International Journal of Accounting and Financial Reporting
ISSN 2162-3082
2017, Vol. 7, No. 1

Impact of the Self-Attribution Bias on the Trading Activity: The Case of the Tunisian Stock Market

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Received: December 18, 2016 Accepted: January 05, 2017 Published: January 28, 2017

doi:10.5296/ijafr.v7i1.10640 URL: http://dx.doi.org/10.5296/ijafr.v7i1.10640

Abstract

The self-attribution bias is the tendency of people to consider themselves as able to influence randomly-generated outcomes. Investors who exhibit such a bias tend to attribute market gains to their ability to select winning stocks and trade actively in the subsequent period. We examined this hypothesis in the Tunisian stock market before and after the 2011 revolution using a causality test between market trading volume and market return. We found that Tunisian investors tend to trade more after observing high market returns and trade less after poor market performance. In the wake of the Tunisian revolution, this effect persists for one-week horizon, but disappears for one-month horizon.

Keywords: Self-attribution, Overconfidence, Trading activity, Tunis Stock Exchange

1. Introduction

The self-attribution bias, also known as "egocentric" or "self-serving attribution" (Miller and Ross, 1975; and Schlenker and Miller, 1977) or "ego-defensive" or beneffectance (Greenwald, 1980), initially took the form of the illusion of control of random events where gains are purely determined by chance as in the case of lottery or coin tosses. This illusion means that people tend to consider themselves as being able to influence randomly-generated outcomes. As a consequence, they tend to attribute their success to their talents and failure to external factors or bad luck. This bias has been documented by, among others, Wolosin, Sherman and Till (1973), Langer (1975), Miller and Ross (1975) and Langer and Roth (1975) through a series of experiments. In financial markets, it has been argued that the self-attribution bias can affect the investors' behavior in the sense that they tend to attribute high market returns or their own portfolio return to their own success.

Since Ross (1989), theoretical and empirical studies have kept arguing that the trading volume on financial markets is too large to be justified in a rational context. Chuang and Lee (2006, p. 2490) noticed that "*Trading motivated from hedging and liquidity purposes seems to explain only a small fraction of the observed trading activity and fails to support a substantial amount of trade in the real world*". In this regard, several behavioral models were developed to explain the excessive trading volume in stock markets based on overconfidence and self-attribution biases (Daniel, Hirshleifer and Subrahmanyam, 1998, Gervais and Odean, 2001; and Scheinkman and Xiong, 2003). To model the effect of overconfidence on the trading volume, Gervais and Odean (2001) motivate their analysis by the self-attribution bias, wherein overconfident investors mistakenly attribute market gains to their ability to select winner stocks and therefore they excessively trade after observing high market returns.

These models were supported by empirical evidence in different markets all over the world. For example, Statman, Thorley and Vorkink (2006) estimated a bivariate VAR model between monthly market trading volume and monthly market return for 1878 US firms listed on NYSE and AMEX during the period 1962-2002 and found a positive and significant association between the past returns and the current trading volume. Glaser and Weber (2009) adopted diverse regression methodologies (panel data, Tobit model and Logit model) of the monthly trading volume on past returns and other variables such as the number of years of experience, the value of the portfolio held by the investor, his age, and different measures of the trading volume, for 3079 German online investors during the period 1997-2001. They found that past market returns and the past portfolio returns are positively and significantly related to the trading volume. Chuang and Susmel (2011) reported similar results on the Taiwanese stock market for the periods 1996-2007 and 2001-2006, respectively. Further evidence was provided by Griffin, Nardari and Stulz (2007) for 31 out of 46 financial markets during the period 1993-2003 with a prevalent effect in developing markets than in developed ones.

To contribute to the literature on emerging markets, we test in this paper the impact of the self-attribution bias on the trading volume in the Tunisian stock market. The remaining of the paper is organized as follows. Section 2 presents the research design. Section 3 describes the data. Section 4 presents the descriptive statistics and performs the unit root tests. Section 5 analyses our empirical results. Section 6 concludes the paper.

2. Empirical Methodology

2.1. The Self-Attribution/Trading Activity Hypothesis

Gervais and Odean (2001) argue that investors who attribute returns from a general increase in the market to their own talents of selecting securities and processing information become overconfident and therefore trade more actively. As a result, periods of market increases tend to be followed by a period of increase in aggregate trading volume. Similarly to Chuang and Lee (2006), the hypothesis of self-attribution/trading volume can be stated as follows:

"Market gains (losses) make self-attribution-victim investors trade more (less) aggressively in subsequent period."

This hypothesis assumes a one-direction-positive causality from market returns to trading volume.

During the post-revolution period, the Tunisian economy suffered very slow or even negative growth especially during the first years. In fact, after the 2011 Tunisian revolution, the country has experienced political and security instability. This period was marked by a panic among investors who carried out massive sales operations. The selling pressure had a considerable negative effect on the stock market, thus causing a continued decline in the TUNINDEX. We, then, expect that the overconfidence of the Tunisian investors will either be dramatically reduced or will fade away during the post-period revolution due to the unfavorable economic climate.

2.2. The Model

To test the relationship between stock returns and trading volume, we refer to Chuang and Lee (2006) who suggested the following model:

$$\begin{cases} V_t = \alpha_{11} + \alpha_{12}|R_t| + \alpha_{13}MAD_t + \sum_{j=1}^{p}\beta_{11j}V_{t-j} + \sum_{j=1}^{p}\beta_{12j}R_{t-j} + \varepsilon_{1t} \\ R_t = \alpha_{21} + \alpha_{22}MAD_t + \sum_{j=1}^{p}\beta_{21j}V_{t-j} + \sum_{j=1}^{p}\beta_{22j}R_{t-j} + \varepsilon_{2t} \end{cases} \quad (1)$$

Where V_t is the trading volume; R_t, market-wide return and MAD_t, Mean absolute cross sectional return deviation. $|R_t|$ and MAD_t are used as control variables.

To estimate this model we use the Seemingly Unrelated Regressions method of Zellner (1962). The lag p is determined using the Schwarz information criterion.

2.3. Construction of the Variables

To test the self-attribution/trading activity hypothesis in the Tunisian market we consider weekly and monthly observations.

2.3.1. Market Return

The continuously compounded weekly return of a security *i* is the natural logarithm of the Wednesday closing price adjusted for dividends to the previous Wednesday stock price. Similarly, monthly return of a stock *i* is the natural logarithm of the end of month *t* stock price adjusted for dividends to the end of month *t-1* stock price. Market return is the value-weighted stock return in week or month *t* where the weight of stock *i* is the stock market capitalization (number of shares outstanding times stock price) to the total market capitalization.

2.3.2. Trading Volume

The trading volume is measured by the turnover as the number of shares traded divided by the number of shares outstanding. The weekly turnover of a security is computed according to Lo and Wang (2000) as the sum of daily turnovers from Thursday to the following Wednesday. The monthly turnover of a security is the sum of daily turnovers of month *t*. To aggregate turnover, we compute the value-weighted turnover.

2.3.3. Mean absolute cross sectional return deviation

Mean absolute cross sectional return deviation is computed as follows:

$$MAD_t = \sum_{i=1}^{N} \omega_i |R_{it} - R_t| \quad (2)$$

Where, R_{it} is the return on stock *i* at time *t*; ω_i is the weight of stock *i*; and N the number of stocks composing our sample at time *t*.

3. Data

Our data consist of the daily closing price, the daily trading volume, the number of shares outstanding and the dividend of all firms listed in the Tunis stock exchange[i] from January 1, 2006 to December 31, 2015. The number of firms increased from 50 at year-end 2006 to 80 at year-end 2015 (Table 1). Daily data are converted to weekly and monthly data as described above. We avoid daily and intraday observations due to the discontinuity problem in such data for some securities in the Tunisian context. To explore the effect of the 2011 Tunisian revolution on the investors' behavior, we divide our full sample period into two sub-periods: 2006-2010 and 2011-2015.

Table 1: Number of firms listed in the Tunis Stock Exchange

Year	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Nbr. of firms	50	52	51	53	57	59	60	68	76	80

Note. The table displays the end of year number of firms.

4. Descriptive Statistics and Unit Root Tests

Table 2 displays the descriptive statistics of the weekly (Panel A) and monthly (Panel B) return, turnover and MAD variables for the full sample period and the two sub-periods. The mean weekly return is 0.01% for the full sample period 2006-2015 and 0.09% for the sub-period 2006-2010; however it's negative (-0.07%) for the post-revolution period 2011-2015.

Table 2: Descriptive Statistics

Panel A. Weekly observations									
	Full sample period: 2006-2015			Sub-period: 2006-2010			Sub-period: 2011-2015		
	R	V	MAD	R	V	MAD	R	V	MAD
Mean	0.0001	0.0026	0.0231	0.0009	0.0031	0.0264	-0.0007	0.0021	0.0198
Median	0.0016	0.0021	0.0190	0.0039	0.0026	0.0198	0.0000	0.0017	0.0183
Maximum	0.0814	0.0237	0.3739	0.0814	0.0237	0.3739	0.0766	0.0171	0.0856
Minimum	-0.2139	0.0001	0.0070	-0.2139	0.0005	0.0075	-0.0911	0.0001	0.0070
Std. Dev.	0.0217	0.0021	0.0262	0.0263	0.0023	0.0357	0.0158	0.0017	0.0085
Skewness	-3.6886	4.3933	10.158	-4.0456	4.0876	7.7033	-0.7025	5.2981	2.9239
Kurtosis	35.737	33.768	125.76	32.077	30.056	69.787	11.682	44.276	18.698
Prob (J-B)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Obs.	520	520	520	261	261	261	259	259	259
Panel B. Monthly observations									
Mean	0.0002	0.0109	0.0539	0.0036	0.0131	0.0650	-0.0032	0.0088	0.0427
Median	0.0041	0.0097	0.0431	0.0122	0.0118	0.0458	-0.0029	0.0080	0.0395
Maximum	0.0894	0.0326	0.3780	0.0894	0.0326	0.3780	0.0602	0.0217	0.0991
Minimum	-0.2354	0.0026	0.0192	-0.2354	0.0038	0.0215	-0.1299	0.0026	0.0192
Std. Dev.	0.0478	0.0053	0.0465	0.0585	0.0055	0.0626	0.0339	0.0041	0.0138
Skewness	-1.6039	0.9420	5.090	-1.7512	0.7175	3.6959	-0.6626	1.1308	1.8063
Kurtosis	8.6185	4.1287	33.066	7.5720	4.0272	17.624	4.8100	4.2528	8.0901
Prob (J-B)	0.0000	0.0000	0.0000	0.0000	0.0204	0.0000	0.0019	0.0002	0.0000
Obs.	120	120	120	60	60	60	60	60	60

Notes: J-B is the Jarque-Béra statistic; Obs. is the number of observations

For monthly observations, it's 0.02%, 0.36% and -0.32%, respectively. The poor stock market performance during the post-revolution period reflects the poor performance of the Tunisian economy during that period. However, the mean weekly turnover has slightly decreased from 0.0031 for the sub-period 2006-2010 to 0.0021 for the sub-period 2011-2015. The monthly turnover has decreased from 0.0131 to 0.0088, respectively. Based on the standard deviation, we note that the returns during the second sub-period are less volatile than the returns during the first sub-period. The probability of Jarque-Béra is less than 5% indicating that the null hypothesis of normality is rejected. Therefore, our series are not normally distributed.

To check the stationarity of the series we use the Augmented Dickey-Fuller test (Dickey and Fuller, 1981). This test is based on three models: a model with a constant and a trend (model 3), a model with a constant (model 2) and a model without constant and trend (model 1). To choose the appropriate model we will adopt a simple sequential strategy that begins with model 3 and applies a joint test of the trend significance. If the trend is significantly different from 0, then model 3 should be adopted to judge the stationarity of the series. If not, we move to model 2. If the constant is significant, we use this model; otherwise, we consider model 1.When no lag is significant in ADF models, a simple DF test is appropriate.

Table 3 shows that the DF statistic is less than the critical values (or similarly, the probability of DF statistic is lower than 1%) for all the variables during the full-sample period and the sub-periods in weekly or monthly frequency. The null of unit root in the series is rejected. R, V and MAD are therefore stationary in level.

Table 3: Unit Root Test

	Weekly observations						Monthly observations					
	R		V		MAD		R		V		MAD	
Periods	M	DF stat	M	DF stat	M	DF stat	M	DF stat	M	DF stat	M	DF stat
Full sample period 2006–2015	1	-22.306 (0.000)	3	-19.466 (0.000)	3	-22.501 (0.000)	1	-9.707 (0.000)	3	-9.301 (0.000)	3	-11.382 (0.000)
Sub-period 2006–2010	1	-15.518 (0.000)	2	-14.12 (0.000)	2	-16.117 (0.000)	1	-7.066 (0.000)	1	-7.174 (0.000)	2	-7.954 (0.000)
Sub-period 2011–2015	1	-13.223 (0.000)	2	-13.791 (0.000)	2	-11.616 (0.000)	1	-3.158 (0.002)	2	-6.323 (0.000)	2	-7.417 (0.000)

Notes: The null hypothesis is that the series has a unit root. Numbers in parentheses are probabilities corresponding to the Dickey-Fuller statistic. M is the model considered to check the stationarity of the series. Critical values are -2.60 (at 1% level) ; -1.95 (5%) ; and -1.61 (10%) for model 1; -3.51; -2.89 and -2.58 for model 2; and -4.04; -3.45 and -3.15 for model 3, respectively

5. Empirical Results

The model (1) estimation results are summarized in table 4. Panel A displays the results corresponding to weekly observations. For the full-sample period, the optimal lag, determined by the Schwartz criterion, is equal to 3. First, the null that the lagged return coefficients are jointly equal to zero $(\beta_{12\,1}=0;\ \beta_{12\,2}=0$ *and* $\beta_{12\,3}=0)$ is rejected at the 5% level (the p-value corresponding to the χ_1^2 is 0.024, less than 5%). This means that we reject the null that *R* does not Granger cause *V* at the 5% level. Second, the sum of the lagged return coefficients is positive $(\beta_{12\,1}+\beta_{12\,2}+\beta_{12\,3}=0.0206)$ and significantly different from zero at the 5% level (p-value = 0.005) which indicates a positive cumulative effect of past weekly returns on current trading volume. Third, the lagged volume coefficients in the second equation $(\beta_{21\,1};\ \beta_{21\,2}$ and $\beta_{21\,3}=0)$ are not jointly significant indicating that we cannot reject the null that *V* does not Granger-cause *R*. This means that there is no causality arising from the weekly trading volume to the weekly return. This implies that there is a one-directional positive causality from the weekly return to the weekly trading volume. Consistently with the self-attribution hypothesis, this finding suggests that past high market returns over the past three weeks incite overconfident investors to trade more actively in the following week. However, past low or negative market returns over the past three weeks causes a decrease in trading volume over the following week. Similar results (available on request) are found for different lags ranging from 1 to 12 weeks. For the two sub-periods, the null that R does not Granger-cause V is rejected at 10% level. The positive cumulative effect of lagged returns on trading volume is significant at 5% level for the pre-revolution sub-period 2006-2010 and 10% for the post-revolution sub-period 2011-2015. This implies that the self-attribution/trading activity hypothesis holds for the two sub-periods.

Our findings are consistent with those of Chuang and Lee (2006) in the U.S market, Glaser and Weber (2009) in Germany and Chuang and Susmel (2011) in Taiwan. Furthermore, in their sample of 46 markets, Griffin et *al.* (2007) considered 20 emerging markets which do not include the Tunisian market. Our findings, therefore, add to the evidence found by the authors.

With monthly observations (Panel B), the optimal lag is equal to 1 for the full-sample period and the two sub-periods. In order to explore the cumulative effect of past returns on current volume we extend the lag *p* to three months (Panel C). We find that the self-attribution hypothesis holds for the full-sample and the pre-revolution sub-period but it is rejected for the post-revolution period. For the post-revolution period, the self-attribution bias exists in the very short term (one week) but it disappears for one-month horizon. This indicates that the Tunis stock exchange is able to “cure” itself from such anomaly in period of crisis. Furthermore, although they exhibit overconfidence in short term, investors lose confidence for one-month horizon and become rational.

6. Conclusion

The self-attribution, one of the facets of the overconfidence bias, refers to the fact that investors attribute market gains to their own talent and losses to bad luck. As a consequence, their trading activity depends on the past market returns. We examined this bias in the Tunisian stock market using a causality test between market trading volume and market return for the period 2006-2015. Our results indicate that Tunisian investors tend to increase their trading volume after observing high market returns and reduce their trading volume after poor market performance. After the Tunisian revolution, this effect persists in the very short term (for weekly observations), but it fades away for one-month horizon indicating that in period of crisis, Tunisian investors lose confidence and become rational.

Table 4: Causality between Return and Trading Volume

	Full sample period 2006-2015				Sub-period 2006-2010				Sub-period 2010-2015			
Endog.	V_t		R_t		V_t		R_t		V_t		R_t	
Exog.	V_{t-j}	R_{t-j}	V_{t-j}	R_{t-j}	V_{t-j}	R_{t-j}	V_{t-j}	R_{t-j}	V_{t-j}	R_{t-j}	V_{t-j}	R_{t-j}
Panel A. Weekly observations												
	Optimal lag 3				Optimal lag 2				Optimal lag 4			
χ_1^2 (p-value)	17.435 (0.0006)	9.447 (0.024)	2.9538 (0.399)	5.3420 (0.148)	2.6900 (0.261)	4.9267 (0.085)	0.1794 (0.914)	7.0850 (0.029)	4.2667 (0.371)	8.0777 (0.089)	2.2605 (0.688)	24.950 (0.000)
Sum lagged coef.	0.2614	0.0206	0.7234	0.1302	0.1231	0.0174	0.1542	0.1575	0.1310	0.0276	0.7971	0.3424
χ_2^2 (p-value)	15.325 (0.0001)	7.9554 (0.005)	1.5871 (0.208)	4.4363 (0.035)	2.1202 (0.145)	4.8932 (0.027)	0.0511 (0.821)	6.2283 (0.013)	1.3460 (0.246)	2.9411 (0.086)	0.8966 (0.344)	8.5610 (0.003)
Adj R^2	0.051		0.3331		0.0155		0.4961		0.0581		0.0767	
Q(6) (p-value)	1.2127 (0.976)		10.348 (0.111)		1.4177 (0.965)		1.9944 (0.920)		2.1599 (0.904)		3.0840 (0.214)	
Panel B. Monthly observation												
	Optimal lag 1				Optimal lag 1				Optimal lag 1			
χ_1^2 (p-value)	4.7633 (0.0291)	11.897 (0.0006)	0.1554 (0.693)	2.0439 (0.153)	4.7633 (0.029)	11.897 (0.001)	0.1554 (0.693)	2.0439 (0.153)	1.4323 (0.231)	1.9093 (0.167)	1.8128 (0.178)	1.8336 (0.176)
lagged coef.	0.1906	0.0335	-0.286	0.1149	0.1906	0.0335	-0.286	0.1149	0.1579	0.0247	1.2772	0.1654
χ_2^2 (p-value)	4.7633 (0.0291)	11.897 (0.0006)	0.1554 (0.693)	2.0439 (0.152)	4.7633 (0.029)	11.897 (0.001)	0.1554 (0.693)	2.0439 (0.153)	1.4323 (0.231)	1.9093 (0.167)	1.8128 (0.178)	1.8336 (0.176)
Adj R^2	0.1272		0.2557		0.1272		0.2557		0.0338		0.0318	
Q(6) (p-value)	3.4146 (0.332)		4.3151 (0.634)		5.7726 (0.449)		8.1874 (0.225)		2.4145 (0.878)		7.9224 (0.244)	
	Lag 3				Lag 3				Lag 3			
χ_1^2 (p-value)	8.1953 (0.042)	12.439 (0.006)	0.4098 (0.938)	1.9238 (0.588)	0.4718 (0.925)	10.2064 (0.017)	3.4757 (0.324)	1.5175 (0.678)	1.6065 (0.658)	0.9294 (0.818)	9.7329 (0.021)	6.8354 (0.077)
Sum lagged coef.	0.3832	0.0327	-0.116	0.1513	0.0558	0.0365	-2.547	0.1159	0.1891	0.0191	-1.873	0.3838
χ_2^2 (p-value)	8.1260 (0.004)	3.9484 (0.047)	0.0107 (0.918)	1.2240 (0.269)	0.0526 (0.819)	2.9268 (0.087)	1.5132 (0.219)	0.4067 (0.524)	0.6066 (0.436)	0.2886 (0.591)	1.7756 (0.183)	3.6673 (0.056)
Adj R^2	0.1312		0.2316		0.0547		0.3874		-0.042		0.1849	
Q(6) (p-value)	5.0239 (0.541)		4.2753 (0.639)		3.8284 (0.700)		8.7073 (0.191)		2.3083 (0.889)		6.8617 (0.334)	

Notes: The χ_1^2 statistic is a joint test of the null hypothesis that the lagged coefficients are equal to zero. The χ_2^2 test statistic is used to test the null hypothesis that the sum of the estimated lagged coefficients is equal to zero. Q(6) is the Ljung-Box Q-statistic.

Acknowledgement

The author would like to thank Mohamed Chaker Chafaï, Noureddine Aridhi and two anonymous referees for their helpful comments and suggestions.

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[i] For a brief description of the Tunis Stock Exchange, the reader can refer to Boussaidi and Abaoub (2016).