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# Abrupt Changes in Volatility: Evidence from TEPIX Index in Tehran Stock Exchange

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**Abstract**

In this paper, we have examined abrupt changes in volatility of TEPIX index in Tehran stock exchange during August 23, 2010 to June 12, 2014. Applying the iterated cumulative sum of squares (ICSS) algorithm proposed by Inclan and Tiao (1994) and the modified version of this algorithm consisting Kappa 1 and Kappa 2 test statistics developed by Sansó et al. (2004), we have specified that the detection of abrupt changes are mainly explained by local economic and political factors and probably they are behind those changes. This finding is in line with that of Aggarwal et al. (1999) who discovered that country-specific factors play a key role in determining those sudden shifts in financial markets. In addition, the results of this study ratify the findings of the previous ones suggesting that, when the abrupt changes are embedded into standard GARCH models, the estimated persistence of volatility is decreased significantly.

**Keywords:** stock return volatility; volatility persistence; ICSS algorithm; GARCH models.
**JEL classification:** C22, C52, C58, G01.

## 1. Introduction

The question about the factors that have a significant role in the dynamics of volatility has always motivated many researchers in the field of finance with objectives to assure economic stability and to get higher rates of return for investors by portfolio diversification. Accordingly, a large literature has been created in the last few decades focused on studying volatility from different aspects. Discovering the manner of volatility is vital for different aspects of financial markets, for example, pricing of financial assets, exercising hedging strategies, and offering efficient regulatory proposals.

Generally, the time-varying properties of the volatility of financial time

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series have long been modeled by GARCH models (see Bollerslev et al., 1992).The GARCH approach usually presumes that there is no shift in volatility. However, in reality, there may potentially be abrupt shifts in volatility. It is, therefore, vital to take account of these shifts in estimating volatility persistence.

Moreover, looking into the financial literature, we found the existence of high volatility persistence in high frequency financial time series data that use GARCH type of models. This persistent specification is a critical element in risk management of asset, formation of investment portfolios, and pricing of derivatives in financial markets, since its existence is tightly associated with the predictability of volatility.

Indeed, the volatility is considered highly persistent if a shock to a given system has a lasting effect and the past volatility can be applied in creating forecasts of expected volatility. Actually, the volatility of financial time series can be affected significantly by rare abrupt changes or regime shifts, related to local and/or global economic and political events. Therefore, another field of research in this context has affirmed the importance of abrupt shifts in volatility and its implication for estimating volatility persistence and has exerted diverse methods to cope with it. Some of the seminal works, which have been conducted in this context, are mentioned below.

Porteba and Summers (1988) have debated that, in assets like stocks, shocks should last for a long period. In fact, if changes of volatility are only transitory, no substantial adjustments to the risk premium will be conducted by the market, and therefore, no significant alterations in the discount factor or in the price of a stock will occur.

Lastrapes (1989), for example, used the ARCH model for exchange rates and discovered that there is a substantial reduction in the estimated persistence of volatility if the controls for monetary regime shifts are introduced in the standard ARCH model. While those monetary regime shifts exogenously specified, Hamilton and Susmel (1994) and Cai (1994) applied a Markov Switching-ARCH model (or SWARCH) and specified the structural changes in the financial time series endogenously. Inclan and Tiao (1994) conducted one of the notable works in this area. They developed an algorithm (so called the iterated cumulative sums of squares (ICSS)) to endogenously detect the time points of these abrupt changes in volatility.

However, in spite of the capability of Inclan and Tiao (1994) method to identify sudden changes in volatility, there are some limitations to it that can potentially influence the accuracy of estimated parameters. Indeed, the ICSS algorithm is usually planned under the assumption that the data in financial markets figures out a Gaussian distribution, and it can create several spurious change points if this assumption violated. As Ross (2013) demonstrates in his study, using the ICSS for heavy-tailed time series can lead to poor results, since extreme observations incorrectly interpreted as being volatility regime shifts.

Therefore, in this paper, besides applying the ICSS algorithm of Inclan and Tiao (1994) to detect the change points in volatility, we have tried using an alternative method that can handle those mentioned limitations. Thus, we applied the modified ICSS algorithm developed by Sansó et al. (2004) and compared the obtained results with the previous method.

The remainder of this paper is organized as follows. After the introduction, section 2 presents review of the previous literature. Section 3 describes the financial data applied in this study. Section 4 presents the methodology for the initial and modified ICSS algorithm and the GARCH models. Section 5 discusses the empirical findings of the study and the final section, section 6, provides the concluding remarks.

## 2. Literature Review

Aggarwal et al. (1999) examine the significant abrupt shifts in the volatility of 11 emerging (in addition of UK, US, Germany, Singapore, and Hong Kong) stock markets. They apply the weekly data from 1985 to 1995. Their study demonstrates that the local and country-specific factors have a leading role in sudden changes.

Hammoudeh and Li (2008) investigate sudden changes in volatility in the Gulf Arab stock markets by applying the iterated cumulative sums of squares (ICSS) algorithm proposed by Inclan and Tiao (1994). In addition, their study conducts the impacts of those sudden changes on the estimated persistence of volatility. Their analysis shows large shifts in volatility of stock markets in the weekly data for the period of 1994 to 2001. The results of their study specify that most of the Gulf Arab markets represent higher degree of sensitivity to significant global events than to local ones. Their finding is in contrast with Aggarwal et al. (1999) analysis. For example, they mention that some events, such as the 1997 Asian crisis, collapse of oil prices in 1998 after the crisis, compliance of the price range mechanism by OPEC in 2000, and the September 11 terrorist attacks, consistently affected the countries of their study. Finally, the paper insists that incorporating those large shifts in volatility models substantially decreases the estimated persistence of volatility in Gulf Arab stock markets.

Wang and Moore (2009) examine sudden changes in volatility in five Central European stock markets. They apply the ICSS algorithm for detecting the changes and use the weekly data over the period 1994 to 2006. Their study suggests that sudden changes in volatility seem to arise from the transition of emerging stock markets, changes in exchange rate policy, and financial disasters. Moreover, based on their finding, when abrupt shifts are considered in the GARCH models, the volatility persistence is substantially decreased in every series. They propose that many previous analyses may have overestimated the degree of volatility persistence in financial markets.

Kang et al. (2009) model the sudden volatility changes in two Asian countries (Japan and South Korea) stock markets during 1986 to 2008. Applying the ICSS algorithm of Inclan and Tiao (1994), they specify that the detection of sudden changes is generally connected to global financial and political events. They also show that effectively governing abrupt changes decreases the persistence of volatility and that incorporating information concerning sudden changes in variance improves the precision of volatility's estimation.

Ewing and Malik (2010) estimate persistence of volatility in oil prices under structural breaks. They compute the persistence of volatility by introducing the endogenously specified structural breaks into a GARCH model. They claim that, in contrast with previous studies, oil shocks disappear very soon but possess a firm initial impact.

Todea and Petrescu (2012) investigate sudden changes in volatility in five investment companies in Romania by applying the ICSS algorithm suggested by Inclan and Tiao (1994). Their findings demonstrate that the events causing unanticipated changes in variance are mainly local ones; the only important global event with negative effect on the volatility regime is the evolution of foreign markets in 2008-2009, following the global financial crisis. In relation to volatility persistence, they find that when the dummy variables dependent on the events that have led to abrupt changes in volatility are incorporated in the GARCH model, the false long memory effect is gone.

As mentioned earlier in introduction, applying the ICSS algorithm in financial data has some sort of limitations. Therefore, in recent years, some alternative methods have been proposed to dominate the limitations in previous techniques. As discussed, one of the novel ideas in this context is applying the modified ICSS algorithm developed by Sansó et al. (2004) to identify change points in volatility. Hence, as follows, we refer to some of studies that have used this new method in their analysis.

Fang et al. (2008) examine the output growth volatility in a cross-country analysis using the nonstationary variance and GARCH models. They have applied the modified ICSS algorithm to identify structural changes in the variance of output growth. According to their findings, the time-varying variance decrease rapidly in Canada and Japan and vanishes completely in Germany, Italy, the UK, and the US as soon as they insert the break in the variance equation of output for the six countries. That is, if researchers overlook a nonstationary variance, the integrated GARCH (IGARCH) effect asserts spurious and the GARCH model shows misspecification.

Karoglou (2010) performs a study on the stock market indices of 27 OECD countries for the period from 1994 to 2006. He examines the hypothesis that abnormal behavior may occur due to joint existence of structural breaks and ARCH effects in the time series data. He then uses multiple econometric tests to identify the abrupt changes in variance. These tests consist of ICSS algorithm of Inclan and Tiao (1994), Kappa tests of Sansó et al. (2004), and Kokoszka and Leipus (2000) type of tests refined by Andreou and Ghysels (2002). In addition, the daily closing values of the stock market indices are applied in the study. Finally, he concludes that when structural breaks are considered, the high persistence of volatility is alleviated and asymmetric effects and risk aversion occurs only provisionally.

Výrost et al. (2011) investigate the relationship of persistence and number of breaks in three Central and Eastern European countries (CEE). They follow the previous works, especially the work of Wang and Moore (2009), who studied stock market returns in five Central and Eastern European countries by applying Iterated Cumulative Sum of Squares (ICSS) algorithm proposed by Inclan and Tiao (1994). Indeed, they complete the previous studies by implementing a modified ICSS algorithm introduced by Sansó et al. (2004). Their results show that the overall reduction in persistence is related both to the number of breaks and to their position, as proposed by the selected break detection tests.

Kumar and Maheswaran (2013) compare the performance of Inclan and Tiao (1994) and Sansó et al. (2004) algorithms. In addition, they examine the effect of regime shifts on the asymmetry and persistence of volatility from the advantage point of modelling volatility in general and, in particular, in evaluating the forecasting capability of the GARCH models in the context of the Indian stock market.

Ross (2013) tries to model financial volatility in the presence of abrupt changes. He proposes a new method that applies concepts from nonparametric statistics to detect structural break points without making such distributional assumptions. Then, he models drift separately through each detected regime. He calls this new approach as Nonparametric Change Point Model (NPCPM). Then, he examines the volatility of various major stock indices and discovers that his technique can potentially exhibit an improved fit compared to the methods that are more popular.

Charles and Darné (2014) examine the volatility persistence in crude oil markets. Their study evaluates the effect of structural changes and outliers on persistency of volatility of three crude oil markets- Brent, West Texas Intermediate (WTI), and Organization of Petroleum Exporting Countries (OPEC) - for the period of January 2, 1985 to June 17, 2010. At the first step, they detect the time points at which structural changes took placed by applying the modified ICSS test introduced by Sansó et al. (2004). Next, they embed this information into the model. Their results represent that the degree of volatility persistence is decreased by applying the changes of variance into the volatility model. Moreover, they find that the crude oil markets are more affected by outliers than by variance changes. They also demonstrate that outliers may bias the estimation of the persistence of the volatility.

## 3. Data and Descriptive Statistics

The dataset consists the daily prices of the TEPIX index in Tehran stock exchange. The data covers the period of August 23, 2010 to June 12, 2014. The daily return of stock exchange index is computed by logarithmic subtraction of prices over the period.

$$r_t = \ln\left(\frac{p_t}{p_{t-1}}\right) = \ln p_t - \ln p_{t-1}. \tag{1}$$

**Table 1. Descriptive statistics of daily return for the TSE index**

| Number of observation | 909 |
|---|---|
| Mean | 0.165 |
| Median | 0.106 |
| Maximum | 3.500 |
| Minimum | -2.721 |
| Std. Dev. | 0.823 |
| Skewness | 0.150 |
| Jarque-Bera | 22.360* |
| Q (8) | 182.06** |
| Q(16) | 196.20** |
| $Q^2(8)$ | 122.36** |
| $Q^2(16)$ | 161.05** |

*- Jarque-Bera statistic indicates the normality of return series at 1% significance level.
**- The Ljung-Box Q-statistics represent that there is serial correlation in data.

In addition, Table 2 demonstrates the three different types of unit root test, which consist of Augmented Dickey Fuller (ADF), Kwiatkowski, Philips, Schmidt, and Shin (KPSS), and Philips-Peron (PP). One of the test statistics (KPSS) has a different null hypothesis compared to the two other test. The null hypothesis of KPSS test shows that the data follows a stationary process, while null hypothesis of the ADF and PP tests represent that the time series has a unit root. All of those test statistics reject at the 1% significance level that the time series contains a unit root. Therefore, we can conclude that the data is a stationary process.

**Table 2. Results of unit root tests**

| | |
|---|---|
| ADF* | -20.402 |
| KPSS** | 0.199 |
| PP* | -21.13 |

*- Represents the rejection of existence of unit root at the 1% significance level.

**- The return series are stationary at 1% significance level.

## 4. Methodology

We first identify shifts in volatility with the two types of iterated cumulative sums of squares (ICSS) algorithms. The first one is proposed by Inclan and Tiao (1994) and the second one, which is a modified version of ICSS, is introduced by Sansó et al. (2004). Then, after the breakpoints of variance changes are identified by those methods, the four GARCH models are estimated; one conventional (or standard) and the three other with dummy variables corresponding to the breakpoints as discovered by each algorithm.

### 4.1. Sudden Changes in Volatility and ICSS Algorithm

According to the work of Inclan and Tiao (1994), the ICSS algorithm is utilized to detect segregated changes in the volatility of stock returns. This algorithm presumes that the series of returns illustrate a stationary variance over a preliminary period until an abrupt shock that changes the variance occurs; afterwards, the variance reverts to stationary until next change occurs in the market. This operation repeats over time, creating a time series of observations with an unknown number of shifts in the variance. Let $\{\varepsilon_t\}$ define a series of independent observations with zero mean and variance $\sigma_t^2$. Assume that the variance in each interval is specified by $\sigma_j^2$; $j = 0,1,\dots,N_t$, where $N_t$ is the whole number of changes in variance in T observations and $1 < K_1 < K_2 < \cdots < K_{N_t} < T$ are the set of change points. Therefore, the variance upon the $N_t$ intervals is defined as

$$\sigma_t^2 = \begin{cases} \sigma_0^2, & 1 < t < K_1 \\ \sigma_1^2, & K_1 < t < K_2 \\ \vdots & \\ \sigma_{N_t}^2, & K_{N_t} < t < T. \end{cases} \tag{2}$$

An aggregate sum of squares is applied to estimate the number of shifts in variance and the time point of every variance variation. The sum of the squared observations from the inception of the series to the $k$th time point is exhibited as

$$C_k = \sum_{t=1}^{k} \varepsilon_t^2, \qquad \text{Where } k = 1, \ldots, T \tag{3}$$

Specify the statistic $D_k$ as follows:

$$D_k = \left(\frac{C_k}{C_T}\right) - \frac{k}{T}, \qquad \text{With } D_0 = D_T = 0 \tag{4}$$

in which $C_T$ is the sum of the squared residuals from the entire sample period. If there are no alterations in variance, the $D_k$ statistic will fluctuate around zero and if $D_k$ plotted against k, it will be similar to a horizontal line. If there are abrupt changes in variance in the series, the statistic values go up or down from zero. The critical values, which specify the upper and lower limits for the drifts under the null hypothesis of stationary variance, define the remarkable change in variance of the series. If the maximum of the absolute value of the statistic $D_k$ exceeds the critical value, then the null hypotheses of no abrupt changes are rejected. Let k* be the amount of k at which $\max_k |D_k|$ is achieved, and if $\max_k \sqrt{(T/2)} |D_k|$ exceeds the critical value, then k* is taken as an estimate of the change point. The term $\sqrt{(T/2)}$ is used to standardize the distribution. According to the study of Aggarwal et al. (1999), the critical value of 1.36 is the 95th percentile of the asymptotic distribution of $\max_k \sqrt{(T/2)} |D_k|$. Thus, upper and lower boundaries can be set at ±1.36 in the $D_k$ diagram.

However, if the series contains several change points, the $D_k$ function alone is not enough to identify the breakpoints. Inclan and Tiao (1994), therefore, developed an algorithm that applies the $D_k$ function to seek systematically for change points at different points of the series. The algorithm acts by assessing the $D_k$ function over various periods and those different periods specified by breakpoints, which are detected by the $D_k$ diagram. After the change points have been identified using the ICSS algorithm, the next step is to create the GARCH models without and with abrupt changes in variance. The Inclan and Tiao (1994) statistic is drafted for i.i.d. processes, which is a rare condition for financial data, where there is sign of heteroskedasticity.

Sansó et al. (2004) demonstrate that the size distortions are vital for heteroscedastic variance processes from Monte Carlo simulations. Indeed, Sansó et al. (2004) find size distortions for the ICSS test when the series are leptokurtic as well as conditionally heteroskedastic, which produce spurious changes in the unconditional variance. To overcome these problems, they adjust the test by explicitly considering the fourth moment properties of the disturbances and the conditional heteroskedasticity, using a nonparametric adjustment based on the Bartlett Kernel. Therefore, the method proposed by Sansó et al. (2004) can be considered as an important rival test for detecting abrupt changes in volatility in financial time series. For this reason, we employ it alongside the Inclan and Tiao (1994) statistic to capture breaks in conditional volatility in data in this study.

The similar algorithm applied without changes for $\kappa_1$ and $\kappa_2$ statistics in the method proposed by Sansó et al. (2004):

$$\kappa_1 = sup_k \left| \frac{1}{\sqrt{T}} B_k \right| \tag{5}$$

where

$$B_k = \frac{C_k - \frac{K}{T} C_T}{\sqrt{\hat{\eta}_4 - \hat{\sigma}^4}} \tag{6}$$

and also, $\hat{\eta}_4 = T^{-1} \sum_{t=1}^{T} \varepsilon_t^4 \ \hat{\sigma}^2 = T^{-1} C_T$ for $k \in \{1, 2, \ldots, T\}$

$\kappa_2$ is also calculated by

$$\kappa_2 = sup_k \left| \frac{1}{\sqrt{T}} G_k \right| \tag{7}$$

where

$$G_k = \frac{1}{\sqrt{\hat{\omega}_4}} \left( C_k - \frac{K}{T} C_T \right) \tag{8}$$

Sansó et al. (2004) suggest applying the non-parametric estimator of $\omega_4$ as follows:

$$\hat{\omega}_4 = \frac{1}{T} \sum_{t=1}^{T} \left( \varepsilon_t^2 - \hat{\sigma}_t^2 \right)^2 + \frac{2}{T} \sum_{t=1}^{m} w\,(l, m) \sum_{t=l+1}^{T} \left( \varepsilon_t^2 - \hat{\sigma}^2 \right) \left( \varepsilon_{t-1}^2 - \hat{\sigma}^2 \right) \tag{9}$$

The $w(l, m)$ in Eq (9) is a Bartlet lag window, admitted by $w(l, m) = (1 - l/(m + 1))$ as which $l = (4\sqrt[5]{T/100})$ and the lag truncation parameter (m) generated according to Newey and West (1994) procedure.

### 4.2. *The GARCH Model*

The standard GARCH (1,1) model can be determined for the case without abrupt changes as follows

$$r_t = \mu + \varepsilon_t, \qquad \varepsilon_t \left| I_{t-1} \sim N\left(0, h_t\right), \quad h_t = \omega + \alpha e_{t-1}^2 + \beta h_{t-1} \right. \tag{10}$$

in which $N(\cdot)$ indicates the conditional normal density with zero mean and variance$h_t$. Also, $I_{t-1}$ is the information set available at $t-1$. If the series represent evidence of autocorrelation identified by autocorrelation function or $Q$-statistics, therefore, autoregressive terms may be employed for the mean equation. As noted earlier in the introduction, the standard GARCH model overestimates the persistency of volatility, since relevant abrupt changes in variance are disregarded. This claim is investigated in studies of Lastrapes (1989) and Lamoureux and Lastrapes (1990). Therefore, to attain reliable estimates for the parameters of the model, it is necessary to include regime shifts in the standard GARCH model specified in Eq (10). Then, the modified GARCH model, which embodied these regime shifts in order to represent abrupt changes in volatility, is expressed as

$$r_t = \mu + \varepsilon_t, \qquad \varepsilon_t \left| I_{t-1} \sim N\left(0, h_t\right), \right. \tag{11}$$

$$h_t = \omega + d_1 D_1 + \cdots + d_n D_n + \alpha e_{t-1}^2 + \beta h_{t-1}$$

where $D_1, \cdots, D_n$ are the dummy variables that take the value of one for each point of abrupt change of variance forwards and zero for the otherwise. The persistence of volatility measured by $\alpha + \beta$ is expected to be smaller than that identified by the standard GARCH model.

## 5. Empirical Results

### 5.1. Abrupt Changes in Variance

The ICSS algorithm computes the standard deviations across change points in order to detect the number of abrupt changes in variance. Fig. 1 displays the return series of TEPIX index in Tehran stock exchange in Iran with the spots of abrupt change and with the ± 3 standard deviations based on Inclan and Tiao (1994) approach. In addition, Table 2 demonstrates the time intervals of abrupt changes in volatility recognized by the ICSS algorithm in this approach. The result of Inclan and Tiao (1994) procedure indicates that there are six abrupt change points which corresponding to seven apart volatility structures.

As mentioned earlier, applying the Inclan and Tiao (1994) procedure for financial data may result some deficiencies and distortions in analysis. Therefore, at this part of study, we employ the Sansó et al. (2004) modified algorithm to solve this problem and simultaneously detect sudden changes in volatility. The results of Kappa 1 and 2 of Sansó et al. (2004) test are represented in Table 3. As we can see, the number of detected breaks by Inclan and Tiao (1994) algorithm and Kappa 2 ($k_2$) are similar. Both of them denote that there are six break points in volatility of data. On the other hand, the kappa 1 ($k_1$) test demonstrates that the number of breakpoints are three. Moreover, the change points that captured by Sansó et al. (2004) method are graphed in Figures 2 and 3.

**Table 3. Abrupt changes in volatility**

| Data series | Time period | S.D | Events |
|---|---|---|---|
| TEPIX | August 23, 2010 - October 18, 2010 | 0.927 | |
| | October 19, 2010 - January 2, 2011 | 0.408 | Significant cuts of government subsidies in economy. |
| | January 3, 2011 - July 2, 2011 | 0.941 | Increasing foreign exchange revenues due to rising oil prices. Accelerating the transfer of public enterprises to the private sector. |
| | July 3, 2011- June 6, 2012 | 0.540 | Reform of monetary, credit and supervision policies in the banking system. |
| | June 9, 2012- September 2, 2012 | 0.482 | Multiple increase in exchange rates. Intensification of International trade and financial sanctions due to nuclear issue. |
| | September 3, 2012 - April 26, 2014 | 0.963 | The national currency devalued by a third. Deteriorating of economy and worsening the inflationary conditions. |
| | April 26, 2014 - June 10, 2014 | 0.422 | The stability returned to foreign exchange market. |

***Note*: Time periods are identified by Inclan and Tiao (1994)' ICSS algorithm.**

In the period of October 19, 2010 until January 2, 2011, where the first sudden changes have placed, the government implemented the policy of economic adjustment under the law of targeted subsidies. Because of executing this law, the price of energy, water, and bread increased substantially. For example, the price of gasoline jumped from 1,000 Rials (Iran National currency) before the implementation of the law to the 4,000 Rials, i.e. 300 percent increase in one day.

In the first half of 2011, foreign exchange revenues of government increased substantially, that the main reason for that event was the increase in crude oil prices (about $15 per barrel on average). Moreover, the growth of government spending and increase lending by banks and credit institutions to facilitate economic sectors, leading to the growth of aggregate demand in this period. In addition, entrance of the stocks of companies, which were transferred to the private sector into the stock market, have had a significant impact on the volume of transactions and the value of capital markets.

In the second half of 2011, Central Bank of Iran (CBI), in order to control the inflation rate, notified a package of policies in the form of adjustments and monetary, credit, and supervision in banking system. Based on those policies, some changes placed in the rate differentials in the banking system. For example, the interest rate of (bonds) with the one year maturity, increased to 20% which had a significant role in reducing the of liquidity growth rate.

On June 26, 2012, United States executed some sort of sanctions against Iranian oil industry (in relation to investment and export activities) relevant with nuclear issue. Because of these sanctions, the export of oil from Iran faced substantial reduction. Besides the US sanctions, the EU also implements its own sanctions on Iran oil industry from July 1, 2012. Consequently, the value of Iran’s national currency plunged substantially. Because of these notable shocks to the economy and collapse of national currency’ value at the first half of 2012, the situation of macroeconomic variables, such as economic growth and inflation, deteriorated significantly so that economic growth in 2012, based on information issued by World Bank, had been plunged to (-5.8%) which was unprecedented in 30 years before. Moreover, the inflation rate achieved to 39.3 % at the end of 2013, which is highest point in 20 years.

After the presidential election on June 11, 2013 and establishment of new government at the end of August of the same year, the hope for improvement in situation of macroeconomic indices emerged. Also, with better engagement of Iran with countries that sanctioned the country, required ground for reduction of occurred damages relevant to imposed sanctions, provided. Due to the proper actions took placed by new government, instability abated substantially in foreign exchange market and the inflation continued to its downward trend. Based on the information that issued by CBI, the point to point inflation reached to 14.7% at the March of 2014 which is a low level for the past 2 years.

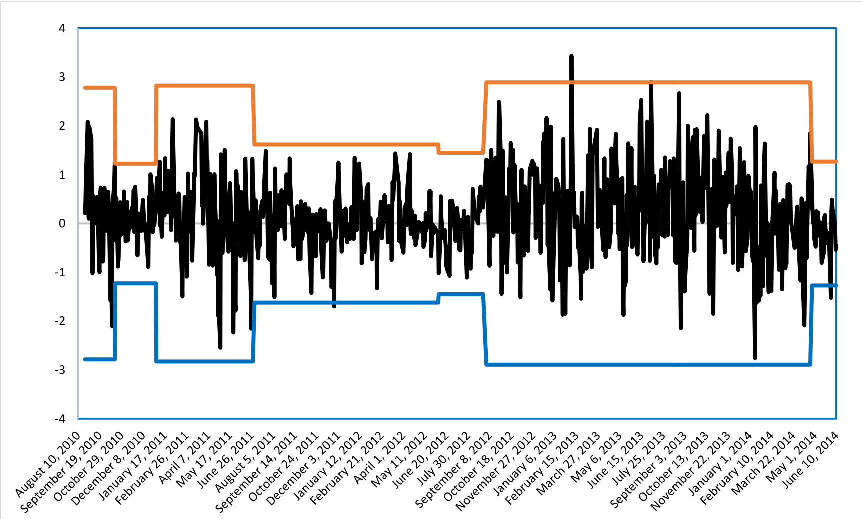


**Fig. 1. Daily returns for TEPIX equity index in Tehran stock exchange and regime shifts in volatility. The period is from August 23, 2010 until June 10, 2014. Regime shifts in volatility are detected by Inclan and Tiao (1994) ICSS algorithm. The lines depicted in chart demonstrate the ± 3 standard deviation during each regime.**

As it is clear in Figure 1, the return series segregated to seven different regime by six sudden change points in volatility which captured by ICSS algorithm. In addition, the period of some regimes are longer than the other regimes. Moreover, in the whole span of data, we can see that the standard division in most of the shift regimes are close to each other.

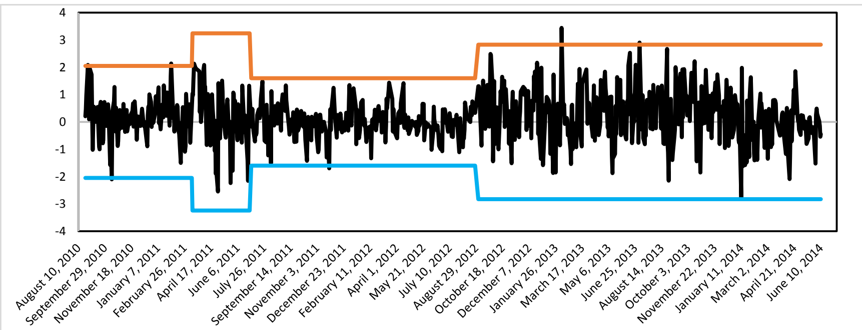


**Fig 2. Daily returns for TEPIX equity index in Tehran stock exchange and regime shifts in volatility. The period is from August 23, 2010 until June 10, 2014. Regime shifts in volatility are detected by kappa 2 ($k_2$) test of Sansó et al. (2004)' ICSS modified algorithm. The lines depicted in chart demonstrate the ± 3 standard deviation during each regime.**

The results of applying the modified ICSS algorithm developed by Sansó et al. (2004) are depicted in Figures 2 and 3. Two different test statistics that include Kappa 1 and Kappa 2 are used to detect the abrupt changes in volatility of return series. The results of Kappa 2 ($k_2$) test indicate that there are four different period about volatility which identified by three sudden changes points.

However, the other test statistics (Kappa 1 ($k_1$)) represented that, similar to the ICSS algorithm of Inclan and Tiao (1994), there are six abrupt changes in volatility, which caused to creation of seven different shift regimes.

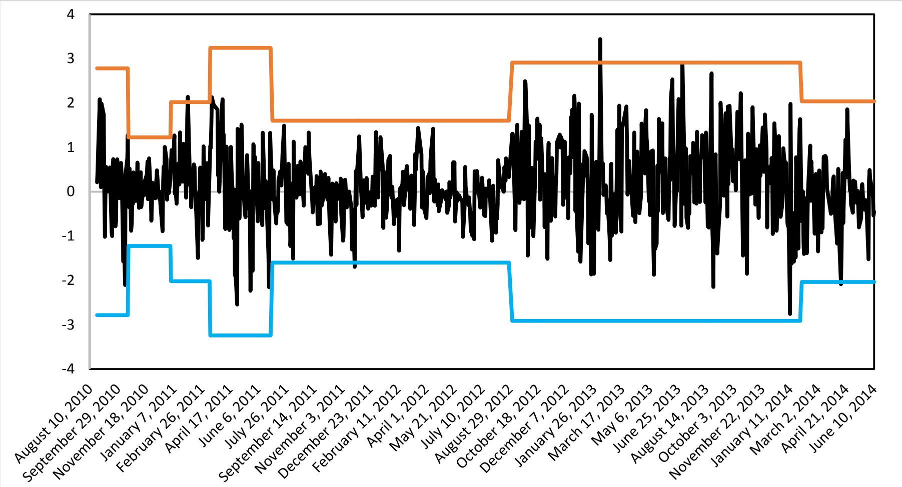


**Fig 3. Daily returns for TEPIX equity index in Tehran stock exchange and regime shifts in volatility. The period is from August 23, 2010 until June 10, 2014. Regime shifts in volatility are detected by kappa 1 ($k_1$) test of Sansó et al. (2004)' ICSS modified algorithm. The lines depicted in chart demonstrate the ± 3 standard deviation during each regime.**

To examine the persistency of volatility, we should estimate the value of $\alpha + \beta$ . The results of those estimates are demonstrated in Table 4. As it is clear, the value of persistency for the standard GARCH model is close to 0.8, which indicates that abrupt changes in volatility have permanent effect.

But, when we compare this result with three different models (the GARCH model with dummy variables detected by Inclan and Tiao (1994) method and the two GARCH models with dummy variables detected by kappa 1 ($k_1$) and kappa 2 ($k_2$) test statistics of Sansó et al. (2004) modified algorithm), we can figure out that the results are obviously distinct from each other. It is clear that, when we incorporate the sudden changes as the dummy variables to the models, the estimated persistence of volatility decreases substantially. In addition, as we can see, most of the parameters are statistically significant at 1% level.

**Table 4. Estimations of volatility model**

| | *Standard GARCH* | *ICSS (Inclan and Tiao)* | *mICSS*** ($\mathbf{k_1}$) | *mICSS*** ($\mathbf{k_2}$) |
|---|---|---|---|---|
| Number of breaks | – | 6 | 3 | 6 |
| $\alpha$ | 0.310* | 0.255* | 0.018 | 0.194* |
| $\beta$ | 0.473* | 0.346* | 0.386* | 0.289* |
| $\alpha+\beta$ | 0.783 | 0.601 | 0.404 | 0.483 |

*- The coefficients are significant at one percent level.

**- The *mICSS* refers to the modified ICSS algorithm developed by Sansó et al. (2004).

## 6. Conclusion

In this paper, we have examined the abrupt changes of volatility and tried to estimate the volatility persistence for the TEPIX index in Tehran stock exchanges during the period of August 23, 2010 to June 12, 2014. The ICSS algorithm proposed by Inclan and Tiao (1994) and the modified version of that method developed by Sansó et al. (2004) have been applied in this study for the detection of sudden changes in volatility. Then, we have tried to incorporate the achieved information from the mentioned algorithms to the GARCH models.

The findings of this paper indicate that abrupt changes in volatility are mainly explained by local economic and political factors and probably they are behind of those changes. One of the main reasons of this phenomenon is that the Tehran stock market is largely independent of other international financial markets. In addition, this finding is in line with that of Aggarwal et al. (1999) who discovered country-specific factors playing a key role in determining those sudden shifts in financial markets.

In addition, the results of this study ratify the findings of the previous ones suggesting that, when the abrupt changes are embedded into standard GARCH models, the estimated persistence of volatility decreased significantly.

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