04 to 22/11/08	Existence
	LL	From 17/03/04 to 22/11/08	Absence
PF10	WL	From 24/11/08 to 01/08/09	Existence
	LL	From 24/11/08 to 01/08/09	Absence
PF11	WL	From 03/08/09 to 17/04/10	Existence
	LW	From 03/08/09 to 17/04/10	Existence
PF12	WW	From 19/04/10 to 25/12/10	Existence
	LW	From 19/04/10 to 25/12/10	Absence
PF13	WL	From 27/10/10 to 0/09/11	Existence
	LL	From 27/10/10 to 03/09/11	Absence
PF14	WW	From 05/09/11 to 12/05/12	Absence
	LL	From 05/09/11 to12/05/12	Absence

Table 9. Linkage relationship between seasonality and return reversals

Total number of observations	28
Number of unfavorable observations	12
Number of favorable observations	16
Percentage	16/28 = 57,14 %

The use of Dummy variable allowed us to achieve the following results:

Table 10. Detection of seasonality effect on return reversals

Portfolio	W /L	μ_1	μ_2	P-value	A	Constatation	Detection	adjusted R-squared
PF1	W1	0.0061	0.010783	0.4203	0.1	Not significant	Absence	0.029831
	L1	0.0105	-0.002645	0.8125	0.1	Not significant	Absence	0.025910
PF2	W2	-0.0011	-0.006751	0.3535	0.1	Not significant	Absence	0.017051
	L2	0.0037	-0.021113	0.0353	0.1	Significant	Presence	0.024324
PF3	W3	undec	Undecided	Undecid	0.1	undecided	undecided	Undecided
	L3	undec	Undecided	Undecid	0.1	undecided	undecided	Undecided
PF4	W4	-0.0180	0.008116	0.6468	0.1	Not significant	Absence	0.038599
	L4	-0.0145	0.000685	0.9672	0.1	Not significant	Absence	0.037306
PF5	W5	-0.0024	-0.000463	0.9522	0.1	Not significant	Absence	0.017954
	L5	0.0024	-0.006514	0.4992	0.1	Not significant	Absence	0.022494
PF6	W6	Indec	Indecided	Indecid	0.1	Indecided	Indecided	Indecided
	L6	Indec	Indecided	Indecid	0.1	Indecided	Indecided	Indecided
PF7	W7	-0.0014	-0.007966	0.8243	0.1	Not significant	Absence	-0.080267
	L7	0.0037	-0.019604	0.5971	0.1	Non significant	Absence	0.086404

PF8	W8	0.0135	0.0076	0.0501	0.1	Significant	Presence	0.024713
	L8	-0.0038	-0.006770	0.4416	0.1	Not significant	Absence	0.020561
PF9	W9	Indec	Indecided	Indecid	0.1	Indecided	Indecided	Indecided
	L9	Indec	Indecided	Indecid	0.1	Indecided	Indecided	Indecided
PF10	W10	-0.0292	0.013699	0.03723	0.1	Significant	Presence	0.3892
	L10	-0.0228	0.006371	0.6715	0.1	Not significant	Absence	0.034859
PF11	W11	-0.0346	0.025204	0.1467	0.1	Non significatif	Absence	0.040739
	L11	-0.0279	0.011307	0.5205	0.1	Non significatif	Absence	0.039256
PF12	W12	Indecd	Indecided	Indecid	0.1	Indecided	Indecided	Indecided
	L12	Indecd	Indecided	Indecid	0.1	Indecided	Indecided	Indecided
PF13	W13	-0.0135	0.013389	0.5788	0.1	Not significant	Absence	0.056204
	L13	-0.0118	0.016935	0.4708	0.1	Not significant	Absence	0.054841
PF14	W14	-0.0118	0.004681	0.6874	0.1	Not significant	Absence	0.027014
	L14	-0.0063	0.012366	0.5498	0.1	Not significant	Absence	0.048204

Table 11. Presence of January effect according to the explanatory variable D regression

Total number of observations	28
Number of unfavorable observations	13
Number of favorable observations	03
Number of undecided observations	12
Percentage	3/16 = 18.75%

Our results prove that seasonality effect contributes to explain this anomaly on Tunisian stock market (security trends reversal) only up to 18.75%, which allows to rule on the fact that there are other fundamental anomalies that may cause such profits of momentum pattern.

5. Conclusion

Momentum or the relative continuity in stock returns corresponds to the tendency of securities that generated a good (bad) performance in the past to reproduce a good (bad) performance in the future. *Jegadeesh and Titman (1993), Lewellen (2002)* postulated that investment strategies, which involve buying securities with the best performing during the three to twelve months, and selling short securities that experienced the worst performance during the same period, are profitable and generate a return of about 1% per month for the next three - twelve months. Our empirical investigation has been based on a weekly database for a period from January 2002 to January 2013 concerning stock prices and the index values of Tunisian market.

Our results demonstrate the existence of winner-loser phenomenon for the selected period on the Tunis Stock Market, in accordance with the over-reaction hypothesis which states that portfolios with the worst past performance outperform, during subsequent periods, those having made good past performance and vice versa. Furthermore, we examined three possible factors that may explain reversals of portfolio returns such as risk, size and seasonality. Our results, in a first stage, show that only 20% of observations seem to be caused by the risk effect; and any change in firm size does exert an explanatory power of this phenomenon only in 30% of cases. As for seasonality or January effect, it appears significantly that portfolio returns were reversed to 55% in January. Moreover, this result seems consistent with those of De Bondt & Thaler (1987); Fama & French (1986); Zarowin (1990) and May (1992) who refer this bias to the investor over-reaction phenomena and accordingly do not obey the Bayes theorem since they pay too much importance to new information at the expense of past ones. This irrational behavior of operators supports over-reaction as a trigger factor of return reversals.

References

Albert, F., & Wang, N. (1998). Strategic trading, asymmetric information and heterogeneous prior beliefs. *Journal of Financial intermediaries*. *1*(3-4), 271-294. http://dx.doi.org/10.1016/s1386-4181(97)00007-4

Alti, A. T., & Lock P. C. (2014). Biased Beliefs, Asset Prices, and Investment: A Structural Approach. *Journal of Finance*. *69*(1), 325-361. http://dx.doi.org/10.1111/jofi.12089

Asparouhova, E. Bessem, B. H., & Kalcheva, I. (2013). Noisy prices and inference regarding returns. *Journal of Finance*. *68*, 665-714. http://dx.doi.org/10.1111/jofi.12010

Baker, M., & Wurgler, J. (2006). Investor Sentiment and the Cross-Section of Stock Returns. *Journal of finance*. *61*(4), 1645-1679. http://dx.doi.org/10.1111/j.1540-6261.2006.00885.x

Barberis, N. Shleifer, A., & Vishny, R. (1998). A model of investor sentiment. *Journal of Financial*. *49*, 307-348. http://dx.doi.org/10.1016/S0304-405X(98)00027-0

Bazak, S., & Makarov, D. (2014). Strategic Asset Allocation in Money Management. *Journal of finance*. *69*(1), 179-217. http://dx.doi.org/10.1111/jofi.12106

Bertrand, M., & Morse, A. (2012). Information Disclosure, cognitive Biases, and Payday Borrowing. *Journal of finance*. *66*(6), 1865-1891. http://dx.doi.org/10.1111/j.1540-6261.2011.01698.x

Brockman, P. and Chung, D.Y (2000). An empirical investigation of trading an asymmetric information and heterogeneous prior beliefs. *Journal of Empirical Finance*. *7*. 417-454. http://dx.doi.org/10.1016/S0927-5398(00)00020-7

Brown,G. W., & Cliff, M. T. (2004). Investor sentiment and the near term stock market. *Journal of Empirical Finance*. *11*, 1-27. http://dx.doi.org/10.1016/S0927-5398(04)00044-1

Buraschi, A., Trojani, F.. & Vedolin, A. (2014). When Uncertainty Blows in the Orchard: Comovement and Equilibrium Volatility Risk Premia. *Journal of Finance*, *19*, 101-137. http://dx.doi.org/10.1111/jofi.12095

Chan, I. Jegadeesh, K., & Lakonishok, J. (1996). Momentum strategies. *journal of Finance*. *51*, 1681-1713. http://dx.doi.org/10.1111/j.1540-6261.1996.tb05222.x

Daniel, K, Hirshleifer, D., & Subrahmanyan, A. (1998). Investor Psychology and security market under-Overreaction. *Journal of Finance. 53,* 1839-1886. http://dx.doi.org/10.1111/0022-1082.00077

DeBondt, W., & Thaler, R. (1985). Does the Stock market Over react? *Journal of Finance, 40*(3), 793-808. http://dx.doi.org/10.1111/j.1540-6261.1985.tb05004.x

De Bondt, W. F. M., & Thaler, R. (1987). Further evidence on investor overreaction and stock market seasonality. *Journal of Finance. 42,* 557-581. http://dx.doi.org/10.1111/j.1540-6261.1987.tb04569.x

De Long, N., Shleifer, B., Summers, F., and Waldman, C. (1990a). Noise trader risk in financial markets. *Journal of Political Economy. 98,* 703-738. http://dx.doi.org/10.1086/261703

De Long, N., Shleifer, B., Summers, F., & Waldman, C. (1990b). Positive feedback investment strategies and destabilizing rational speculation. *Journal of Finance. 45,* http://dx.doi.org/10.2307/2328662

Durham,G. R., Hertzel, M. J., & Spencer, J. M. (2005). The market impact of trends of sequences in performance: New Evidence.

Fama,E. (1998). Market efficiency, long terms returns and behavioral finance. *Journal of Financial Economics*.49.283-306. http://dx.doi.org/10.1016/S0304405X(98)00026-9

George, T., & Huang, C. (2004). Week Hieg and Momentum investing. *Journal of Finance, 59*(5), 211-229. http://dx.doi.org/10.1111/j.1540-6261.2004.00695.x

Gervais, S. Heaton, J. B., & Odean, T. (2011). Overconfidance, Compensation Contrasts, and Capital Budgeting. *Journal of finance. 66,* 1735-1576. http://dx.doi.org/10.1111/j.1540-6261.2011.01686.x

Hirshleifer, D. (2001). Investor Psychology and Asset Pricing. *Journal of Finance. 56,* 1533-1597. http://dx.doi.org/10.1111/0022-1082.00379

Hong, H., & Stein, J. C. (1999). A unified theory of under reaction momentum trading and overreaction in asset markets. Journal *of Finance. 54,* 21-43. http://dx.doi.org/10.1111/0022-1082.00184

Jegadeesh, N., & Titman, S. (1993). Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. *Journal of Finance. 48*(1), 65-91. http://dx.doi.org/10.1111/j.1540-6261.1993.tb04702.x

Jegadeesh, N. and Titman, S. (2001a). Profitability of Momentum Strategies: An Evaluation of Alternative Explanations. *Journal of Finance. 56*(2), 699-720. http://dx.doi.org/10.1111/0022-1082.00342

Jegadeesh, N., & Titman,S. (2001b). Momentum. SSRN P45

Jegadeesh, N., & Titman,S. (2002). Cross sectional and time series determinants of momentum returns. *Review of Financial Studies. 15*(1), 143-157. http://dx.doi.org/10.1093/rfs/15.1.143

Kahneman, D. et Tversky A. (1979). *Prospect theory: an analysis of decision under risk.* Economica. 47. (2), 263-292.http://dx.doi.org/10.2307/1914185

Kogan, L., Ross, S.A., wang, J., & Westerfiled, M. M. (2006). The Price Impact And survival of Irrational Traders. *Journal of finance, 61,* 195-230. http://dx.doi.org/10.1111/j.1540-6261.2006.00834.x

Lee, C. M., Shleifer, A., & Thaler, R. (1991). Investor sentiment and the closed end fund puzzle. *Journal of finance, 46*, 75-110. http://dx.doi.org/10.1111/j.15406261.1991.tb03746.x

Lewellen, J. (2002). Momentum and auto correction in stock returns. Review *of financial studies, 15*(2), 533-563. http://dx.doi.org/10.1093/rfs/15.2.533

Loewenstein, M., & Willard, G. A. (2006).The limits of investor behavior. *journal of finance. 61*, 231-258. http://dx.doi.org/10.1111/j.1540-6261.2006.00835.x

Orlean, A. (1994). Bayesian Interactions and collective dynamics of opinion. *Journal of Economics Behavior and Organization. 28*(2), 257-274. http://dx.doi.org/10.1016/0167-2681(95)00035-6

Roewenhorst, K. G. (1998). International momentum strategies. *Journal of Finance*. 53(1), 267-284. http://dx.doi.org/10.1111/0022-1082.95722

Roewenhorst, K. G. (1999).Local return factors and turn over in emerging stock markets. *Journal of Finance*. *54*(4), 1439-1464. http://dx.doi.org/10.1111/0022-1082.00151

Scherbina, A. (2004). Analyst disagreement, forecast Bias and Stock Returns. Harvard Business school *working paper series N05. 2003* http://dx.doi.org/10.1086/261843

Shiller, R. J. (2000b). «*Irrational Exuberance* »Princeton UP , Oxford.

Titman, S., & Daniel, K. (2008). Market Reactions to Tangible and Intangible Information » *Journal of finance*, Vol LXI, 1605-1643

Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and Biases. *Science*. *185*(4157), 1124-1131. http://dx.doi.org/10.1126/science.185.4157.1124

Tversky, A., & Kahneman, D. (1982). *Judgment under uncertainty: heuristics and biases*. Cambridge University Press, ISBN-13: 978-0521284141

Zhang, X. F. (2006). Information Uncertainty and Stock Returns. *Journal of Finance, 61*, 105-139. http://dx.doi.org/10.1111/j.1540-6261.2006.00831.x

Ziegler, A. (2001). Optimal portfolio Choice under heterogeneous beliefs. *European Finance, Review, 4*, 45-59. http://dx.doi.org/10.1111/j.1540-6261.2006.00831.x