Does the Overconfidence Bias Explain the Return Volatility in the Saudi Arabia Stock Market?

Majid Ibrahim AlSaggaf

Department of Finance and Insurance, College of Business, University of Jeddah, Saudi Arabia

Abstract: This paper examines the effect of the overconfidence bias on the return volatility in Saudi Arabia stock market for the period 2007-2018. Using market data of return and trading volume, we found that the investors' overconfidence helps explain the return volatility more than any other factor.

Keywords: Overconfidence, investor' psychology, excessive volatility.
JEL classification:C52; G14

1. Introduction

The overconfidence is one of the important biases documented in the psychology literature that characterizes human behavior. For example, using a series of experiments, Fischhoff, Slovic and Lichtenstein (1977) and Alpert and Raiffa (1982) showed that people tend to be overconfident. Stock markets are an appropriate field to study such a bias since investors are usually dealing with high quantity of information, trying to formulate judgments on the stock price evolution under uncertainty, managing high trading volume, etc. One of the implications of the overconfidence bias on stock markets is the excessive stock price volatility. Benos (1998) underline that investors overweight their signal than they should rationally do and then submit high orders. Consequently, trading volume and price volatility increase when overconfident investors participate in the market. Such a relation was theoretically modelized by Daniel, Hirshleifer and Subrahmanyam (1998) to explain the investor under reaction and overreaction in stock markets.

Using intraday data for a sample of 205 stocks listed on the NYSE, Darrat, Zhong and Cheng (2007) found that, in the absence of public information, overconfident investors tend to overreact to their private signals and therefore trade too aggressively; however; when public information arrive to the market, investors who exhibit a self-attribution bias cause excessive return volatility. As underlined by Daniel, Hirshleifer and Subrahmanyam (1998), the self-attribution arises when public information confirms the investors' prior private information. Chuang and Lee (2006) suggested detecting the overconfidence bias through the cumulative effect of lagged market returns on the current trading volume. To explain the excessive volatility observed in the U.S. markets, they decomposed the trading volume into a component caused by overconfidence and a component due to other factors. They found that the weekly excessive volatility is mainly explained by the investors' overconfidence for the period 1963-2001.

Kumari and Mahakud (2015) constructed an investor sentiment index based on ten aggregate sentiment proxies related to the market in India. They found a significant impact of this index on the aggregate monthly market return volatility of the BSE Sensex and the S&P CNX Nifty for the period 2000-2013.Using all the stocks listed on the NYSE, AMEX and Nasdaq, Jiang, Peterson and Doran (2014) found that overconfident trading in presence of short-sale constraints helps explain the overpricing of idiosyncratic volatility during the period 1988-2012.Using a daily international data for the period 2000-2012, Jlassi, Naoui and Mansour (2014) found that the overconfidence bias contributes to the market return volatility explanation more than any other factor in 18 out of 27 countries. Abbes (2013) has studied this relation in 8 developed stock markets and 7 emerging stock markets during the period 1999-2009 using daily index prices and trading volume. She found that the overconfidence helps explain the return volatility in most of these markets during the full sample; however, such effect disappears during the global financial crisis period July 2007-December 2009 due to the loss of confidence by the investors.

As a contribution to the emergent markets empirical literature, this paper studies the impact of the overconfidence bias on the return volatility in the Saudi Arabia stock market. The reminder of the paper is organized as follows. The second section presents the research methodology; the third section presents the empirical results and the fourth section concludes the paper.

2. Methodology

The purpose of this paper is to test whether the overconfidence bias causes an excessive return volatility in the Saudi Arabia stock market.

2.1. The overconfidence/volatility hypothesis

Odean (1998), Gervais and Odean (2001), Chuang and Lee (2006), and Heaney et al. (2007) showed that the return volatility increases with the investor overconfidence. Of course, the overconfidence is not the sole explanation for the excessive volatility. Other explanations have been discussed in the literature. For example, according to Lee and Rui (2001), trading activity can be classified into two types of trading: informational trading and non-informational trading. Admatti and Pfleiderer (1988) defined the total trading volume as the respective contribution of the traded, Liquidity traders and market makers. Benos (1998) considers that the trading volume comes from the contributions of four categories of investors in the financial markets: rational traders, overconfident traders, liquidity traders and market makers.

It has been shown that overconfident investors attribute past market gains to their ability to select stocks and, later, they trade excessively. In this framework, past market returns help predict future market trading volume. Based on this literature, we decompose the trading volume into two components to distinguish between the trading volume caused by overconfidence investors and the effect of other factors as follows:

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

$$= [\textstyle\sum_{j=1}^{p} \beta_j R_{t-j}] + [\alpha + \varepsilon_t]$$

$$V_t = OVER_t + NONOVER_t (1)$$

The constant and the residual terms in this equation represent the trading volume component unrelated to the investors' overconfidence *($NONOVER_t$)*. The difference between the trading volume and the sum of the constant and the residual measures the overconfidence due to the cumulative effect of lagged returns on trading volume ($OVER_t$). These two components are incorporated in the variance equation of the following ARMA(1,1)EGARCH(1,1) model:

$$R_t = c + \alpha_1 R_{t-1} + \alpha_2 \varepsilon_t$$

$$log\sigma_t^2 = \omega + \beta_1 log\sigma_{t-1}^2 + \beta_2 \left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \beta_3 \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \beta_4 OVER + \beta_5 NONOVER (2)$$

Where R_t is the Market return, ε_t is the conditional error, and σ_t^2, the conditional volatility. The conditional error is assumed to follow a Generalized Error Distribution (GED).

The financial literature modeling the stock return volatility usually uses EGARCH model developed by Nelson (1991). This is because this model can detect the asymmetric relationship between stock returns and return volatility. This relationship means that a negative shock of returns has a greater effect on volatility than a positive shock with the same magnitude.

This model helps distinguish between the effect of overconfidence on return volatility and the effect of other factors. The coefficient β_4 captures the impact of the overconfidence bias on the volatility, while β_5 reflects other potential explanations not specified in the model. Our purpose is to compare the two coefficients. If the overconfidence explains the return volatility more than the other factors do, we should find that $\beta_4 > \beta_5 > 0$.

2.2. Data

We used daily price and daily trading volume data of the Saudi Arabia stock market (*Tadawul All Share Index, TASI*) during the period from 01/06/2007 to 10/28/2018. The data is collected from the Saudi Arabia stock market (*Tadawul*[1]). Based on this data, we constructed weekly and monthly data to examine whether the overconfidence bias depends on the investment horizon. As mentioned above, to estimate our model, we need return and trading volume series.

The daily market return is the natural logarithm of the price index at day *t* divided by the index price at day *t-1*:

[1]https://www.tadawul.com.sa

$$R_t = Ln(\frac{P_t}{P_{t-1}}) \quad (3)$$

The weekly market return is computed as the return from Tuesday's closing price to the following Tuesday's closing price. If the following Tuesday's price is missing or Tuesday is a holiday, then Monday's price is used. The monthly market return is computed as the return from end of month *t-1* closing price to the following end of month *t* closing price.

The weekly trading volume is computed as a summation from Wednesday's trading volume to the following Tuesday's trading volume. The monthly trading volume is the sum of the daily trading volume during the month. We use the natural logarithm of the number of shares traded as a measure of the trading volume.

2.3. Descriptive statistics

Table 1 presents the descriptive statistics of the trading volume *V* and the market return *R* for our sample period. The market generates, on average, a positive daily return of 0.0036% and a daily trading volume of 19.156. For weekly horizon, the market performance is on average negative with -0.0039% return. For a monthly horizon, the market return, on average, reaches 0.0714%. Moreover, the standard deviation of the market return increases with the investment horizon. For all the series, except monthly trading volume, the p-value corresponding to the Jarque and Bera statistic is less than 5%, which indicates that the series are not normally distributed.

Table 1. Descriptive statistics

	Daily		Weekly		Monthly	
	R	*V*	*R*	*V*	*R*	*V*
Mean	0.000036	19.156	-0.000039	20.708	0.000714	22.290
Median	0.000025	19.157	0.002151	20.757	0.004185	22.294
Maximum	0.000254	20.576	0.153529	22.029	0.178952	23.303
Minimum	0.000023	17.741	-0.232211	18.450	-0.297753	21.525
Std. Dev.	0.000026	0.4197	0.034002	0.4968	0.068624	0.3720
Skewness	3.824455	0.1042	-1.206774	-1.0954	-0.650216	0.1232
Kurtosis	25.86443	2.9014	9.939987	6.2820	5.458315	2.5230
Jarque-Bera	71377.3	6.531783	1378.96	397.7275	45.4398	1.6935
Probability	0.0000	0.0382	0.0000	0.0000	0.0000	0.4287
Observations	2947	2947	613	613	141	141

2.4. Unit root test

To test the stationarity of the series *R* and *V* for daily, weekly and monthly observations, we use the Augmented Dickey-Fuller test of Dickey and Fuller (1981). Table 2 presents the ADF statistic and the corresponding probability resulting from the test. For all the series, the probability is less than 5%, rejecting the null hypothesis that the series has a unit root. Therefore, *R* and *V* are stationary in level.

Table 2. Unit root test

	Daily		Weekly		Monthly	
	t-Statistic	[Prob].	t-Statistic	Prob.	t-Statistic	Prob.
R	-12.36985	[0.000]	-25.33074	[0.000]	-10.58274	[0.000]
V	-8.245368	[0.000]	-6.834234	[0.000]	-6.825957	[0.000]

Note: Null hypothesis: "the series has a unit root"

3. Empirical results

Table 3 reports the estimation results of the model (2) for our sample period using daily, weekly and monthly observations. For daily observations, the coefficients β_4 and β_5 are not significantly different form zero. This indicates that neither overconfidence nor other factors help explain the return volatility. Similar results can be deduced for weekly observations.

For a one-month horizon, β_4 is positive (β_4 = 3.2188) and significantly different from zero at the 1% level(z stat. = 2.902). this means that investors' overconfidence helps explain the observed return volatility in the Saudi Arabia stock market. In fact, an increase of the overconfidence predicts an increase of the return volatility. Moreover,β_5 is positive (0.1431) and statically significant indicating evidence of other potential explanation of market volatility. The effect of the overconfidence on return volatility is higher than that of other effects since $\beta_4 > \beta_5$.

To test the null hypothesis that $\beta_4 = \beta_5$, we use a Wald test. The test yields a chi-squared statistic, χ^2, and a corresponding p-value. The p-value is equal to 0.002, less than 1%. The null is, then, rejected at the 1% level. This means that the effect of the overconfidence on market volatility is significantly greater than the other potential factors.

These results are consistent with the findings of Chuang and Lee (2006) in the U.S. Market.

Table 3. Overconfidence and market volatility

	Daily		weekly		monthly	
c (z-Statistic)	0.0000	(74.98)	0.0023	(2.616)	0.0042	(0.890)
α_1 (z-Statistic)	0.0671	(51.08)	0.7153	(3.967)	-0.8454	(-47.96)
α_2 (z-Statistic)	-0.0655	(-51.75)	-0.6896	(-3.619)	0.9926	(33.44)
ω(z-Statistic)	-21.093	(-15.87)	-1.8394	(-1.437)	-3.1488	(-65.20)
β_1(z-Statistic)	0.0977	(22.31)	0.9268	(31.90)	0.9940	(166.5)
β_2(z-Statistic)	-0.1384	(-0.903)	0.3495	(4.583)	-0.1123	(-32.21)
β_3(z-Statistic)	-0.5184	(-3.513)	-0.0863	(-1.405)	-0.0248	(-0.543)
β_4(z-Statistic)	-0.0594	(-0.050)	0.2687	(0.581)	3.2188	(2.902)
β_5(z-Statistic)	0.0578	(0.863)	0.0507	(0.896)	0.1431	(17.77)
χ^2 [p-value]	0.0095	[0.922]	0.2019	[0.653]	9.1896	[0.002]
Adj.R^2	-0.1885		0.0036		0.0278	
Log likelihood	31441.6		1347.87		201.61	

χ^2 is a Wald test statistic used to test for the null that "$\beta_4 - \beta_5 = 0$"

4.Conclusion

Theoretical and empirical studies motivated by psychology studies have shown that the overconfidence bias has many implications on stock markets. One of these implications is the excessive volatility. We examined such effect on an emergent market, the Saudi Arabia stock exchange, for a period of 12 years (2007-2018) using daily, weekly and monthly data on market return and market trading volume. We measured the overconfidence bias as the cumulative effect of past market returns on trading volume. The conditional volatility is modelized using an exponential generalized autoregressive conditional heteroscedastic (EGARCH) model. Our results indicate that the overconfidence helps explain the monthly return volatility more than other factors do. Moreover, in shorter horizon such as daily and weekly horizon investors tend to be rational; however, for a longer horizon such as monthly horizon, they seem to be irrational.

In future research, it will be appropriate to study other effects of the overconfidence bias on stock markets such as the investors' overreaction to private information, the excessive trading volume and the underestimation of risk.

References

[1] Abbes MB (2013). Does overconfidence bias explain volatility during the global financial crisis? *World transition economy research*, 19:291–312

[2] Admati, A., Pfleiderer, P., 1988. A theory of intraday patterns: Volume and price variability. *Review of Financial Studies* 1:3–40.

[3] Benos A. V. (1998). Aggressiveness and survival of overconfident traders. *Journal of Financial Markets*. 1: 353-383

[4] Chuang W. I. and B. S. Lee (2006).An empirical evaluation of the overconfidence hypothesis. *Journal of Banking and Finance*. 30(9):2489-2515.

[5] Daniel K., Hirshleifer D., Subrahmanyam A.(1998). Investor psychology and security market under and overreactions. *Journal of Finance*. 53(6):1839-1885.

[6] Darrat AF., Zhong M.,Cheng LTW. (2007). Intraday volume and volatility relations with and without public news. *Journal of Banking and Finance*. 31:2711-2729.

[7] Dickey DA, Fuller WA(1981). Likelihood ratio statistics for autoregressive time series with unit root. *Econometrica*. 49(4):1057-1072.

[8] Fischhoff B., Slovic P., Lichtenstein S.(1977). Knowing with certainty: The appropriateness of extreme confidence. *Journal of Experimental Psychology: Human Perception and Performance*.3(4):552-564.

[9] Gervais S., Odean T. (2001). Learning to Be Overconfident. *The Review of Financial Studies*. 14(1):1-27.

[10] Heaney R., Foster FD, Gregor S., O'Neil T., Wood R. (2007). Volatility in returns from trading. *The Journal of Behavioral Finance*. 8(8):35-42.

[11] Jlassia M., Naoui K., Mansour W. (2014). Overconfidence behavior and dynamic market volatility: evidence from international data. *Procedia Economics and Finance*.13:128 – 142.

[12] Kumari J., Mahakud J. (2015). Does investor sentiment predict the asset volatility? Evidence from emerging stock market India. *Journal of Behavioral and Experimental Finance*. 8:25-39.

[13] Lee BS, Rui OM. (2002). The dynamic relationship between stock returns and trading volume: domestic and cross-country evidence. *Journal of banking and finance*. 26:51-78.

[14] Nelson D. (1991). Conditional heteroskedasticity in asset returns: A new approach. *Econometrica*. 59:347-370.

[15] Odean T. (1998). Volume, volatility, price, and profit when all traders are above average. *The Journal of Finance*. 53(6):1887-1934.