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Unusual behavior: reversed leverage effect bias

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Abstract:
According to the literature on risk, bad news induce higher volatility compared to good news. Although parametric procedures used for conditional variance modeling are associated with model risk, this may affect the volatility and conditional value at risk estimation process either due to estimation or misspecification risks. For inferring non-linear financial time series, various parametric and non-parametric models are generally used. Since the leverage effect refers to the generally negative correlation between an asset return and its volatility, models such as GJRGARCH and EGARCH have been designed to model leverage effects. However, in some cases, like the Tehran Stock Exchange, the results are different in comparison with some famous stock exchanges such as the S&P500 index of the New York Stock Exchange and the DAX30 index of the Frankfurt Stock Exchange. The purpose of this study is to show this difference and introduce and model the "reversed leverage effect bias" in the indices and stocks in the Tehran Stock Exchange.

Keywords: Reversed Leverage Effect Bias, volatility, Stock market.
JEL Classifications: G40, G41.

1 Introduction

The leverage effect refers to the observed tendency of an assets returns to be negatively correlated with the assets volatility. Normally, rising asset prices are accompanied by decreasing volatility, and vice versa. In fact, the term leverage refers to one possible economic interpretation of this phenomenon, developed by Black (1976) and Christie (1982). In addition, when asset prices decline, companies become mechanically more leveraged since the relative value of their debt mounts relative to that of their equity. So, it is natural to expect that their stock becomes riskier and more volatile. Since this is only a hypothesis, this explanation is sufficiently prevalent in the literature, to the extent that the term leverage effect has been adopted to explain the statistical regularity in question. It has been shown

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that the effect is generally asymmetric: other things equal, declines in stock prices are accompanied by larger increases in volatility than the decline in volatility that accompanies ascending stock markets (see, e.g., [29]; and Engle and [42]). Moreover, various discrete-time models with a leverage effect have been shown by [43]. Since this kind of effect would be related to investors behavior, in this part we introduce some behavioral biases. Since the introduction of the efficient market by [1] [10], which is based on the belief that market participants always act in a rational and wealth-maximizing manner and prices reflect all available information, many studies have introduced different biases such as representativeness heuristic bias, meaning that people frequently make the mistake of believing that two similar things or events are more closely correlated than they actually are. This representativeness heuristic is a common information processing error in behavioral finance theory (Kahneman and Tversky, 1973). Anchoring bias occurs when people rely too much on the pre-existing information or the first information they find when making decisions [36]. Mental accounting means people often act differently depending on the source of the money they earn. Investors, for example, tend to distinguish between dividend and capital gains [18]. Overconfidence means that people tend to overestimate their knowledge (Pallier et al, 2002). Stock split effect logically means the stock split of a company should not affect its value. However, much evidence suggests that dividing a firm's stock will raise the stock prices (Desai and Jain, 1997) and [22]. The dividend yield effect indicates that a stock with a high dividend will have a higher performance and is more appropriate than the market average [26] and [20]. Insider transaction effect means that individuals with special information typically earn higher returns and can even predict stock price movements" [11]. Country effect means that "each of the calendar and non-calendar effects, depending on the type of a country and the economic system governing it, shows different effects with different severity and weaknesses" [14]. Neglected firms effect means that "companies that are underestimated by institutional investors and market analysts, according to [3], typically have higher returns than other firms". Index effect refers to "the impact on companies' share prices included in a stock index, such as the Standard and Poor's (S&P) 500" (Harris and Gurel, 1986). Mean reversion over the long run is a theory used in finance that suggests that stock prices and historical returns will eventually revert to the long-run mean or average level of the entire data set. In other words, the largest loser investor over the next 3 to 5 years becomes the largest lucrative investor over the next 3 to 5 years [8]. Generally, behavioral bias in the following two forms affects investors' behavior. Market Overreaction Effect is an emotional response to new information about a security, which is led either by greed or fear. Investors, overreacting to news, cause the security to become either overbought or oversold until it returns to its intrinsic value (Yulong, Tang & Tanweer, 2005). Based on the Market Underreaction Effect, the under-reaction evidence shows that security prices under-react to news such as earnings announcements. If the news is good, prices keep trending up after the initial positive reaction; if the news is bad, prices keep trending down after the initial negative reaction (Abarbanell and Bernard, 1992). These two behavioral abnormalities in the capital market, in addition to creating inefficiencies in the market, can cause, or even reverse, the impact of good and bad news. We know that based on the literature on risk, the bad news has a greater effect than good news in creating turbulence [7]. However, in some cases, like Tehran's capital market, according to the previous studies, such as [27], the effect of good news is more than bad news. Accordingly, this research is aimed at introducing and modeling a new bias, called Reversed Leverage Effect Bias. Generally, as the stock price declines, the share of debt in the financial structure of the enterprise increases as well, thus shareholders bear higher risk and it is logical that bad news or negative returns should be accompanied by more volatility according to [29], [30], [17], [12], but in some cases, the opposite happens and more volatility occurs due to positive returns and good news that we call Reversed Leverage Effect Bias. The purpose of the present study is to model and measure this behavioral bias, show this difference and introduce and model the "reversed leverage effect bias" in the indices and stocks in the Tehran Stock Exchange.

2 The literature on conditional risk and models

Although parametric procedures used for conditional variance modeling are associated with model risk, this may affect the volatility and conditional value at risk estimation process either due to estimation or misspecification risks. For inferring non-linear financial time series, various parametric and non-parametric models are generally used (Telmoudia and et. al., 2015). In this part, some of the most important of them are presented. The general autoregressive conditional heteroscedastic (GARCH) models have been investigated where the functional form is assumed to be known. Also, for extracting information from high-dimensional market data and convenient owing to its unique non-parametric, non-assumable, noise-tolerant and adaptive properties, the support vector machine (SVM) model is considered as a volatility model. SVM is less affected by model misspecification and provides a good generalization performance. Specifically, these methods are applied in risk management such as conditional value at risk denoted by VaR estimation (Cao, 2001). Since model risk may affect the volatility and conditional value at risk estimation process either due to estimation or misspecification risks, non-parametric artificial intelligence models (AI models) can be considered as alternative models because they do not rely on an explicit form of volatility. In fact, in a non-parametric framework, artificial intelligence models denoted by AI do not assume any functional form. The support vector machine (SVM) model is considered as a volatility model that extracts information from high-dimensional market data and convenient owing to its unique non-parametric, non-assumable, noise-tolerant and adaptive properties. Furthermore, if an autoregressive-moving-average (ARMA) model is assumed

ARCH for the error variance, the model is a generalized autoregressive conditional heteroscedasticity (GARCH) model.

In that case, the GARCH (p, q) model (where p is the order of the GARCH terms σ_{i-1}^2 or the variance of the previous day and q is the error terms of the previous day, following the notation of the original paper (Bollerslev, 1986)(, is given by

$$\sigma_i = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i} + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2 \tag{1}$$

GJR-GARCH Using GJR-GARCH, we can model the leverage effects proposed by [39] and (French et al., 1987). The Glosten-Jagannathan-Runkle GARCH (GJR-GARCH) model by Glosten, Jagannathan, and Runkle (1993) also models asymmetry in the ARCH process. The leverage effect is modeled in the GARCH process. If $\varepsilon_{t-1} > 0$, then $I = 0$ and if $\varepsilon_{t-1} < 0$, then $I = 1$ and leverage effects can be tested with $\gamma > 0$.

$$\sigma_i = \omega + \sum_{i=1}^{p} (\alpha_i + \gamma_i I(\varepsilon_{t-1}))\varepsilon_{t-j} + \sum_{j=1}^{q} \beta_j \sigma_{t-j} \tag{2}$$

EGARCH The exponential generalized autoregressive conditional heteroskedastic (EGARCH) model by [28] is another form of the GARCH model. Formally, in an EGARCH (p, q) : If $\gamma \neq 0$ is significant, then the effects of the shocks on the conditional variance are asymmetric. In this model, leverage effects can be tested by assuming $\gamma < 0$.

$$log(\sigma_i^2) = \omega + \alpha_i |\frac{\varepsilon_{i-1}}{\sigma_{i-1}}| + \gamma(\frac{\varepsilon_{i-1}}{\sigma_{i-1}}) + \beta_i log(\sigma_{i-1}^2) \tag{3}$$

In this equation, denotes asymmetry. In the symmetric model, for all values and the coefficient γ is zero.

[39] used a moving average model, exponential moving average, random walk, and various GARCH models to predict Shanghai and Shenzhen indices in the stock exchange of China. He concluded that no single model could have the best performance in all conditions. For example, asymmetric models like GJRGARCH and EGARCH in Shenzhen index had a better performance than other GARCH models, but asymmetric models were not appropriate for conditional risk forecast in the Shanghai index. [1] investigated the Egyptian stock exchange from 1998 to 2009. He found that the EGARCH model predicted volatility better than other models. [25] tested EGARCH, GARCH, ARCH, and GJR-GARCH models in the S&P index and reported that asymmetric models such as GJR-GARCH and EGARCH were better predictors than the type of error distribution for more accurate prediction of volatility. [9] studied the daily returns of stock in the Stockholm stock exchange and concluded that asymmetric GARCH models like EGARCH with student distribution along with ARIMA (0, 0, 1) model provided a more precise prediction of GARCH

models. Andreea [2] investigated volatility in the Euro exchange rate versus the Romanian currency and found that asymmetric EGARCH and PGARCH models were more powerful than symmetric GARCH models for estimation of risk and returns. The results of studies by [15, 16] on Hong Kong stock exchange, [32], [35], [23] on Netherlands stock exchange, [6] on North and East Africa stock exchange, Nilsson (2017) on Sweden stock exchange, and [9] on the daily return of stock in Stockholm stock exchange indicated that asymmetric GARCH modes like GJR-GARCH as well as the other models considering leverage effects for prediction of risk had a better performance than symmetric GARCH models.

3 Reversed Leverage Effect Bias (New concept)

Theoretically, it is argued that by stock price decline and negative return, the share of debt in the financial structure of the enterprise will increase, so shareholders bear more risk and expect an increase in future stock returns volatility [12]. Many other studies have shown that negative momentums (bad news) have greater effects on returns volatility than positive momentum with the same size so that volatilities in the stock markets are asymmetric [17] [30], [21], [24], [29]. However, in some cases, like the Tehran Stock Exchange, the results are different in comparison with some famous stock exchanges like the S&P500 index of the New York Stock Exchange and the DAX30 index of the Frankfurt Stock Exchange. The purpose of this study is to show this difference and introduce and model the "reversed leverage effect bias" in the indices and stocks in the Tehran Stock Exchange. In fact, introducing this new concept could be the novelty of this study.

4 Methodology

In order to model Reversed Leverage Effect Bias, two models of GARCH and GJRGARCH were used. We know that when the Reversed Leverage Effect Bias is present, the gamma coefficient is positive in the EGARCH model and is negative in the GJRGARCH model. Therefore, in this research, by introducing a new model, the effects of the Reversed Leverage Effect Bias were calculated with equation (4).

$$RLEB = (\frac{|AR(l)_1| + |AR(l)_2|}{2})[e^{\frac{\gamma_1 - \gamma_2}{2}}] \tag{4}$$

where $AR(1)_1$ is autoregressive coefficients of EGARCH Model, $AR(1)_2$ is autoregressive coefficients of GJR-GARCH Model, γ_1 is coefficient of leverage effects of EGARCH model and γ_2 is coefficient of leverage effects of GJR-GARCH model, RLEB is Reversed Leverage Effect Bias.

5 Results

Table 1 presents the descriptive data of the Tehran Stock Exchange index, the DAX index of the Frankfurt Stock Exchange, and the S&P index of the New York Stock Exchange.

Table 1: Descriptive data

Index	average daily return	median daily return	standard deviation
price index	0.00162	0.00042	0.0099
DAX Index	0.000086	0.00081	0.0127
DAX Index	0.000086	0.00081	0.0127
SP Index	0.000285	0.00052	0.011

As indicated in column 5 of Table 2, in the price index of the Tehran Stock Exchange, the gamma coefficient (γ) is negative for the GJR-GARCH model and positive for the EGARCH model (i.e. good news or positive returns have more effect on volatility than bad news or negative returns), which is in line with the results of previous studies such as the study by Mehrara and Abdoli (2008). As

Table 2: price index of the Tehran Stock Exchange

GARCH family	$AR(l)$	α	β	γ
GARCH	0.32	0.32	0.7	-
P-value	0.00000	0.00000	0.00000	-
GJRGARCH	0.32	0.42	0.73	-0.29
P-value	0.0000	0.0000	0.00000	0.00000
EJRGARCH	0.3	0.44	0.93	0.17
P-value	0.00000	0.00000	0.00000	0.0000

shown in columns 2 and 4 of Tables 3 and 4, in C, the gamma coefficient (γ) is positive for the GJR-GARCH model and negative for the EGARCH model (i.e. bad news or negative returns have more effect on volatility than good news or positive returns). Based on formula 4 for estimating the Reversed Leverage Effect Bias, first, the gamma coefficient of the EGARCH model was subtracted from the gamma coefficient of the GJRGARCH model, and after dividing it into two, it was inserted in the exponential function. As shown in Table 5, the order of priority from the highest to the lowest of Reversed Leverage Effect Bias was the price index of Tehran Stock Exchange (39%), the S&P500 index of the New York Stock Exchange (0.058) and finally, the DAX30 index of the Frankfurt Stock which was without Reversed Leverage Effect Bias.

Table 3: DAX30 index of the Frankfurt Stock Exchange

GARCH family	$AR(l)$	α	β	γ
GARCH	0.0063	0.12	0.85	-
P-value	0.82	0.00000	0.00000	-
GJRGARCH	0.0086	0.009	0.88	0.17
P-value	0.71	0.31	0.00000	0.00000
EJRGARCH	0.009	0.15	0.96	-0.13
P-value	0.7	0.00000	0.00000	0.0000

6 Conclusion and suggestions

In this study, we demonstrated that the leverage effect has a different outcome in some stock markets. Generally, bad news induces a higher volatility compared to good news. We know that parametric procedures used for conditional variance modeling are associated with model risk; this may affect the volatility and conditional value at risk estimation process either due to estimation or misspecification risks. For inferring non-linear financial time series, various parametric and non-parametric models are generally used. Since the leverage effect refers to the generally negative correlation between an asset return and its volatility, models such as GJRGARCH and EGARCH are designed to model leverage effects. However, in some cases, like the Tehran Stock Exchange, the results are different in comparison with some famous stock exchanges like the S&P500 index of the New York Stock Exchange and the DAX30 index of the Frankfurt Stock Exchange. Moreover, in this research, a new behavioral bias called ”reversed leverage effect bias” was introduced and then measured in the form of an innovative modeling. As the findings of this study have shown, during the period from 2014-05-16 to 2020-05-17, the price index of the Tehran Stock Exchange had the highest reverse behavioral bias and the DAX30 index of the Frankfurt Stock Exchange had no reverse behavioral bias. Therefore, the results of this study indicated that the DAX index of the Frankfurt Stock Exchange would be more normal. Also, the S&P index of the New York Stock Exchange showed that this index would be relatively more normal than the Tehran Stock Exchange. In fact, we have shown the different outcomes and introduced and modelled the ”reversed leverage effect bias”. It could be a sign of an abnormal stock market that is influenced by unusual parameters.

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Table 4: DAX30 index of the Frankfurt Stock Exchange

GARCH family	$AR(l)$	α	β	γ
GARCH	-0.07	0.24	0.72	-
P-value	0.02	0.00000	0.00000	-
GJRGARCH	-0.086	0.0025	0.78	0.35
P-value	0.00000	0.31	0.00000	0.00000
EJRGARCH	0.07	0.22	0.94	-0.24
P-value	0.0015	0.00000	0.00000	0.0000

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Table 5: Reversed Leverage Effect Bias

Index name	$AR(l)_1$	$AR(l_2)$	γ_1	γ_2	Reversed Leverage Effect Bias
price index	0.32	0.3	0.17	-0.29	0.39
DAX Index	-	-	-0.13	0.17	0
SP Index	-0.07	-0.085	-0,24	0.35	0.058

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