Hakki Arda Tokat (USA)

# Re-examination of volatility dynamics in Istanbul Stock Exchange


## Abstract

It is well known that ignoring the regime changes in standard GARCH models results in overestimation of volatility persistence. In this study, by applying iterated cumulative sums of squares (ICSS) algorithm on weekly data of ISE 30 and ISE 100 indices, sudden change points in variance are endogenously detected. For ISE 30 index, two sudden changes points associated with three different volatility regimes and for ISE 100 index, six break points and seven distinct volatility regimes are identified. This information is then integrated to a GARCH(1,1) model and it is found that the volatility persistence is not as high as it has been previously shown in the literature. Under the circumstances created by the recent global financial crisis, the results have important implications for financial investors who are interested in understanding the volatility pattern in stock markets. The findings also point to the review of common perception that the volatility in financial markets is highly persistent.


**Keywords:** ISE, volatility, iterated cumulative sums of squares (ICSS), volatility persistence.
**JEL Classification:** G14.

## Introduction

Explaining the variation in stock market prices is a fundamental problem of financial economics. As the stock market volatility represents uncertainty and is taken as the risk component in financial analyses, its explanation is crucial for financial decision making. In this context, modeling the dynamics of the variance of stock returns by an ARCH specification has become very popular since its introduction by Engle (1982) and Bollerslev (1986). The variants of GARCH model have been extensively used in modeling high-frequency financial time series data.

One common implication of conditional variance models is high persistency of shocks to volatility. Determining the volatility persistence is an important step in financial analyses as shown in Poterba and Summers (1986); an increase in expected volatility persistence reduces the current asset prices. In addition to importance of the implication for financial decision making, it is also important for investors to consider whether or not a major event may cause a sudden change in conditional volatility. Given the key role that shocks play in determining the volatility persistence, the detection of changes in volatility regimes is critical in portfolio and risk management.

This paper first detects the time periods of sudden changes in return volatility and then introduces this information as a new parameter into a volatility model to re-examine the volatility persistence in Turkish stock exchange market. The Turkish stock market is a particularly motivating case to study as it holds a number of distinct characteristics. Firstly, it is the largest and one of the most liquid markets in the MENA region (Middle East and North African). Besides its regional dominance, Turkish stock market has been the magnet for foreign investors in the post-2001 crisis period. The Istanbul Stock Exchange (ISE) market hit its historical high at the beginning of 2006 and foreign capital flows have been shown to be the driving force for the accelerated upward movement[1]. Despite its increasing popularity, Turkish stock market has also been characterized by its high volatility component. For example, in the period from 1990 to 2005, Turkey, along with Brazil, has a quite high level of volatility (as measured by standard deviation) in weekly local returns, at 0,071 (Brazil with 0,076). As a comparison, during this time period, Chile and South Africa were among the less volatile emerging markets, with standard deviations of 0,024 and 0,026, respectively[2]. Besides, during the current global financial crisis, the ISE has been one of the most negatively affected exchanges among the emerging markets reflecting its high degree of vulnerability to global financial conditions.

In the light of the highly volatile behavior of ISE, it is important to examine the presence of any sudden changes in variance. Clearly, any finding on the impact of these sudden shifts on measured or estimated volatility persistence would be quite useful information for financial investors as well as policymakers. An accurate assessment of return volatility is critical for implementing international portfolio diversification and hedging strategies and it also assumes significance for proper evaluation of monetary policy changes that aim at managing international capital flows.

It is known that volatility persistence is overestimated when regime shifts are ignored in modeling



[1] IMF, Global Financial Stability Report, April 2006.
[2] These figures are calculated by using the data from Global Financial Database.

conditional volatility (Lastrapes, 1989). Then, the standard GARCH model should be augmented with regime shifts to get reliable parameter estimates of the conditional variance equation (Lamoureux and Lastrapes, 1990). However, most of the studies use models with a pre-specified number of regime shifts. As an alternative to augmented GARCH modeling, dividing the financial time series into sub-periods by determining the potential break points is another approach used in the previous literature. In an analysis of volatility behavior in Istanbul Stock Exchange, Aygören (2006) investigates whether there are regime shifts in volatility by considering the structural breaks and dividing the data set into five sub-periods. Sub-periods are determined exogenously and the important economic and political events, crises that occurred in the sample period are chosen as the structural break points. However, specifying the number of structural breaks is not easy under the conditions of emerging stock markets; each with unique characteristics and is subjected to frequent structural economic, political and social changes. A solution to this problem is to determine the regime shifts endogenously. In this study, the shifts in volatility are detected by using iterated cumulative sums of squares (ICSS) algorithm. The ICSS method permits to detect the number of sudden changes in times series, and also to estimate the time point and the magnitude of each sudden change which could be in both negative and positive direction. As the ICSS algorithm assumes constant variance within a regime, which contradicts with the heteroscedastic behavior of financial data, a modified version of the model, taking care of the conditional heteroscedasticity, is used for the analysis.

Weekly returns of ISE 100 and ISE 30 indices are examined from January 1990 to April 2007. For ISE 30 index, three sudden changes points associated with four different volatility regimes are detected. Owing to longer data span, the examination of ISE 100 index indicates six break points in variance and seven distinct volatility regimes. The standard GARCH model is augmented with a set of control variables to account for sudden changes in variance. The comparison of the results of standard GARCH model and the augmented GARCH model reveals that the volatility persistence is significantly reduced when the regimes shifts are considered in volatility. The results suggest that previous studies on Turkish stock exchange may have significantly overestimated the volatility persistence. Besides, the sudden changes in variance may be overlooked with standard diagnostic tests, which may have serious consequences for financial decision making and risk management. At last, it is believed that the context of this research is very appropriate, since the volatility in stock markets has been a priority for investors and policymakers during the current worldwide financial crisis.

## 1. Methodology and data

The statistical analysis used in this study to test for the persistency of volatility shocks under the presence of regime shifts is conducted as a two-step procedure. In the first step, sudden change points in the variance of stock returns are detected based on ICSS algorithm introduced by Inclan and Tiao (1994). The detected break points indicate the time at which discrete shifts in the variance of stock returns occur. The analysis of events corresponding to the periods of volatility changes is followed by the second step which calculates the volatility persistence in the presence of those breaks.

**1.1. Detection of sudden changes in variance.** Inclan and Tiao's (1994) ICSS (*the iterated cumulative sums of squares*) algorithm focuses on detecting the occurrence of changes in variance in time series due to a sudden shock that changes the variance until a next shock. The method assumes stationary variance of a time series over an initial period of time until disturbed by an exogenous shock, thus resulting in a sudden change in variance. Let $\varepsilon_t$ be a series with zero mean and unconditional variance $\sigma^2_t$. Let the variance within each interval is given by $\tau^2_j$, $j = 0, 1\ldots N_T$, where $N_T$ is the total number of variance changes over $T$ observations, and $1 < \kappa_1 < \kappa_2 < \ldots < \kappa_{NT} < T$ are the corresponding change points,

$$\begin{aligned} \sigma^2_t &= \tau^2_0 \quad 1 < t < \kappa_1 \\ &= \tau^2_1 \quad \kappa_1 < t < \kappa_2 \\ &\ldots \\ &= \tau^2_{NT} \quad \kappa_{NT} < t < N_T. \end{aligned} \tag{1}$$

Denote $C_k$, as the cumulative sum of squared observations from the first observation to the $k^{\text{th}}$ point in time. Define $D_k$ statistic as:

$$D_k = (C_k / C_T) - k/T$$

$$k=1,\ldots, T \text{ with } D_0 = D_T = 0. \tag{2}$$

If the series has constant variance, $D_k$ will look like a horizontal line when plotted against $k$. However, if there is a sudden change in variance, the $D_k$ value will plot as a positive or negative drift away from zero. Significant changes in variance are determined by the critical values obtained from the distribution of $D_k$ under the null hypothesis of no change in variance. If the maximum absolute value of $D_k$ is greater than the critical value, then the null hypothesis of homogeneous variance is rejected. Let $k^*$ is the value at which $\max_k \sqrt{T/2}|D_k|$ is obtained. If the maximum of $\sqrt{T/2}|D_k|$ is larger than the predetermined boundary, then $k^*$ is taken as the time point of a structural break. The factor $\sqrt{T/2}$ standardizes the distribution.

Aggarwal, Inclan and Tiao (1999) use a critical value of 1.36 which is the 95th percentile of the asymptotic distribution of $\max_k \sqrt{T/2}|D_k|$ and set the upper and lower boundaries at ±1.36 in the $D_k$ plot. However, the assumption of constant variance within each regime has to be taken care of as the financial data are known to show conditional heteroscedasticity. I follow Malik (2005) and Sanso, Arago, and Carrion (2004) and use the critical value of 1.4058 which corrects for kurtosis and explicitly accounts for conditional heteroscedasticity. Sanso et al. (2004) obtained this higher critical value by fitting the response surfaces on powers ($p_j$ = 0) of the sample size for a 5% significance level via Monte Carlo simulations. In case of failure to properly adjust the critical values, the null hypothesis will be over-rejected and thus the standard ICSS algorithm is likely to detect more spurious breakpoints on conditionally heteroscedastic data. Sanso et al. (2004) confirm this claim by using Monte Carlo simulations and present examples from real financial data.

Additionally, when the entire series is examined simultaneously, multiple change points are difficult to detect due to the "masking effect". Therefore, Inclan and Tiao (1994) designed an iterative algorithm based on repeated applications of $D_k$ on different segments of the series, dividing consecutively after a change point is identified. After the change points have been detected, the next step analyzes the corresponding events during the periods of change in volatility.

**1.2. ICSS-GARCH combined model.** Since the interest here is to investigate the sudden changes in volatility, I focus on the estimation of a simple but standard GARCH model. The GARCH (1,1) model can be written as

$$R_t = \mu + R_{t-1} + \varepsilon_t, \qquad e_t|I_{t-1} \sim N(0,h_t), \tag{3}$$

$$h_t = \omega + \alpha\varepsilon^2_{t-1} + \beta h_{t-1}, \tag{4}$$

where $R_t$ is the return series, $N$ is the conditional normal density with a zero mean and variance $h_t$ and $I_{t-1}$ is the information set available at time $t$-1.

One of the basic assumptions of standard GARCH models is that the standardized error terms are normally distributed. However, in our estimations, the conditional distribution of error terms did not show this behavior and for this reason, Bollerslev and Wooldridge's (1992) *Quasi Maximum Likelihood* estimation process was used for the estimations[1]. The ICSS algorithm is applied to the residual series ($\varepsilon_t$) obtained from the equation (3). Following the detection of sudden change points in variance by ICSS algorithm, dummy variables are introduced into the variance equation of the GARCH model to account for the shifts in the volatility in stock returns. Then the ICSS-GARCH combined model is given by

$$R_t = \mu + R_{t-1} + \varepsilon_t, \qquad \varepsilon_t|I_{t-1} \sim N(0,h_t), \tag{5}$$

$$h_t = \omega + \sum d_i D_i + \alpha\varepsilon^2_{t-1} + \beta h_{t-1}, \tag{6}$$

$$I = 1,$$

where $D_i$ is the dummy variable taking the value of one from the point of a sudden change in variance onwards and 0 otherwise, and $n$ is the number of volatility regimes as identified by the ICSS procedure. Additionally, an autoregressive process of order one, AR(1), specification for mean equation is used if a series shows significant autocorrelation as detected by the Ljung-Box Q-statistic.

**1.3. Data.** The data consist of daily closing values for the Istanbul Stock Exchange (ISE) 100 and ISE 30 indices. Data cover the 16-year period of January 1990-April 2007[2]. For the analysis, the daily stock market indices are transformed into weekly rates of return based on Wednesday prices. If there was no trading on Wednesday, the stock index value of the last trading day is used. The analysis used weekly rather than daily returns as they have less potential bias due to bid-ask effect, non-trading, etc. Consistent with the literature, the return series are generated as:

$$R_t = \log(P_t) - \log(P_{t-1})),$$

where $P_t$ is the price index.

**1.4. Descriptive statistics.** Table 1 presents descriptive statistics for ISE 30 and ISE 100 weekly return series. Both series are found to be leptokurtic (fat tails) with extra kurtosis. The mean is positive for both series and the standard deviation is higher for ISE 30 return series. The volatility pattern can be observed from the plot of daily returns of each series in Figure 1. Since no significant autocorrelation is detected by Ljung-Box statistics in neither series, the mean equations are modeled without an AR(1) specification.

[1] As the financial series show leptokurtic (fat tail) behavior, conditional normality behavior of standardized error terms is generally rejected. For this reason, robust standard errors were calculated by using the method of Quasi-maximum likelihood estimation which yields unbiased standard errors even if the distribution is not normal (Bollerslev and Wooldridge, 1992).

[2] Series for ISE 30 starts from 01.01.1997.

Table 1. Descriptive statistics for Istanbul Stock Exchange ISE 100 and ISE 30 index returns

| Series | Mean | Std. deviation | Kurtosis | Q (16) | N |
|---|---|---|---|---|---|
| ISE 30 | 0.0071 | 0.069 | 5.75 | 18.66 | 537 |
| ISE 100 | 0.0084 | 0.069 | 5.53 | 14.86 | 903 |

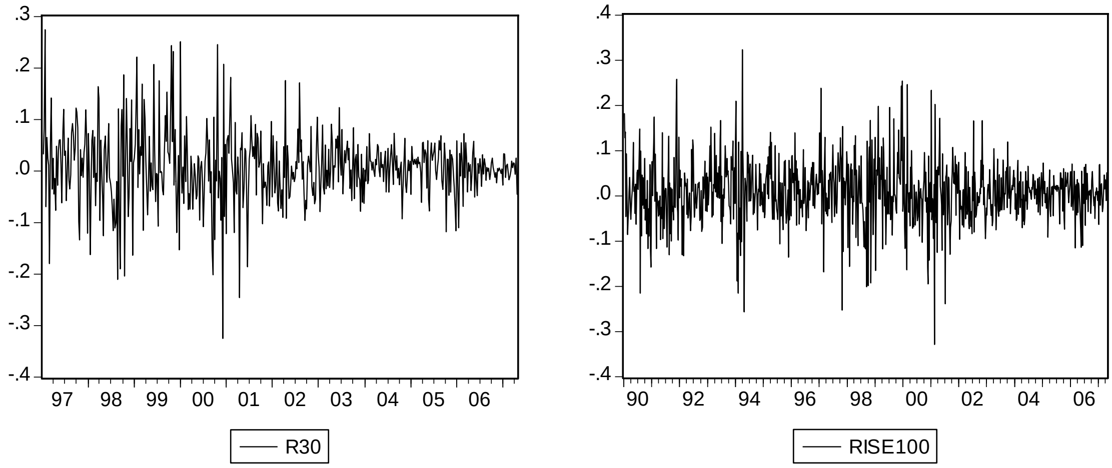



**Fig. 1. Daily returns of ISE 30 and ISE 100 indexes**

## 2. Empirical results

Table 2 reports the number and time of sudden changes in variance detected by the ICSS algorithm. For ISE 30 index, there are two break points and so three different volatility regimes are detected. One interesting point is the decreasing trend in volatility. The break points which are perceived as an improvement and resulted in the decrease in volatility seem to be affected generally by the government's announcements on privatization efforts, introducing of policies empowering the banking system in the aftermath of 2001 financial crisis (July 11$^{th}$, 2001) and the new laws passed as a result of policies followed for EU membership (October 8$^{th}$, 2003).

For ISE 100 index, six break points and seven different volatility regimes are detected, which can be attributed to a larger data set. Again, as a result of reforms and financial liberalization policies (passing of insiders' trading law, etc.) at the beginning of nineties, decreasing trend in volatility is observed (February 26, 1992). While the effects of 1994 crisis are seen in the short lasting third volatility period (SD = 0.143), the government's announcement on the new welfare policy for decreasing budget deficit and fighting with inflation (April 24$^{th}$ announcements) coincides with the break point where the lower volatility period has started (April 27$^{th}$, 1994).

Surprisingly, the only global event that affects Turkish stock market seems to be the 1997 Asian crisis; the break point at which the volatility is climbed to a higher level happens to be at the same time with Asian crisis. Figure 2 graphically shows the break points of conditional variance and related volatility regimes for ISE 30 and ISE 100 indexes. Within the bands of ±3 standard deviation, the start and the end of volatility regimes can be seen clearly.

In sum, it can be stated that the economic and political events referred above and the break points and regime shifts in volatility detected by ICSS algorithm are related to some extent. On the other hand, it should also be considered that the market participants form their expectations in advance and react accordingly. Thus, instead of connecting the detected break points with these events, it makes more sense to conclude that important political changes and financial crises may be a contributing factor in the sudden change of conditional variance. The purpose of this paper is to identify the time periods of sudden changes in volatility rather than inspect the factors causing the sudden changes.

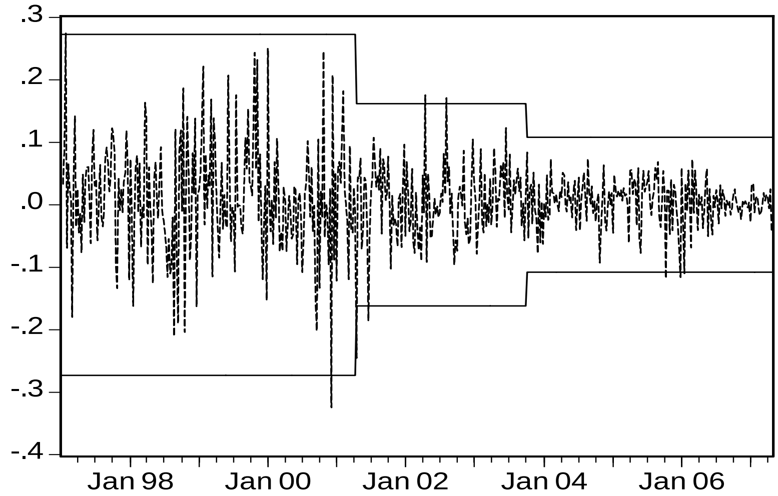
Table 2. Structural break points in volatility

| | # of break points | Period | Standard deviation |
|---|---|---|---|
| ISE 30 | 3 | January 1, 1997 – July 10, 2001 | 0.091 |
| | | July 11, 2001 – October 7, 2003 | 0.054 |
| | | October 8, 2003 – April 25, 2007 | 0.036 |

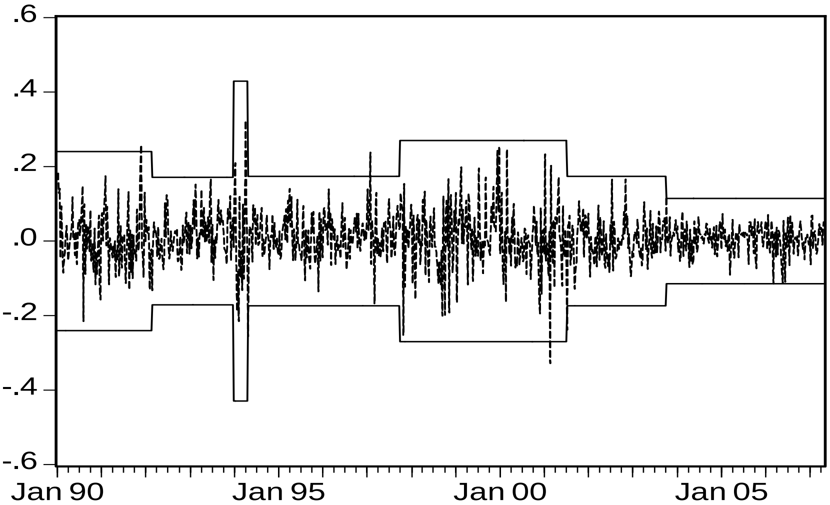
Table 2 (cont.). Structural break points in volatility

| | # of break points | Period | Standard deviation |
|---|---|---|---|
| ISE 100 | 6 | January 3, 1990 – February 25, 1992 | 0.080 |
| | | February 26, 1992 – December 28, 1993 | 0.057 |
| | | December 29, 1993 – April 26, 1994* | 0.143 |
| | | April 27, 1994 – September 30, 1997 | 0.058 |
| | | October 1, 1997 – July 10, 2001* | 0.090 |
| | | July 11, 2001 – October 7, 2003 | 0.058 |
| | | October 8, 2003 – Apri 25,l 2007 | 0.038 |

Note: * period of increasing volatility.




2a. ISE 30




2b. ISE 100

**Fig. 2. Return of ISE 30 and ISE 100 indexes**

The next step after detecting the break points is including these points in the standard GARCH model. First, following Aggarwal, Inclan ve Leal (1999), dummy variables representing the detected break points and controlling the different volatility regimes are added into the variance equation of GARCH(1,1) model. As Lamoureux and Lastrapes (1990b) stated, when regime shifts are taken into consideration, the persistence of estimated volatility shocks are significantly diminishing. To elevate this point, GARCH model without controlling the regime shifts is also estimated and the results are reported in Table 3.

Table 3. GARCH (1,1) models

| Standard GARCH model | | | | | | |
|---|---|---|---|---|---|---|
| | A | β | α + β | Wald test $\chi^2$ | $TR^2$ | Q(16) |
| ISE 30 | 0.08<br>(0.000)<br>[0.019] | 0.915<br>(0.000)<br>[0.018] | 0.995 | 0.52<br>(0.47) | 0.061<br>(0.98) | 0.616 |
| ISE 100 | 0.129<br>(0.000)<br>[0.0018] | 0.847<br>(0.000)<br>[0.031] | 0.976 | 1.97<br>(0.163) | 0.382<br>(0.764) | 0.206 |
| ICSS - GARCH combined model | | | | | | |
| | A | β | α + β | Wald Test $\chi^2$ | $TR^2$ | Q(16) |
| ISE 30 | 0.025<br>(0.25)<br>[0.022] | 0.85<br>(0.000)<br>[0.07] | 0.875 | 3.38<br>(0.07) | 0.046<br>(0.986) | 0.735 |
| ISE 100 | 0.047<br>(0.07)<br>[0.027] | 0.56<br>(0.000)<br>[0.099] | 0.67 | 16.18<br>(0.000) | 0.139<br>(0.96) | 0.366 |

Notes: The values in the parentheses show p-values, in brackets show standard deviations. Q (16) is the Ljung-Box statistic and $TR^2$ is an ARCH-LM test. Wald Test tests the hypothesis that $\alpha + \beta = 1$.

For the two different indexes, standardized residuals of the two different GARCH models (controlled and uncontrolled regimes) are investigated by ARCH-LM and Ljung-Box test and the results show that there is no problem with the model performance. The interesting point here is that the success of the standard GARCH model might lead the researcher to ignore the regime changes in variances. If the regime changes matter in effecting volatility persistence, then overlooking the sudden changes will be a problem. When estimated results in Table 3 are examined, it is clear that the regime changes do affect the volatility persistence. When the regime changes are considered, the persistence of shocks (the sum of estimated ARCH and GARCH parameters, $\alpha + \beta$) is significantly diminishing for both ISE 30 and ISE 100.

As the results suggest, ignoring the regime changes in the presence of sudden changes can lead to biased and invalid results on the degree of volatility persistence that exits in stock returns. Therefore, it is vital to test the break points in volatility and if there are any, to control them.

## Conclusion

In this study, the time of the sudden changes in volatility in the Istanbul Stock Exchange over the January 1990-April 2007 period is detected and this information is utilized for GARCH modeling of volatility. Although it is known that accounting for regime shifts in conditional volatility reduces the degree of volatility persistence, the way the regime changes are identified is of special importance. Unlike the most previous research on GARCH modeling, the regime shifts are not introduced to the model exogenously but are determined from the data by using ICSS algorithm. Endogenously determined regime shifts are incorporated to the GARCH model and the effect of shocks on volatility persistence is re-examined. As parallel to previous studies (Aggarwal, Inclan ve Leal, 1999; Lamoureux ve Lastrapes, 1990a), it is found that the volatility persistence is significantly reduced when the regime shifts are considered in modeling volatility.

The markets are open to economic and political events and these events may cause sudden changes and regime shifts in financial time series. From this perspective, it is important to cautiously interpret the previous studies showing the high volatility persistence of stock returns. As it is shown in this study, controlling the possible regime changes in conditional variance and use of this information in modeling volatility improve the accuracy of estimations. This approach is believed to be very useful for financial professionals as well as researchers for their portfolio allocations.

## References

1. Aggarwal R., Inclan C., R. Leal. Volatility in Emerging Stock Markets // Journal of Financial and Quantitative Analysis, 1999. – №34. – pp. 33-55.
2. Aygören H. An Empirical Analysis of Volatility Behavior for Istanbul Stock Exchange // Iktisat, Isletme ve Finans, 2006. – № Dec. 2006. – pp. 95-110.
3. Bollerslev T. Generalized autoregressive conditional heteroscedasticity // Journal of Econometrics, 1986. – №31. – pp. 307-27.

4. Cai A. Markov model of switching-regime ARCH // Journal of Business and Economic Statistics, 1994. – №12. – pp. 309-316.
5. Engle R.F. Autoregressive Conditional Heteroskedasticity with estimates of the Variance of UK Inflation // Econometrica, 1982. – №50. – pp. 987-1008.
6. Hamilton J.D., R. Susmel. Autoregressive conditional heteroskedasticity and changes in regime // Journal of Econometrics, 1994. – №64. – pp. 307-333.
7. Inclan C., G.C. Tiao. Use of Cumulative Sums of Squares for Retrospective Detection of Changes of Variance // Journal of the American Statistical Association, 1994. – №89. – pp. 913-923.
8. Lastrapes W. Exchange rate volatility and U.S. monetary policy: an ARCH application // Journal of Money, Credit and Banking, 1989. – №21. – pp. 66-77.
9. Lamoureux C., W. Lastrapes. Persistence in variance, structural change and the GARCH model // Journal of Business & Economic Statistics, 1990a. – №8. – pp. 225-234.
10. Lamoureux C., W. Lastrapes. Heteroskedasticity in Stock Return Data: Volume versus GARCH Effects // Journal of Finance, 1990b. – №45. – pp. 221-229.
11. Lunde A., P.R. Hansen. A forecast comparison of volatility models: does anything beat a GARCH(1,1)? // Journal of Applied Econometrics, 2005. – №20.7. – pp. 873-889.
12. Pagan A. The Econometrics of Financial Markets // Journal of Empirical Finance, 1996. – №3. – pp. 15-102.
13. Pagan A., G. Schwert. Alternative Models for Conditional Stock Volatility // Journal of Econometrics, 1990. – №.45. – pp. 267-290.
14. Poterba, J.M., L. Summers. The persistence of volatility and stock market fluctuations // American Economic Review, 1986. – №76. – pp. 1143-51.
15. Sansó A., Aragó V., J.L. Carrion. Testing for Constant Variance in Financial Time Series // Revista de Economía Financiera, 2004. – №4. – pp. 32-53.