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Bahmani, Mohammad and Sheikh Ahmadi, Sayed Amir and Sanginabadi, Bahram

Islamic Azad University, Sanandaj Branch, Iran, Islamic Azad University, Sanandaj Branch, Iran, University of Hawaii at Manoa

20 November 2013

Journal of Scientific Research & Reports
3(10): 1361-1374, 2014; Article no. JSRR.2014.10.006

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Return Volatility and Asymmetric News of Computer Industry stocks in Tehran Stock Exchange (TEX)

Mohammad Bahmani[1], Sayed Amir Sheikh Ahmadi[1] and Bahram Sanginabadi[2*]

[1]*Department of Computer Engineering, College of Engineering, Kurdistan Science and Research Branch, Islamic Azad University, Sanandaj, Iran.*
[2]*Department of Economics, Urmia University, Iran.*

Authors' contributions

This work was carried out in collaboration between all authors. Author SASA redacted the article. Authors MB and BS designed the study, performed the statistical analysis, managed the analyses of the study and wrote the article. All authors read and approved the final manuscript.

Original Research Article

Received 20th November 2013
Accepted 15th March 2014
Published 5th April 2014

ABSTRACT

According to leverage and volatility feedback effects there are relationships between the return and the risk of stocks in the stock markets. Using daily and weekly data of Computer industry index in Tehran stock Exchange (TEX), this study investigates both leverage and volatility feedback effects applying GARCH family models and Full Information Maximum Likelihood (FIML) estimation method, during 01/2007- 10/2013 period. According to GARCH-M model estimations the first hypothesis of the research (Return volatility of computer industry in TEX affects the return significantly) cannot be rejected for daily data during 02/2010 to 10/2013 (the 2nd period) which both return and return volatility were much more volatile rather than 01/2007 - 02/2010 (the 1st period), but this hypothesis can be rejected for daily data in the 1st period and weekly data in both periods. According to EGARCH and TGARCH estimations the second main hypothesis of the research (a negative return makes return volatility of computer industry in TEX more volatile) cannot be rejected for both daily and weekly data in the 1st period, but can be rejected for both data during the 2nd period.

**Corresponding author: E-mail: b.sanginabadi@yahoo.com;*

Keywords: Computer industry; Tehran stock exchange; return volatility; asymmetric news
JEL classification: E60; G00; G32.

1. INTRODUCTION

There are five important Iranian companies in Tehran Stock Exchange that provide a variety of services including hardware and software services for both the public and the private sectors. However, the Iranian Computer Industry and its computer markets are different from those of other countries. Actually, for a long time tight foreign sanctions deeply has affected Iranian economy. Indeed, the sanctions cut off the Iranians commercial relations with other countries. As a result in recent years the exchange rates were very volatile and increased in an unprecedented rate. Such changes affected the Iranian economy deeply [1]. Furthermore, in recent year the Iranian Economic Growth was negative and Iranians experienced one of the highest rates of inflation in the world[1]. Also, some recent studies have reported the returns in Tehran Stock Exchange (TEX) very volatile [See, e.g., [2] and [3]. In addition, for a long time the computer industry has been one of the direct victims of the sanctions. However, in May 2013 U.S. Department of the Treasury stated that United States is issuing a General License authorizing the exportation to Iran of certain services, software, and hardware incident to personal communications[2]. Indeed, in recent years the computer industry in TEX has been very volatile and has experienced lots of changes in the prices. Considering such a situation, through this study we try to answer the following questions:

- How return volatility of computer industry in TEX affected the return in the recent years?
- Was return volatility of computer industry in TEX symmetric or asymmetric?
- If there were asymmetries in the news, was the bad news stronger or the good news?
- What were the differences between daily and weekly data of computer industry in TEX regarding to all of the questions raised above?

There are two important theoretical explanations that can help to answer these questions: volatility feedback effect and leverage effect. To answer the questions, we apply GARCH models and estimate them by Full Information Maximum Likelihood (FIML) method. Indeed, among the various methods by which the variance can be estimated, the ARCH model estimated by [4] to specifically model conditional variances and the GARCH model introduced [5] have become the standard tools for variance modeling. GARCH in mean models are able to capture the volatility feedback effect and we apply it to answer the first questions raised above. The exponential GARCH or EGARCH introduced by [6] and the threshold GARCH or TGARCH introduced by [7] can capture the leverage effect stylized fact where positive and negative shocks have asymmetric effects with negative shocks having a greater impact on volatility than positive shocks [8]. So we apply TGARCH and EGARCH models to answer the second and the third questions above. In addition, to answer the forth question we estimate all of the models applying both the daily data and weekly data of computer industry in TEX. In finance literature there are two main theoretical explanations for asymmetric volatility reaction patterns: leverage hypothesis documented by [9] and volatility feedback effects presented by [10] and [11]. According to leverage hypothesis, a negative shock to returns decreases the value of a firm's equity and hence increases the

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[1] *The Central Bank of Iran*
[2] *U.S. Department of the Treasury, 2013, Available at: http://www.treasury.gov/press-center/press-releases/Pages/jl1961.aspx*

debt-to-equity ratio, rendering equity riskier and more volatile [9,12,13]. While the leverage effect explanation suggests that a negative return should make the firm more levered, hence riskier and therefore lead to higher volatility; the volatility feedback effect is consistent with the same correlation but reverses the causality: increases in volatility lead to negative returns. According to the theory of volatility feedback effect, an unexpected increase in squared volatility leads to an immediate decline in the stock price, because cash flows discounted at a higher rate [14]. So, the two main- hypotheses that we try to test them in this article are as follow:

- Return volatility of computer industry in TEX affects the return significantly.
- A negative return makes return volatility of computer industry in TEX more volatile.

The importance of time varying volatility has been recognized for a long time in financial literature and lots of researches have been done to both investigate the effects of time series volatilities on different variables and study asymmetries in the news in different stock markets around the world.

On comparing the magnitude of the two effects, [15,16] have found that the volatility feedback effect dominates the leverage effect empirically. On the other side, many studies like [6,17,18] argued that volatility increases more following negative returns than positive returns and the relationship between expected returns and volatility is insignificant, or even negative empirically [19]. Lots of studies using more efficient volatility measures suggest a significant positive risk return trade-off relationship [See, e.g., [20,21,22]]. Some recent studies that investigated leverage and volatility feedback effects include [23,8,13,24,25,26] among others. Furthermore, several researchers have investigated volatilities in TEX: [27] tested volatility feedback effect in TEX and didn’t find a significant relation between expected volatility and return. [28] investigated the influence of world price of gold and oil on TEX index. [29] using GARCH models tried to model TEX calendar effects. [30] tried to forecast divided stock price index volatility in TEX. [31] investigated the effects of financial crisis on TEX. [32] using a multivariate model investigated indexes spillovers in TEX. [33] applying multivariate FIGARCH investigated volatility and return transmission of cement industry stock prices. [34,35] tried to forecast volatilities in TEX. [36] using Bootstrap Resampling Method estimated value-at-risk in TEX. [37] applying multivariate GARCH approach investigated long-run relationship between the volatility of effective exchange rate and industrial return index in TEX. [38] studied volatility trend in TEX. [2] investigated the effects of anticipated and unanticipated stock return volatility of automobile manufacturing industries in TEX. [3] investigated the casual and contemporaneous relations of stock returns, trade volume, and volatility in TEX.

Although, the leverage and volatility feedback effects have been studied in Tehran Stock Exchange Markets [See, e.g., [27,39], but we couldn’t find any study that investigates leverage or volatility feedback effects for the Iranian Computer industry.

The rest of the paper is structured as follows: section 2 provides Material and Methods. Section 3 lays out Results and Discussion, and finally section 5 concludes the paper.

2. MATERIALS AND METHODS

In this article using both daily and weekly data of the Computer Industry stocks in Tehran Stock Exchange we test the volatility feedback effect and the leverage effect hypothesis. So we use both daily and weekly indexes data of computer industry in the Tehran Stock Exchange to get daily return and weekly return. As [27], we apply the following equation to get daily return:

$$Y_{d\,t} = (\frac{TI_t - TI_{t-1}}{TI_{t-1}}) \times 100 \tag{1}$$

Which $Y_{d\,t}$ is daily return on the day number t and TI_t is the computer industry index in TEX on day number t and TI_{t-1} is the computer industry index in TEX on day number t-1. In addition we get weekly return through the following equation:

$$Y_{wt} = (\frac{TI_{t_1} - TI_{t_0}}{TI_{t_0}}) \times 100 \tag{2}$$

Which Y_{wt} is weekly return, TI_{t_0} is the Computer Industry index on the first day of the week, and TI_{t_1} is the index on the last day of the week.

2.1 FIML Estimations

Full Information Maximum Likelihood (FIML) estimates the likelihood function under the assumption that the contemporaneous errors have a joint normal distribution. Provided that the likelihood function is correctly specified, FIML is fully efficient.

2.1.1 GARCH-M model

In order to investigate the effects of return volatilities on return we apply GARCH-M models using Full Information Maximum Likelihood (FIML) method. GARCH-M models allow the conditional mean to depend on its own conditional variance [40][3]. As [40] we estimate the GARCH-M model as follow:

$$Y_t = \alpha + \sum_{i=1}^{m} \beta_i X_t + \theta\sigma_t^2 + u_t \tag{3}$$

$$u_t \mid \Omega_t \sim iid\ N\,(0, \sigma_t^2)$$

$$\sigma_t^2 = \gamma_0 + \sum_{i=1}^{p} \delta_i \sigma_{t-i}^2 + \sum_{j=1}^{q} \gamma_j u_{t-j}^2 \tag{4}$$

Where Y_t is return, $X_t$includes lags of Y_t, and Ω_t is information matrix.

2.1.2 T-GARCH and E-GARCH models

In addition we apply TGARCH and EGARCH models to learn whether the effects of the good news and the bad news on stock return are symmetric or asymmetric. A major restriction of the ARCH and GARCH specifications is the fact that they are symmetric. By this we mean

[3]*Asteriou and Hall, 2007, P. 263*

that what matters is only the absolute value of the innovation and not its sign (because the residual term is squared). Therefore, in ARCH/GARCH models a big positive shock will have exactly the same effect in the volatility of the series as a big negative shock of the same magnitude. However, for equities it has been observed that negative shocks (or "bad news") in the markets have a larger impact on volatility than positive shocks (or "good news") of the same magnitude. The main target of these models is to capture asymmetries in terms of negative and positive shocks [40][4]. To do that, TGARCH simply adds into the variance equation a multiplicative dummy variable to check whether there is statically significant difference when shocks are negative shocks [40][5]. We estimate Threshold GRCH or TGARCH were introduced independently by [7,18] as follow:

$$Y_t = \alpha + \sum_{i=1}^{m} \beta_i X_t + u_t \tag{5}$$

$$u_t \mid \Omega_t \sim iid\ N(0, \sigma_t^2)$$

$$\sigma_t^2 = \gamma_0 + \sum_{i=1}^{q} (\gamma_i + \upsilon_i d_{t-i}) u_{t-i}^2 + \sum_{j=1}^{q} \delta_j \sigma_{t-j}^2 \tag{6}$$

Where d_t takes the value of 1 for $u_{t-i} \prec 0$, and 0 otherwise. Moreover Ω_t is information matrix. In this model, good news, $u_{t-i} \succ 0$, and bad news, $u_{t-i} \prec 0$, have differential effects on the conditional variance; good news has an impact of γ_i, while bad news has an impact of $\gamma_i + \upsilon_i$. If $\upsilon_i \succ 0$, bad news increases volatility, and we say that there is a leverage effect for the i-th order. If $\upsilon_i \neq 0$, the news impact is asymmetric, while if $\upsilon_i = 0$ the impact is symmetric [40][6].

We apply Exponential GARCH model or EGARCH proposed by [6] as follow:

$$Y_t = \alpha + \sum_{i=1}^{m} \beta_i X_t + u_t \tag{7}$$

$$u_t \mid \Omega_t \sim iid\ N(0, \sigma_t^2)$$

$$\log(\sigma_t^2) = \gamma + \sum_{j=1}^{q} \varsigma_j \left| \frac{u_{t-j}}{\sqrt{\sigma_{t-j}^2}} \right| + \sum_{j=1}^{q} \xi_j \frac{u_{t-j}}{\sqrt{\sigma_{t-j}^2}} + \sum_{i=1}^{p} \delta_i \log(\sigma_{t-j}^2) \tag{8}$$

Where the γ, ς s, and ξ s are parameters to be estimated. The EGARCH model allows for the testing of asymmetries as well as the TGARCH model. To test for asymmetries the parameters of importance are ξ s. If $\xi_1 = \xi_2 = \ldots = 0$, then the model is symmetric. The impact is asymmetric if $\xi_j \neq 0$. The presence of leverage effect can be tested by the

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[4] *Asteriou and Hall, 2007, P. 267*
[5] *Asteriou and Hall, 2007, P. 267*
[6] *Asteriou and Hall, 2007, P. 267*

hypothesis that $\xi_j \prec 0$. When $\xi_j \prec 0$, then positive shocks (good news) generate less volatility than negative shocks (bad news) shocks [40][7].

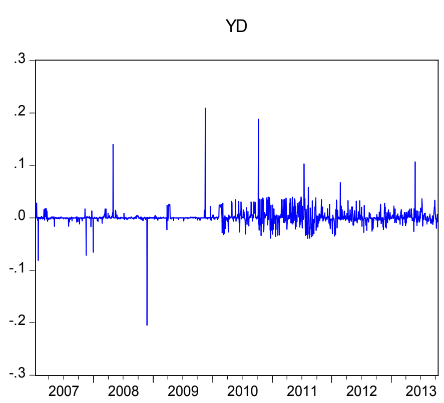
3. RESULTS AND DISCUSSION

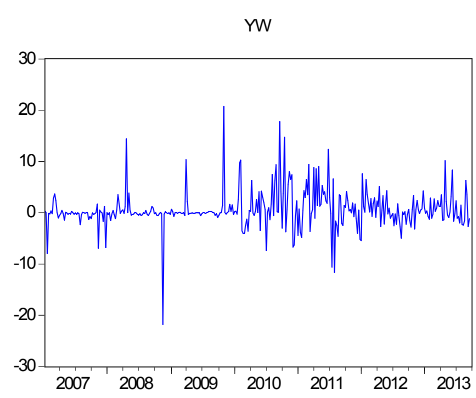
3.1 Data

This paper uses the daily and weekly data of Computer Industry at Tehran Stock Exchange over 01/2007 to 10/2013. All the data is gathered from Tehran Stock Exchange website[8]. Summary statistics for the series are given in Table 1. Fig. 1 shows the daily and weekly return of Computer Industry at TEX (equation (1) and (2)). As the figures show, there are much more fluctuations in the returns in the recent years. In addition Fig. 2 shows GARCH (1,1) which we consider it as Return volatility proxy.

Table 1. Summary statistics of variables

	Daily		**Weekly**	
	Return (Y_{dt})	**Return Volatility (σ_{dt}^2)**	**Return (Y_{wt})**	**Return Volatility (σ_{wt}^2)**
Mean	0.001391	0.000201	0.613874	13.35510
Median	0.000000	0.000188	0.004750	12.06908
Maximum	0.208993	0.003390	20.76571	37.01391
Minimum	-0.204787	1.66E-05	-21.82083	11.07072
Std. Dev.	0.014599	0.000133	3.667393	3.375928
Skewness	2.131072	20.46484	0.664867	3.120671
Kurtosis	71.76795	454.8001	12.04049	15.90228
Jarque-Bera	348721.1	15117619	1214.210	2987.197
Probability	0.000000	0.000000	0.000000	0.000000
Sum	2.452956	0.354144	214.2422	4660.930
Sum Sq. Dev.	0.375514	3.09E-05	4680.520	3966.118
Observations	1763	1763	349	349





[7]Asteriou and Hall, 2007, P. 269
[8]http://www.tse.ir/

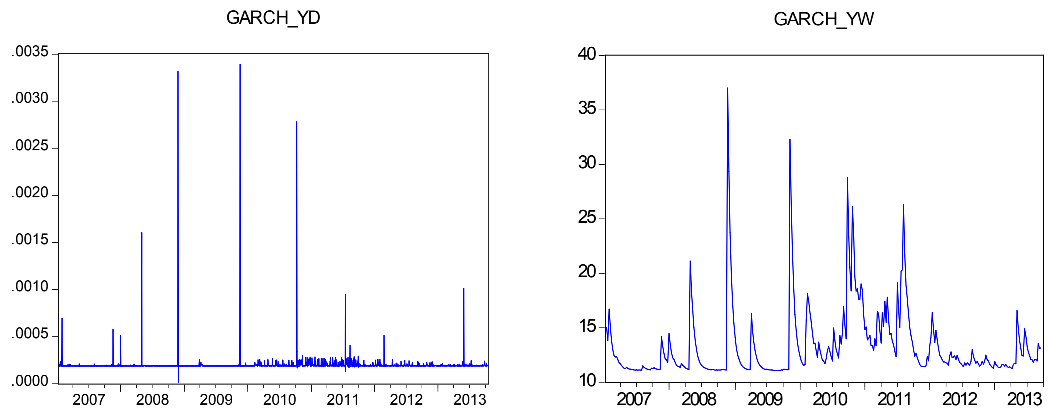


Fig. 2. Left: Daily Return Volatility (σ_{dt}^{2}), Right: Weekly Return Volatility (σ_{wt}^{2})

As can be seen through all the four figures above in 2010 the form of volatilities completely changes in a way that from the early months in 2010 onwards we are facing much more volatile returns and return volatilities for both daily and weekly data.

We apply Zivot-Andrews unit root test developed by [41] to test the null hypothesis of unit root against the break-stationary alternative hypothesis during all of the research period time because ZA unit root test not only gives us the results of stationary test considering one break in the series, but also it gives us an important break time in the series [41]. As the results in Table 2 show ZA unit root test results confirm that for all of the series the null hypothesis can be rejected and the series are stationary. Furthermore, for all the four series the results of ZA test give us a break date in the series all in Feb 2010.

Table 2. ZA unit root test results

	TB$_{ZA}$	τ_{ZA}
Y_{dt}	02/09/2010	-24.899***
Y_{wt}	02/11/2010	-8.413***
σ_{dt}^{2}	02/03/2010	-42.477***
σ_{wt}^{2}	02/17/2010	-8.440***

*The null hypothesis in ZA unit root test is that the series contains a unit root with drift that exclude any structural break, while the alternative hypothesis implies that the series is a trend-stationary process with a one-time break occurring at an unknown point in time [41]. [41] has provided the Critical values: -5.57, -5.08, and -4.82 at 1%, 5%, and 10% levels of significance respectively. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels*

All of the four series figures and the time breaks in Table 2 give us a clue that there are two different behaviors in series before and after Feb 2010; there are less volatile data before Feb 2010, but much more volatile data after that month. So we provide different estimates for each of the two different periods before and after Feb 2010.

In this paper, in addition to ZA unit root tests Augmented Dickey-Fuller (ADF) (documented by [42,43] and Phillips-Perron (PP) (presented by [44] tests have been used to test for stationary. Table 3 and 4 show the ADF and PP test results for the first period (before Feb 2010) and for the second period (after Feb 2010) respectively. The tests for the ADF and PP are applied with intercept, trend and intercept and non-intercept or trend. In this manner results show that for both periods all of the series are stationary.

Table 3. ADF and PP unit root tests results (1st period)

	Y_{dt}	ΔY_{dt}	Y_{wt}	ΔY_{wt}	σ_{dt}^2	$\Delta\sigma_{dt}^2$	σ_{wt}^2	$\Delta\sigma_{wt}^2$
$\tau_\mu(ADF)$	-26.38***	-15.77***	-11.82***	-9.46***	-28.86***	-16.11***	-5.71***	-14.39***
$\tau_T(ADF)$	-26.41***	-15.76***	-11.92***	-9.43***	-28.87***	-16.10***	-5.79***	-14.34***
$\tau(ADF)$	-26.38***	-15.78***	-11.85***	-9.49***	-2.16**	-16.12***	-1.55	-14.44***
$\tau_\mu(PP)$	-26.57***	-328.8***	-11.83***	-141.3***	-28.86***	-822.1***	-5.76***	-21.38***
$\tau_T(PP)$	-26.59***	-328.3***	-11.92***	-149.2***	-28.87***	-823.0***	-5.85***	-21.28***
$\tau(PP)$	-26.58***	-329.1***	-11.86***	-134.3***	-23.03***	-823.0***	-1.09	-21.51***

Sample:01/2007-02/2010

τ_μ Represents the most general model with intercept, τ_T is the model with intercept and trend and τ is the model without intercept and trend. Both in ADF and PP tests, unit root tests were performed from the most general to the least specific model by eliminating trend and intercept across the., ** and ***denotes rejection of the null hypothesis at the 10%, 5% and 1% level*

Table 4. ADF and PP unit root tests results (2nd period)

	Y_{dt}	ΔY_{dt}	Y_{wt}	ΔY_{wt}	σ_{dt}^2	$\Delta\sigma_{dt}^2$	σ_{wt}^2	$\Delta\sigma_{wt}^2$
$\tau_\mu(ADF)$	-22.36***	-13.96***	-12.43***	-10.42***	-30.14***	-16.08***	-4.60***	-13.22***
$\tau_T(ADF)$	-22.45***	-13.95***	-12.57***	-10.39***	-30.24***	-16.08***	-5.20***	-13.19***
$\tau(ADF)$	-22.01***	-13.97***	-11.75***	-10.45***	-1.14	-16.09***	-0.523	-13.25***
$\tau_\mu(PP)$	-2236***	-224.6***	-12.65***	-39.91***	-30.15***	-617.7***	-4.72***	-18.03***
$\tau_T(PP)$	-22.50***	-224.5***	-12.74***	-39.76***	-30.24***	-620.6***	-5.40***	-17.98***
$\tau(PP)$	-22.27***	-224.8***	-12.33***	-40.04***	-11.60***	-618.3***	-0.607	-18.08***

Sample: 02/2010-10/2013 represents the most general model with intercept, is the model with intercept and trend and is the model without intercept and trend. Both in adf and pp tests, unit root tests were performed from the most general to the least specific model by eliminating trend and intercept across the., ** and ***denotes rejection of the null hypothesis at the 10%, 5% and 1% level*

3.2 Empirical Results

Table 5 shows the results of GARCH-M model estimations (equation (3) and (4)) for daily data during the first and second time periods. As the results show for the 1st period the coefficient of θ is negative, but it is statically insignificant. So according to these results during 01/2007 to 02/2010, daily return volatility of computer industry didn't affect the return. However, based on the results for the 2nd period the coefficient of θ is negative and statically significant at 1% significance level. So according to the results in Table 5 for the Computer Industry stocks in TEX the negative effect of daily return volatility on the daily return cannot be rejected during 02/2010 to 10/2013.

Table 5. Estimated GARCH-M model (Daily)

	1st period			*2nd period*		
	Coefficient	**Std. Error**	**Z-Statistic**	**Coefficient**	**Std. Error**	**Z-Statistic**
α	0.000295	0.001476	0.200165	0.009212	0.003053	3.017391***
β_1	0.053287	0.145249	0.366867	0.440466	0.032187	13.68470***
θ	-0.147219	7.808966	-0.018853	-39.19764	15.02311	-2.609157***
γ_0	0.000190	7.04E-07	269.6408***	0.000205	1.06E-07	1942.690***
δ_1	0.073894	4.61E-05	1604.328***	0.074584	0.000103	722.4282***
γ_1	-0.014024	0.000245	-57.16334***	-0.097886	0.000248	-394.4053***

1st period Sample: 01/2007-02/2010. 2nd period Sample: 02/2010-10/2013.
**, ** and ***denotes the significance level at the 10%, 5% and 1%*

Table 6 provides the results of GARCH-M model estimations (equation (3) and (4)) for weekly data during the time periods before and after Feb 2010. As can see in both periods the coefficients of θ are negative, but statically insignificant. So according to GARCH-M model estimations for the Computer Industry stocks in TEX for the weekly data the return volatility does not affect the return neither before Feb 2010 period nor after that time.

Table 6. Estimated GARCH-M model (Weekly)

	1st period			*2nd period*		
	Coefficient	**Std. Error**	**Z-Statistic**	**Coefficient**	**Std. Error**	**Z-Statistic**
α	0.147671	3.311945	0.044587	1.836847	1.562932	1.175257
β_1	0.313330	0.739936	0.423456	0.098449	0.151661	0.649141
θ	-0.005988	0.293124	-0.020430	-0.064570	0.104212	-0.619600
γ_0	3.300973	0.059598	55.38709***	3.416812	0.067874	50.34034***
δ_1	0.051954	7.66E-05	677.8731***	0.054204	0.000252	215.3893***
γ_1	0.701565	0.003808	184.2147***	0.690397	0.004769	144.7536***

1st period Sample: 01/2007-02/2010. 2nd period Sample: 02/2010-10/2013.
**, ** and ***denotes the significance level at the 10%, 5% and 1%*

Table 7 shows the results of TGARCH model estimations (equations (5) and (6)) for daily data during the two different time periods before and after Feb 2010. For the 1st period, because the coefficient of υ_i term is positive and statically significant, that indeed for the daily data of Computer Industry stocks in TEX before Feb 2010 there are asymmetries in the news. Specifically bad news has larger effects on the volatility of the series than good news. Because $\upsilon_i \succ 0$, bad news increases volatility, and there is a leverage effect for the first order. On the other hand for the 2nd period, the coefficient of υ_i term is negative and statically significant, which indicate that for the daily data of Computer Industry stocks in TEX after Feb 2010 there is asymmetries in the news, but bad news has smaller effects on the volatility of the series than good news.

Table 7. Estimated TGARCH model (Daily)

	1st period			*2nd period*		
	Coefficient	**Std. Error**	**Z-Statistic**	**Coefficient**	**Std. Error**	**Z-Statistic**
α	0.000249	0.000471	0.528934	0.001581	0.000605	2.613399***
β_1	0.062990	0.058872	1.069945	0.317282	0.020585	15.41352***
γ_0	0.000193	6.56E-07	293.6441***	0.000204	9.61E-08	2125.802***
γ_1	0.073305	8.54E-05	858.3018***	0.074639	5.42E-05	1378.129***
υ_1	0.001257	0.000217	5.783719***	-0.002938	0.000151	-19.41072***
δ_1	-0.028755	0.000217	-132.5607***	-0.092639	0.000302	-307.0557***

1st period Sample: 01/2007-02/2010. 2nd period Sample: 02/2010-10/2013.
**, ** and ***denotes the significance level at the 10%, 5% and 1%*

Table 8 provides the results of TGARCH model estimations (equations (5) and (6)) for weekly data during the two different time periods before and after Feb 2010. For the 1st period, the results provided in Table 8 like the results in Table 7 the coefficient of υ_i term is positive and statically significant, so for the weekly data of Computer Industry stocks in TEX before Feb 2010 there are asymmetries in the news and bad news has larger effects on the volatility of the series than good news. Furthermore, because $\upsilon_i \succ 0$, bad news increases volatility, and there is a leverage effect for the first order. In addition, for the 2nd period the results provided in Table 8 as results in Table 7 show the coefficient of υ_i term is negative and statically significant, which indicate that for the weekly data of Computer Industry stocks in TEX after Feb 2010 there is asymmetries in the news and bad news has smaller effects on the volatility of the series than good news.

Table 8. Estimated TGARCH model (Weekly)

	1st period			*2nd period*		
	Coefficient	**Std. Error**	**Z-Statistic**	**Coefficient**	**Std. Error**	**Z-Statistic**
α	0.092694	0.302936	0.305987	0.958491	0.340678	2.813482***
β_1	0.043417	0.360088	0.120574	0.083486	0.082596	1.010769
γ_0	3.306428	0.013285	248.8926***	3.333125	0.037539	88.79127***
γ_1	0.049644	7.14E-05	695.5413***	0.056486	0.000111	508.8882***
υ_1	0.004541	0.000113	40.20203***	-0.009092	0.000209	-43.44322***
δ_1	0.701311	0.000697	1006.335***	0.698200	0.002619	266.6272***

1st period Sample: 01/2007-02/2010. 2nd period Sample: 02/2010-10/2013.
**, ** and ***denotes the significance level at the 10%, 5% and 1%*

Table 9 represents the results of EGARCH model estimations (equations (7) and (8)) for the daily data during the first time period and second time period. For the 1st period, because the coefficient of ξ_1 is negative and statically significant at 5% level, that indeed for the daily data of Computer Industry stocks in TEX before Feb 2010 bad news has larger effect on the volatility of the series than good news. In other words, the impact is asymmetric and the existence of leverage effect cannot be rejected. On the other hand, for the 2nd period the coefficient of ξ_1 is positive and statically significant at 1% level. That means the impact is asymmetric, but unlike the first period, in the second period bad news has smaller effect on the volatility of the series than good news.

Table 9. Estimated EGARCH model (Daily)

	1st period			*2nd period*		
	Coefficient	**Std. Error**	**Z-Statistic**	**Coefficient**	**Std. Error**	**Z-Statistic**
α	0.000248	0.000473	0.525383	0.001600	0.000602	2.657578***
β_1	0.068804	0.069020	0.996875	0.310788	0.023930	12.98715***
γ	-10.10642	0.023462	-430.7549***	-9.117968	0.019933	-457.4389***
ς_1	0.190417	0.003418	55.70442***	0.162912	0.001832	88.92862***
ξ_1	-0.006301	0.002489	-2.531654**	0.016077	0.001443	11.14036***
δ_1	-0.175562	0.003304	-53.13301***	-0.056970	0.002397	-23.77177***

1st period Sample: 01/2007-02/2010. 2nd period Sample: 02/2010-10/2013.
**, ** and ***denotes the significance level at the 10%, 5% and 1%*

Table 10 shows the results of EGARCH model estimations (equations (7) and (8)) for the weekly data during the first time period and the second time period. For the 1st period like what we saw in Table 9 the coefficient of ξ_1 is negative and statically significant which means for the weekly data of Computer Industry stocks in TEX before Feb 2010 the impact is asymmetric and bad news has larger effect on the volatility of the series than good news. In other words, the existence of leverage effect cannot be rejected. On the other hand for the 2nd period, like the results in Table 9, in Table 10 the coefficient of ξ_1 is positive and statically significant at 1% level which means that for weekly data of Computer Industry stocks in TEX after Feb 2010 the impact is asymmetric and unlike the results presented in the first period, in the second period bad news has smaller effect on the volatility of the series than good news.

Table 10. Estimated EGARCH model (Weekly)

	1st period			*2nd period*		
	Coefficient	**Std. Error**	**Z-Statistic**	**Coefficient**	**Std. Error**	**Z-Statistic**
α	0.091831	0.328598	0.279462	0.939630	0.338056	2.779511***
β_1	0.054423	0.475829	0.114375	0.101092	0.074896	1.349759
γ	0.518380	0.033723	15.37160***	0.488152	0.034874	13.99747***
ς_1	0.163160	0.002054	79.44476***	0.122399	0.003258	37.56365***
ξ_1	-0.006483	0.001739	-3.727521***	0.018487	0.001147	16.11911***
δ_1	0.773972	0.012769	60.61516***	0.777061	0.013450	57.77420***

1st period Sample: 01/2007-02/2010. 2nd period Sample: 02/2010-10/2013.
**, ** and ***denotes the significance level at the 10%, 5% and 1%.*

4. CONCLUSION

In this article we applied GARCH models and estimated them by FIML method to investigate leverage and volatility feedback effects of computer industry in TEX. The figures show that return and return volatility were less volatile before Feb 2010, but much more volatile after that month. Also ZA unit root test suggests time breaks for the series in Feb 2010. So we provided different estimations for each of the two different periods before and after Feb 2010.

According to results of GARCH-M model estimations during 01/2007 - 02/2010 (the 1st period), daily return volatility of computer industry didn't affect the return, but during 02/2010 to 10/2013. (the 2nd period) daily return volatility affected the return negatively and significantly. However, based on the results of GARCH-M model, weekly return volatility affected the return neither in the 1st period nor in the 2nd period. So according to these results the first hypothesis of the research (Return volatility of computer industry in TEX affects the return significantly) cannot be rejected for daily data during the 2nd period which both return and return volatility were much more volatile rather than the 1st period. Based on the results of GARCH-M estimations this hypothesis rejected for daily data in the 1st period and weekly data in both periods.

The results of EGARCH and TGARCH confirm asymmetries in the news for both daily and weekly return volatility in both periods. For both daily and weekly data, the results of EGARCH and TGARCH show that in the 1st period bad news has larger effects on the volatility of the series than good news, but in the 2nd period bad news has smaller effect on the volatility of the series than good news. So according to these results the second main hypothesis of the research (a negative return makes return volatility of computer industry in TEX more volatile) cannot be rejected for both daily and weekly data in the 1st period, but rejected for both data during the 2nd period.

ACKNOWLEDGEMENTS

The authors thank two anonymous referees for helpful comments that greatly improved the article.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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