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Volatility Shifts and Persistence in Variance: Evidence from the Sector Indices of Istanbul Stock Exchange

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Abstract

This study examines the impact of volatility shifts on volatility persistence for three major sector indices of Istanbul Stock Exchange (ISE) and ISE National 100 index over the period beginning from 1997 and ending in 2009. The exponential generalized autoregressive conditional heteroskedasticity (EGARCH) model is extended by taking account of the volatility shifts which are determined by using iterated cumulative sums of squares (ICSS) and modified ICSS algorithms such as Kappa-1 (κ-1) and Kappa-2 (κ-2). The results indicate that the inclusion of volatility shifts in the model substantially reduces volatility persistence and suggest that the sudden shifts in volatility should not be ignored in modelling volatility for Turkish sector indices.

Keywords: Stock return volatility, volatility shifts, persistence, Turkish stock market

JEL classification: C22, C52, C58

1. Introduction

It is important for investors, fund managers and policy makers to determine the volatility of stock markets for pricing the financial assets, managing risks and predicting future volatility. In estimating volatility, autoregressive conditional heteroskedasticity (ARCH) family models have gained attention and are used by many finance researchers as they are simple to implement and able to cover the stock return volatility features such as clustering and mean-reverting. However, the shortcoming of these models might be the overestimation of the persistence of volatility, which might cause misinterpretation on volatility persistence and spurious volatility modelling (see for example Lastrapes, 1989; Lamoureux and Lastrapes, 1990; Malik, 2003; Ewing and Malik, 2005). The standard ARCH models assume that there is no shift in volatility, yet especially in emerging markets there

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may potentially be sudden changes in volatility since these countries run into economic, political and social events more often than the developed markets. It is therefore important to take account of these shifts in estimating volatility persistence particularly for emerging markets.

In this context, the volatility of the Turkish stock market which is one of the most important and highly volatile emerging markets in the world that has experienced many financial crises, causing shifts in volatility, is examined. Since most of the investors prefer to hold mutual funds or sector index funds to achieve efficient portfolios rather than holding individual securities, in this paper besides the ISE-100 index, the major sector indices are examined including ISE-Financial (ISE-FIN), ISE-Industrial (ISE-IND), and ISE-Service (ISE-SRV). The sample period begins from 1997 and ends in 2009, covering major economic and financial events in Turkey such as the domestic and global financial crisis, government elections, changes in the monetary and fiscal policies and improvements in the EU adaptation process which might cause sudden changes in volatility. These events might have a systematic effect on the whole market or might only affect a particular sector. Therefore, the investors and managers of index funds need to determine whether these major events cause shifts in volatility in the whole market or a particular sector in order to create much better diversified portfolios, to predict the future volatility of these index funds properly and to value them accurately.

Hence, the major aim of this paper is to explore an effective model for volatility of the Turkish stock market and sector indices by considering the sudden shifts. In order to achieve this objective, similar to the previous studies, initially, the time points of the shifts in volatility are determined endogenously by utilising the iterated cumulative sums of squares (ICSS) algorithm which was introduced by Inclan and Tiao (1994). It was widely evidenced that financial data have time-varying variance and excess kurtosis; however, the ICSS algorithm assumes constant variance and mesokurtosis within a regime. Thus, different from the previous studies, modifications of this model including Kappa-1 (κ-1) and Kappa-2 (κ-2) which were developed by Sanso et al. (2004) are applied. κ-1 only corrects the non-mesokurtosis, whereas κ-2 corrects both the non-mesokurtosis and persistence in conditional variance. In addition, there is an attempt to interpret the major events around the time points of increased volatility. Then, the exponential generalised ARCH (EGARCH) model (Nelson, 1991) is employed incorporating these volatility shifts to measure the effect of a shock on volatility persistence in an asymmetric fashion. To the best of our knowledge, this is the first study to examine this issue for Turkish stock market by using such an econometric methodology that is explained below in detail.

The rest of the paper is structured as follows: Section 2 briefly reviews the previous studies. Section 3 presents the methodology. Section 4 describes the data and sample statistics. Section 5 presents the empirical results and Section 6 concludes the paper.

2. Literature Review

Lamoureux and Lastrapes (1990) and Hamilton and Susmel (1994) found that there was a considerable reduction in the estimated persistence of volatility of stock returns when regime shifts were incorporated in the standard ARCH model. While the former determined the regime shifts in returns exogenously, the latter determined them endogenously by employing Markov-Switching ARCH (SWARCH) models. Most of the recent empirical studies focus on the structural changes in volatility rather than returns and use the ICSS algorithm to identify sudden changes in volatility endogenously. Among these studies firstly Aggarwal et al. (1999) used the ICSS algorithm to investigate the large shifts in the volatility of eleven emerging stock markets in Asia and Latin America, in addition to the U.S., Germany, the U.K., Hong Kong and Singapore stock markets. They used weekly data from 1985 until 1995 and found the local and country-specific factors to be the dominant causes behind the sudden changes. The October 1987 stock market crash in the U.S. was the unique global factor that affected numerous emerging markets in their sample. Later studies followed the study of Aggarwal et al. (1999) and detected the sudden changes in variance endogenously by using ICSS and incorporate these shifts in the ARCH family models to find the effect of a shock on persistence of volatility. Among these studies Malik, Ewing and Payne (2005) examined the Canadian Stock Market by using weekly data from June 1992 and October 1999. They investigate the impact of regime changes on volatility persistence and conduct ICSS algorithm to detect sudden changes in the volatility and incorporate those shifts into variance equation of GARCH model to avoid overestimating the volatility persistence. They conclude that the persistent volatility is reduced after considering sudden volatility changes in stock returns. In this manner, their findings are consistent with the Lamoureux and Lastrapes (1990), Aggarwal, Inclan, and Leal (1999). Ewing and Malik (2005) investigate the existence of asymmetry in the predictability of the volatilities of small and large companies in the USA. They use ICSS algorithm to detect large changes in the unconditional variance of stock returns and incorporate this information in Bivariate GARCH model. According to their results, spillover effects between small and large cap stock returns disappears when endogenously determined volatility shifts are taken into consideration. Moreover, they observe significant decline in the transmission of volatility between those stock returns. Hence, they suggest not ignoring regime changes to estimate degree of volatility transmission more accurately. Fernandez (2005) conducts ICSS algorithm and Wavelet Analysis (WA) to investigate the existence of structural breaks in the four stock indices and four interest rates series. Dataset consists of Emerging Asia, Europe, Latin America and North America indices of Morgan Stanley Capital International (MSCI). Fernandez (2005) focuses on the effects of the Asian crisis and the terrorist attacks of September 11, 2001 on the volatility of those stock indices and the interest rate series of the Central Bank of Chile. Empirical findings suggest that ICSS algorithm and WA detects several breakpoints in the data. Fernandez (2005) concludes that those sudden changes in the unconditional variance of series should be considered. Wang (2006) conducts a study to examine the impact of financial liberalisation on the volatility of several stock indices during the period from 1986 to 1998. They use daily returns data at a daily frequency. Wang (2006) applies ICSS algorithm to detect structural breaks due to the announcement of liberalisation. According to the empirical findings, there exists several breakpoints in the unconditional variance of the daily returns of South Korea, Malaysia, Philippines, Thailand, Taiwan, Turkey, Argentina, Brazil, Chile, and Mexico for over ten years. According to analytical results, the volatility of stock returns increased significantly for the markets of Thailand, Brazil, Chile, and Mexico whereas unconditional volatility remains unchanged for the rest. Hammoudeh and Li (2006) examined the volatility of Gulf Arab stock markets using weekly data from 1994 to 2001. In contrast to the study of Aggarwal et al. (1999) they found that most of the Gulf Arab stock markets were more sensitive to major global events such as the 1997 Asian crisis and the September 11th attack than to local and regional factors. Fernandez (2007) investigates the impact of political events in the Middle East on stock markets worldwide. She applied ICSS algorithm and WA to detect the structural breaks in the unconditional variance of several stock markets. The data in the analysis includes Israel, Turkey, Morocco, Egypt, Jordan, Pakistan, and Indonesia, the UK, Germany, Japan, the US, and Spain, and four international indices for the period spanning from April 2000 to March 2005. Fernandez (2007) concludes that the war in Iraq has a significant impact on the volatility of several Middle East and Emerging Asian countries. Moreover, volatility of stock markets is affected from Middle East conflicts. Thus, she suggests estimating financial risks by considering breakpoints in the volatility. Fernandez and Lucey (2008) conduct a study to investigate the determinants of volatility shifts on ten emerging markets, namely Argentina, Brazil, Chile, India, Indonesia, Mexico, Philippines, Singapore, South Africa, and Turkey. They use three statistical approaches, ICSS algorithm, WA, and Bai-Perron's (2003) test to determine the breakpoints in the both mean level and variance of the time series at a weekly frequency, over the period from January 1996 to April 2006, giving in total 536 observations. ICSS algorithm and WA tend to estimate more breakpoints than Bai- Perron's structural breaks test. Fernandez and Lucey (2008) observe that volatility shifts are mostly associated with local political or economic events rather than global events. Marcelo et al. (2008) uses Spanish stock market data at weekly frequency covering the period between January 3, 1990 and January 5, 2005. They conduct their analysis in two steps: First, they apply ICSS algorithm to detect volatility shifts and then they incorporate this piece of information to EGARCH model. Their motivation behind using EGARCH model is to conduct their analysis to better capture the asymmetric behaviour. They observe that volatility persistence is significantly reduced when endogenously determined volatility shifts are taken into account. Moreover, their findings reveal that spillover effects are declined after sudden changes are considered. Wang and Moore (2009) examined the stock markets of transition economics of EU using weekly data over the period 1994-2006 and found that the sudden changes in volatility aroused from the evolution of emerging stock markets, exchange rate policy changes and financial crises. Kasman (2009) investigates the volatility shifts in the stock markets of the BRIC countries, Brazil, Russia, India and China. He works with daily data covering the period between 1990 and 2007 to investigate the effects of sudden volatility shifts on persistence of volatility. Kasman (2009) applies ICSS algorithm to detect the time of breakpoints and incorporate this in GARCH model. Empirical findings suggest that persistence of volatility is dramatically declined when sudden changes in volatility are taken into account. Thus, he states that previous literature may overestimate the persistence of volatility because they do not consider structural breaks in the data due to the economic or political events during the time period. Lastly, Karaoglou (2010) conducts a study on the stock market indices of 27 OECD countries for the period spanning from 1994 to 2006. He hypothesises that abnormal behaviour may arise because of the joint existence of structural breaks and ARCH effects in the time series data. Karaoglou (2010) employs several econometric tests to determine the sudden changes in variance. These tests include ICSS algorithm of Inclan and Tiao (1994), Kappa tests of Sanso et al. (2004) and Kokoszka and Leipus (2000) type of tests refined by Andreou and Ghysels (2002). Daily closing values of the stock market indices are used in the analysis. The paper concludes that when structural breaks are taken into account high persistence of volatility reduced and asymmetric effects and risk aversion arises only temporarily. All of these papers suggested that when sudden changes were taken into account in the GARCH models, the persistence of volatility was reduced significantly and argued that the findings of the previous studies could have overestimated the degree of the persistence of volatility existing in the stock market data.

While the aforementioned studies examined the stock markets on country basis, Malik and Hassan (2004) examined five major sector indices of the U.S. stock market from January 1992 to August 2003 by applying the same methodology and argued that most of the volatility breaks are associated with global events rather than sector-specific news. Their study has important implications for index investing. Although, investing into index funds is a passive strategy, portfolio managers have to revise the composition of their index funds especially after the major events which might cause shifts in volatility.

In this paper, similar to the study of Malik and Hassan (2004), the three major sector indices of ISE and ISE 100 index are examined, yet, unlike the previous studies in addition to the ICSS algorithm, modified ICSS algorithms such as κ-1 and κ-2 are applied to determine the sudden changes on volatility. These algorithms will be discussed in detail in the following section.

3. Methodology

3.1 Detecting Time Points of Shifts in Variance

First, ICSS algorithm is implemented to detect sudden changes in the variance of a stock return series. The algorithm assumes that the financial series displays a stationary variance over an initial time period, and then there is a sudden shock that alters the variance which becomes stationary again until another shock hits the market (Hammoudeh and Li, 2008).

ICSS algorithm is based on D_k statistics and tests the null hypothesis of constant unconditional variance. D_k statistics is computed as follows:

$$D_k = \frac{C_k}{C_T} - \frac{k}{T} \quad D_0 = D_T = 0 \quad \text{with} \quad k = 1, \ldots, T \tag{1}$$

where $C_k = \sum_{t=1}^{k} \varepsilon_t^2, k = 1,...,T$ [1]. C_k is the cumulative sum of squares of ε_t. Then, the test proposed by Inclan and Tiao (1994) can be written as follows:

$$IT = \sup_k \left| \sqrt{T/2} D_k \right| \tag{2}$$

where $\sqrt{T/2}$ is used to standardise the distribution. One can conclude that k^*, which is the point of k at which $\sup_k |D_k|$ is obtained, is a change of variance when $IT = \sup_k \left| \sqrt{T/2} D_k \right|$ exceeds the predetermined boundary estimated by the Inclan and Tiao (1994). The asymptotic distribution of the test under the assumption that $\varepsilon_t \sim i.i.d.N(0,\sigma^2)$ [2] is based on the following notation:

$$IT \Rightarrow \sup_r \left| W^*(r) \right| \tag{3}$$

where $W^*(r) \equiv W(r) - rW(1)$ is a Brownian Bridge, W(r) is a standard Brownian motion and $\Rightarrow$ denotes weak convergence of the associated probability measures (Sanso et al., 2004).

Since financial data have generally excess kurtosis (greater than three), and inconstant variance over time, there might be some drawbacks using aforementioned IT test. Because IT algorithm assumes $\varepsilon_t \sim i.i.d.N(0,\sigma^2)$ IT statistic can be oversised when error terms follow a GARCH process (Rapach and Strauss, 2008; de Pooter and van Dijk, 2004; Sanso et al., 2004). Rapach and Strauss (2005) also note that IT test is plagued by size distortions if ε_t follows a dependent process. To overcome these shortcomings, Sanso et al. (2004) proposed two tests; κ-1 and κ-2 which consider the fourth moment properties of the disturbances and the conditional heteroskedasticity. In this paper, in addition to the ICSS algorithm, these tests are employed to detect sudden changes[3].

κ-1 test corrects for non-mesokurtosis and it is a generalised form of IT. The asymptotic distribution of the κ-1 test under the conditions of $\varepsilon_t \sim i.i.d.(0,\sigma^2)$ *and* $E(\varepsilon_t^4) \equiv \eta_4 < \infty$ can be written as follows:

$$IT \Rightarrow \sqrt{\frac{\eta_4 - \sigma^4}{2\sigma^4}} \sup_r \left| W^*(r) \right| \tag{4}$$

[1] Note that D_k statistics have value around zero. However, when change in unconditional variance occurs, D_k statistics take values different from zero in either sign, negative or positive.

[2] ε_t are a zero mean, normally, identically and independently distributed random variables.

[3] Potter and Dijk (2004) imposed a restriction to conventional ICSS algorithm in order to prevent breaks from being identified unrealistically close together. They imposed minimum distance restriction between breakpoints for daily data as 63 or 126 business days. We do not report the mathematical details about this procedure, and the results of the procedure since Potter and Dijk's (2004) procedure fit for purpose with Sanso et al. (2004) procedure; and both tests also suggest the same time points of volatility shifts. We thank two anonymous referees for their suggestions.

Thus, the distribution that has nuisance parameters and numerous distortions can occur when critical values of maximisation of a Brownian Bridge are used. It is possible to experience that null hypothesis of constant variance might be rejected too many times when distribution is heavily tailed, in other words, leptokurtic[4] ($\eta_4 > 3\sigma^4$). However, when distribution is platykurtic (negative excess kurtosis), the test becomes so prudent that there would not be too many conclusions of inconstant variance. Hence, Sanso et al. (2004) suggest following correction for the IT test to be free of nuisance parameters for identical and independent zero-mean random variables:

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

where $B_k = \dfrac{C_k - \frac{k}{T} C_T}{\sqrt{\hat{\eta}_4 - \hat{\sigma}_4}}$ and $\hat{\eta}_4 = \dfrac{1}{T}\sum_{t=1}^{T} \varepsilon_t^4$ *and* $\hat{\sigma}^2 = \dfrac{1}{T} C_T$. Asymptotic distribution under the same conditions of equation 5 can be adjusted as follows: $\kappa_1 \Rightarrow \sup_r \left| W^*(r) \right|$.

In case of a conditionally heteroskedastic process, IT and κ-1 lose power because they have an assumption of independence of the random variables which is not appropriate for the financial data (Bollerslev et al., 1992; 1994). To correct for non-mesokurtosis and persistence in conditional variance some additional assumptions on ε_t are required similarly following Herrndorf (1984) and Phillips and Perron (1988). Sanso et al. (2004) assume that sequence of random variables, $\{\varepsilon_t\}_{t=1}^{\infty}$ is consistent with the following conditions:

1. $E(\varepsilon_t) = 0$ *and* $E(\varepsilon_t^2) = \sigma^2 < \infty$ *for all* $t \geq 1$;
2. $\sup_t E\left(|\varepsilon_t|^{\psi+\varepsilon} \right) < \infty$ *for some* $\psi \geq 4$ *and* $\varepsilon > 0$;
3. $\omega_4 = \lim_{T\to\infty} E\left(\frac{1}{T} \left(\sum_{t=1}^{T} (\varepsilon_t^2 - \sigma^2) \right)^2 \right) < \infty$ *exists, and*
4. $\{\varepsilon_t\}$ *is α-mixing with coefficients* α_j *which satisfy* $\sum_{j=1}^{\infty} \alpha_j^{(1-2/\psi)} < \infty$

If the second and the third conditions hold, it is not the case that ε_t in data sequence are distributed as student-t distribution with three degrees of freedom. ω_4 is the long-run variance of the zero mean variable $\xi_t = \varepsilon_t^2 - \sigma^2$. Fourth condition controls for the degree of independence of the data sample and shows a trade-off between serial dependence and the existence of high order moments (Sanso et al., 2004: pp. 5).

In the light of the facts that κ-2 test is based on following equation:

$$\kappa_2 = \sup_k \left| \frac{1}{\sqrt{T}} G_k \right| \tag{6}$$

[4] Under normal distribution $\eta_4 = 3\sigma^4$ and $IT \Rightarrow \sup_r \left| W^*(r) \right|$

where $G_k = \frac{1}{\sqrt{\hat{\omega}^4}}\left(C_k - \frac{k}{T}C_T\right)$ and $\hat{\omega}^4$ is a consistent estimator[5] of ω_4. Consequently, under four conditions above IT, κ-1 and κ-2 can be written as follows:

$$IT \Rightarrow \sqrt{\frac{\omega_4}{2\sigma^4}}\sup_r\left|W^*(r)\right| \tag{7}$$

$$\kappa_1 \Rightarrow \sqrt{\frac{\omega_4}{\eta_4 - \sigma^4}}\sup_r\left|W^*(r)\right| \tag{8}$$

$$\kappa_2 \Rightarrow \sup_r\left|W^*(r)\right| \tag{9}$$

3.2. EGARCH Model without and with Shifts in Variance

After the time points of the shifts in variance are identified, the volatility persistence in the presence of these shifts are calculated. We begin with the estimation of EGARCH model without shifts in variance.

Nelson (1991) developed the EGARCH model that accounts for the asymmetry effect of news and posits no constraints on the coefficient of variance equation since it models logarithm of conditional variance. EGARCH specification is as follows:

$$\ln(h_t) = \alpha_0 + \sum_{i=1}^{p}\beta_i \ln(h_{t-i}) + \sum_{j=1}^{q}\alpha_j\left(\left|\frac{\varepsilon_{t-j}}{\sqrt{h_{t-j}}}\right|\right) + \sum_{k=1}^{r}\xi_k\left(\frac{\varepsilon_{t-k}}{\sqrt{h_{t-k}}}\right) \tag{10}$$

where ξ is the asymmetry coefficient. If ξ is negative and statistically significant, one might conclude that the relationship between volatility and returns is negative, or to put it another way, the effect of shock on the conditional variance would be (α_j - ξ_k). It is important to note that EGARCH specification is built to use *standardised* square root of ε_{t-j}^2 to provide a more accurate interpretation about shocks to the natural logarithm of conditional variance (Enders, 2010, pp.156-157). β is the measure of persistence and if it is less than one, EGARCH specification is assumed to be covariance stationary. The EGARCH model with sudden changes in variance can be expressed as follows[6]:

$$\ln(h_t) = \alpha_0 + \sum_{i=1}^{p}\beta_i \ln(h_{t-i}) + \sum_{j=1}^{q}\alpha_j\left(\left|\frac{\varepsilon_{t-j}}{\sqrt{h_{t-j}}}\right|\right) + \sum_{k=1}^{r}\xi_k\left(\frac{\varepsilon_{t-k}}{\sqrt{h_{t-k}}}\right) + \sum_{l=1}^{\eta_b} d_{b,l}DUM_{b,l,t} \tag{11}$$

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[5] Sanso et al. (2004) also suggest using non-parametric estimator of ω_4:
$\hat{\omega}_4 = \frac{1}{T}\sum_{t=1}^{T}\left({}_t^{2} - \hat{}^{2}\right)^2 + \frac{2}{T}\sum_{l=1}^{m} w(l,m)\sum_{t=l+1}^{T}\left({}_t^{2} - \hat{}^{2}\right)\left({}_{t-l}^{2} - \hat{}^{2}\right)$ where *w (l, m)* is a lag window. It should be added when $\xi_t = \varepsilon_t^2 - \sigma^2$ and then $\hat{\omega}_4 \to E(\xi_t^2) = \eta_4 - \sigma^4$.

[6] Bollerslev, Chou and Kroner (1992), Hansen and Lunde (2001) suggest using *p=q=1* specification which outperforms in many applications.

n_b is the number of structural breaks of return in market b, $DUM_{b;l;t}$ represent the dummy variables taking a value of 1 from each point of sudden change in variance onwards, 0 otherwise. In financial literature, statistical fat-tailed distributions, namely Student-t or GED that capture leptokurtosis should be used rather than normal distribution. In this paper, as Nelson (1991) suggested, errors are assumed to be distributed according to GED which has a probability density function as follows:

$$f(\varepsilon_t) = \frac{v \exp\left[-\left(\frac{1}{2}\right)\left|\frac{\varepsilon_t}{\lambda\sqrt{h_t}}\right|^v\right]}{2^{\left(1+\frac{1}{v}\right)}\lambda\sqrt{h_t}\,\Gamma\left(\frac{1}{v}\right)} \tag{12}$$

where *v* is the shape parameter indicating the thickness of the tail compared to the Gaussian distribution. *v* denotes that the distribution has thicker or thinner tails, if *v* is less than two, and greater than two, respectively. Γ is the usual gamma function and λ is identical to $\left[\left(2^{(-2/v)}\Gamma(1/v)\right)/\left(\Gamma(3/v)\right)\right]^{0.5}$. Moreover, conditional log-likelihood function can be written as:

$$L(\varepsilon_t)_{GED} = \sum_{t=1}^{T}\left[\ln\left(\frac{v}{\lambda}\right) - 0.5\left|\frac{\varepsilon_t}{\lambda\sqrt{h_t}}\right|^v - \left(\frac{v+1}{v}\right)\ln(2) - \ln\left[\Gamma\left(\frac{1}{v}\right)\right] - \frac{1}{2}\ln(h_t)\right] \tag{13}$$

4. Data and Descriptive Statistics

Daily returns of ISE indices are employed including ISE-100, and sector indices including ISE-FIN, ISE-IND, and ISE-SRV. Continuously compounded daily returns series are calculated by taking the difference of the natural logarithm of price indices[7]. Log-returns of price series are calculated as follows: $r_t = \ln\left(P_t / P_{t-1}\right)$ where r_t denotes *continuously compounded return* at time *t*, P_t and P_{t-1} denote value of index at time *t* and time *t-1* respectively, and *ln* is the natural logarithm.

Table 1 presents the descriptive statistics for our sample. ISE-FIN is the most volatile index with the highest standard deviation. Skewness and kurtosis statistics depict that the series are skewed and leptokurtic respectively. In addition, Jarque-Bera test statistics suggest that there is strong evidence of rejecting the null hypothesis of normal distribution for all. Ljung-Box statistics for returns and squared returns up to 10, 20, and 40 lags indicate the existence of serial correlation. According to the Engle's (1982) ARCH-LM[8] test (TR^2), evidence of ARCH effect is detected revealing time-varying conditional distribution.

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[7] Return series is mostly used in financial literature instead of price series because of several appropriate statistical properties, namely stationarity, ergodicity. In addition, return of an asset is a complete and scale-free of the investment, put another way, returns are unit-free (Campbell, Lo, & Mackinlay, 1997), (Tsay, 2002), (Brooks, 2008).

[8] Engle (1982) proposed this test to check the necessity of modelling volatility with ARCH model.

5. Empirical Results

5.1 Integration

Before investigating the impact of volatility shifts on the persistence of variance, unit root tests are used, namely Augmented Dickey-Fuller (ADF), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) to find out whether return series are stationary or not. Table 2 (in Appendix) indicates the results of conventional unit root tests namely, Augmented Dickey Fuller (1979) (ADF), and Kwiatkowski et al. (1992). All series are found as integrated of order zero (0), in other words, they are all stationary regardless the trend variable is included.

Since daily returns are stationary, I(0), and symptom of ARCH effect is detected in the residuals, it is appropriate to conduct ARCH family models to model volatility. Thus, we applied EGARCH model under the assumption of a GED structure for the errors.

5.2 Volatility Shifts in Variance

Before the EGARCH model is estimated, the possible volatility shifts in unconditional variance are determined endogenously by using ICSS algorithm, κ-1 and κ-2. Table 3 (in Appendix) reports time points of volatility shifts for the aforementioned indices. After κ-2 procedure is applied, three important shifts in the volatility of the ISE-100 and ISE-FIN indices and one for the ISE-IND and ISE-SRV indices are observed. κ-2 procedure detected a significant increase in volatility in March 2003 in all sector indices and ISE 100 index. This could be due to the Iraq War which began on March 20, 2003 with the invasion of Iraq. Turkish stock market decreased by 11.29% during the week from March 17-21, 2003. In addition, the second round of the Assembly session including governmental decree to send Turkish troops to Iraq was another source of this volatility increase. The first volatility shift of ISE-100 index on March 25, 2003 is due to the concerns that Iraq war could last longer than expected. At this date, ISE-100 index decreased to the lowest level of the last five months and trading volume decreased substantially.

There was a significant increase in volatility of ISE-FIN on June 8, 2004. The closing price of the index reached its maximum level on that date. In addition to the positive developments in international markets, decreases on the Turkish Treasury bill rates, the value of U.S. dollar against Turkish Lira (TL) and the inflation rate of May were the major determinants of this increasing trend in Turkish stock market. Moreover, shift in volatility was observed for ISE-100 index on June 14, 2004. In contrast to the previous week, the price index declined. This could be due to the expectations on the ground that FED would increase the interest rates and the results of the EU parliamentary elections were not promising for Turkey. The shift in volatility in both ISE-100 and ISE-FIN indices on July 18, 2007 might be the result of the general elections in Turkey. During the third week of July, Turkish stock market increased substantially due to the effect of the optimistic expectations of investors on the grounds that eventually a single party government would again be formed after the elections in Turkey.

The results of the κ-2 procedure indicate that the stock market indices were mostly influenced by domestic factors. Although some sudden changes after the 1997 Asian currency crisis, 1999 Russian crisis, 2000-2001 Turkish banking crisis and the most recent U.S. financial crisis were observed, when both ICSS algorithm and κ-1 were applied these shifts were not observed when κ-2 was employed. It can be on the grounds that κ-2 detects only deep (essential, radical) regime shifts. If the changes of the indices on the figures in Appendix are analysed, these radical shifts can clearly be seen. ISE indices exibit a dramatic increase after 2003 and the index level goes further away from the level of 1998-2003 period rapidly. In addition, it can be clearly observed that the speed of increase in the index levels during the 2004-2007 period is somewhat higher than that of the 2003-2004 period. On the other hand, the shift during the 2003-2004 period is higher than the shifts for the following one-year periods. The shift in 2007 can be explained on the grounds that the index was testing its peak level after the 2004-2007 period and then it had begun to fall sharply depending on the effects of the global financial crisis. According to the results of the κ-2 procedure, it is observed that sector specific risks have a significant impact on the volatilities of each index since the timing and number of shifts in the unconditional variance of ISE-SRV are slightly different from the other indices. Moreover, one can conclude that the sector specific risks of the ISE-FIN index and those of the ISE-100 indices are very similar. This is evident from the close similarity between them in terms of the calculated number and timing of their volatility shifts. It is noteworthy that volatility shifts in the year 2004 for the ISE-100 and ISE-FIN are sequential indicating a possible lead-lag relationship between the two. This might be the evidence that ISE-100 is mostly led by the companies listed on the ISE-FIN index.

5.3 EGARCH estimation without and with Sudden Changes in Variance

After the sudden changes in variance are detected, the GED-EGARCH (1,1) model is employed to estimate volatility with or without taking those volatility shifts into account. The main reason behind implementing EGARCH model is to account leverage effect[9] on equity index volatility. Moreover, asymmetric GARCH models are generally the better fit to high frequency data (e.g. daily data) for equity indices (Alexander, 2008: 147). The results are reported in Table 4 and 5 (in Appendix) where the former is for models without dummy variables, and the latter for models with dummy variables that represent determined volatility shifts[10].

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[9] Leverage effect refers to that negative shocks often increase volatility to a greater extent than positive shocks because negative returns imply a larger proportion of debt through a reduced market value of the firm, which leads to a higher volatility.

[10] We have estimated GED-EGARCH (1,1) model four times: once without dummy variables and the remaining three estimation with volatility shifts identified by ICSS, κ-1, and κ -2 respectively.

Table 4 and 5 indicate that β coefficients in all models are statistically significant at 1% level. Asymmetry coefficients (ξ) are found less than zero and significant at least 10% level indicating that negative shocks lead to higher subsequent volatility than positive shocks both in ISE-100 and the ISE sector indices. In other words, good news has a smaller effect on the conditional volatility than bad news. β coefficients, measure of persistence shocks are close to unity in the models which do not consider the volatility shifts. High degree of persistence in variance suggests that shocks on volatility die out slowly over time. Following Lamoureoux and Lastrapes (1990), half-life shock[11] which measures the number of days a shock to conditional variance reduces to half its original size was also reported. Average half-life shock for the models without dummy variables is calculated as 26.05 days[12]. The results with volatility shifts determined by conventional ICSS algorithm are summarised in the Panel-A of Table 5 (in Appendix). For all models, degree of persistence declines by at least 28% and estimated half-life shocks decreases dramatically to the 1.32 days on average. The findings from models of Panel-A are consistent with the results of papers discussed in the literature review section. That is, degree of persistence of shocks on variance might be overestimated, if volatility shifts (i.e. determined by ICSS algorithm) are not considered. However, another problem arising here is that the number of breakpoints in the data period could be overestimated. Panel-B and Panel-C of Table 5 (in Appendix) show the results of models with volatility shifts determined according to κ-1 and κ-2 tests respectively[13].

The degrees of persistence decline in models in Panel-B and Panel-C are, on average, 11.84%, and 7.27% respectively. In addition, half-life shocks in those models are, on average, estimated as 4.43 and 6.65 days respectively. Overall, controlling for the fourth moment properties and conditional heteroskedastic process diminishes the number of breakpoints determined by ICSS algorithm dramatically. From now on, since the breakpoints are spurious in ICSS, only the results of Panel-C will be discussed in detail, as suggested by Sanso et al. (2004). All indices except ISE-SRV show decline in volatility persistence by around 6.5%; however, the largest decline in the degree of persistence belongs to ISE-SRV index with a 9.4%. Coefficients including all breakpoints in models are highly significant. For ISE-100 and ISE-FIN indices, there are no ARCH effects and no serial dependency in the level of residuals. Although, there is evidence of ARCH effect up to 1 lag, and autocorrelation up to 12 lags for the ISE-IND index, those problems of modelling disappear in the high levels of lags. Nevertheless, modeling volatility of the ISE-SRV index is not successful by amended EGARCH (1,1) since there are significant ARCH effects up to 1 and 4 lags respectively.

11 For EGARCH specification, half-life is calculated as follow: $-\ln(2)/\ln(\beta)$.

12 Average half-life shock is computed by conducting half-life formula to the mean of persistence.

13 Volatility shifts in variance equation for the models in Panel-B and C are all statistically significant at conventional levels. However, dummy variables in models of Panel-A are not all significant. Since degrees of persistence in models with all volatility shifts, and with only significant shifts are very similar, we only present the former ones.

6. Conclusion

The major aim of this paper is to determine an effective model for volatility of the ISE-100 index and three major sector indices of ISE including ISE-FIN, ISE-IND and ISE-SRV by taking into account the sudden changes in variance. To achieve this goal initially, time points of volatility shifts are determined endogenously by implementing ICSS algorithm which was introduced by Inclan and Tiao (1994) and was widely used by the finance researchers. However, the ICSS algorithm that assumes constant variance and mesokurtosis within a regime detects more breaks and finds less evidence of dependent processes, such as GARCH dynamics. Thus, differently from the previous studies, modifications of this model including κ-1 and κ-2 tests which were developed by Sanso et al. (2004) are applied. κ-1 only corrects the non-mesokurtosis whereas κ-2 corrects both the non-mesokurtosis and persistence in conditional variance.

In addition, the major events corresponding to these volatility shifts are analysed and it is found that the global and domestic political and economic factors lead these sudden changes in variance. There were not observed any sector specific factors that cause significant shifts in variance. Then, these sudden changes are incorporated in the EGARCH model introduced by Nelson (1991) to measure the effect of a shock on volatility persistence in asymmetric fashion and significant reductions in the volatility persistence are found after these sudden changes are accounted for. This also indicates that parameter estimates of (E)GARCH process are changing significantly in the subsamples defined by sudden shifts in the conditional volatility. The results suggest that investors and fund managers have to pay attention to both domestic and global shocks in their portfolios since these shocks might influence the risk-return trade-off and the composition of the optimal asset allocation. The results are also consistent with the findings of previous studies on the persistence in volatility and evidence by means that ignoring sudden changes might result in overestimation on the degree of volatility persistence and inaccuracy of volatility estimations of ISE indices for fund managers and investors.

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Appendix

Figure 1: Daily ISE-100 index prices and returns

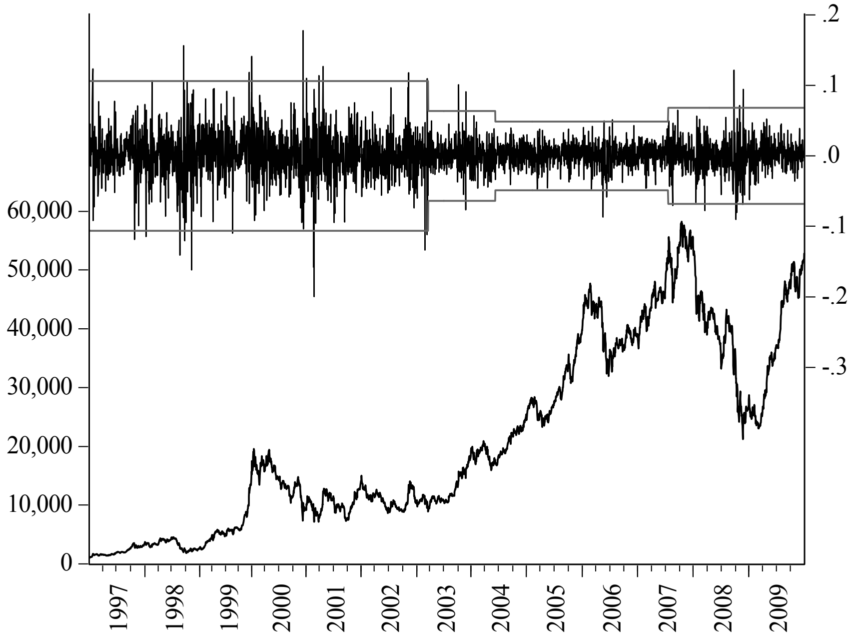

Figure 2: Daily ISE-IND index prices and returns

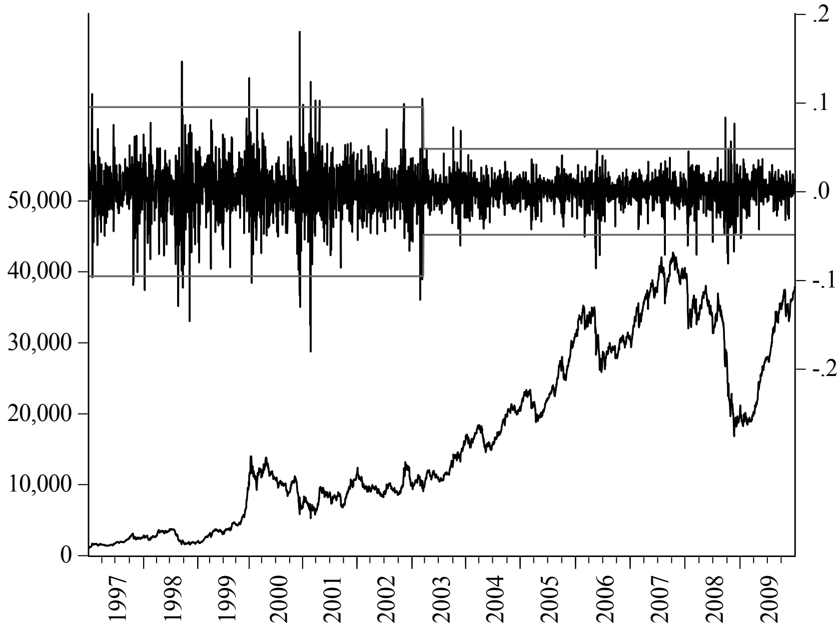

Figure 3: Daily ISE-FIN index prices and returns

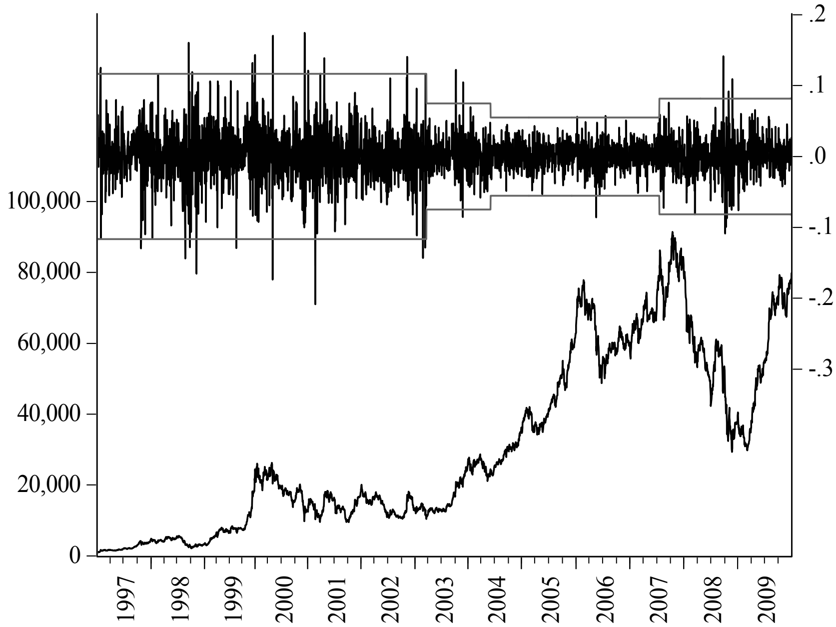

Figure 4: Daily ISE-SRV index prices and returns

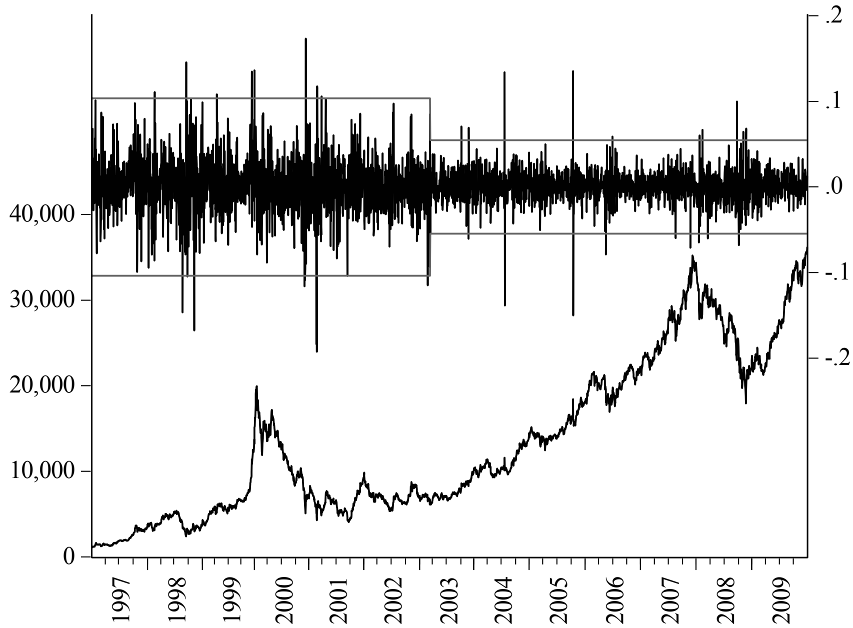

Table 1: Descriptive statistics

	ISE-100	**ISE-IND**	**ISE-FIN**	**ISE-SRV**
Mean	0.12%	0.11%	0.14%	0.11%
Std. Dev.	0.0283	0.0248	0.0316	0.0272
Skewness	-0.0293	-0.2123	0.0015	0.0147
Kurtosis	7.6752	9.1239	7.1324	8.9231
Maximum	0.1777	0.1804	0.1746	0.1733
Minimum	-0.1998	-0.1801	-0.2084	-0.1926
J-B	2944.87*	5076.06*	2300.39*	4726.14*
TR^2(1)	246.02*	472.47*	208.99*	242.51*
TR^2 (5)	388.08*	616.49*	299.97*	431.12*
TR^2 (10)	409.85*	625.67*	326.13*	438.49*
Q(10)	36.27*	37.90*	33.69*	22.16**
Q(20)	59.62*	62.63*	57.28*	39.27*
Q(40)	93.54*	92.30*	91.44*	68.12*
Q_S(10)	783.86*	1223.10*	577.63*	866.88*
Q_S(20)	1006.10*	1450.30*	750.44*	1041.02*
Q_S(40)	1324.90*	1779.60*	977.30*	1256.25*

Note: J-B denotes Jarque-Bera (1980) normality test statistics. *, and ** denote statistical significance at level of 1% and 5%, respectively. TR^2(.) is the ARCH-LM test statistics up to 1, 5, and 10 lags respectively. Q(.) and Q_S(.) are the Ljung-Box statistics for returns and squared returns up to 10, 20, and 40 lags, respectively. Our data covers the period from January 2nd 1997 to December 31st 2009 including 3233 observations all obtained from Electronic Data Delivery System of the Central Bank of the Republic of Turkey (www.tcmb.gov.tr).

Table 2: Unit root tests

		ADF		KPSS	
Index		Level	First Diff.	Level	First Diff.
ISE-100	η_μ	-2.1594	-14.4708*	6.2637*	0.2412
	η_τ	-2.7766	-14.5122*	0.6097*	0.0609
ISE-IND	η_μ	-1.9200	-14.0028*	6.4166*	0.2257
	η_τ	-2.4781	-14.0392*	0.7863*	0.0416
ISE-FIN	η_μ	-2.3163	-14.4066*	6.1767*	0.2861
	η_τ	-2.8683	-14.4572*	0.5875*	0.0729
ISE-SRV	η_μ	-2.1419	-15.0342*	5.9647*	0.1822
	η_τ	-3.0161	-15.0610*	0.3310*	0.0926

Note: η_τ and η_μ refer to the test statistics with and without trend, respectively. * denotes rejection of null hypothesis at 1% significance level.

Table 3: Volatility Shifts in Unconditional Variance

	ISE-100			ISE-IND			ISE-FIN			ISE-SRV		
	IT	**K-1**	**K-2**	**IT**	**K-1**	**K-2**	**IT**	**K-1**	**K-2**	**IT**	**K-1**	**K-2**
1	17-03-97	07-08-98	25-03-03	07-03-97	17-11-00	25-03-03	08-01-97	26-09-03	25-03-03	31-03-97	17-11-00	19-03-03
2	27-06-97	25-11-98	14-06-04	18-06-97	27-04-01		22-01-97	01-12-03	08-06-04	26-05-97	30-03-01	
3	24-10-97	25-11-99	18-07-07	30-06-97	06-12-01		04-02-97	08-06-04	18-07-07	27-06-97	19-03-03	
4	23-02-98	01-03-00		24-10-97	01-11-02		30-06-97	06-07-07		10-10-97		
5	07-08-98	17-11-00		27-02-98	25-03-03		10-10-97	05-09-08		02-03-98		
6	25-11-98	27-04-01		07-08-98	10-09-08		23-02-98	01-12-08		07-08-98		
7	08-12-99	14-04-03		25-11-98	24-11-08		07-08-98	08-06-09		24-11-98		
8	01-03-00	10-09-08		09-12-99	20-02-09		24-11-98			08-09-99		
9	07-12-00	01-12-08		01-03-00			08-12-99			25-11-99		
10	25-07-01	20-05-09		27-11-00			31-01-00			07-03-00		
11	01-11-02			07-12-00			05-05-00			17-11-00		
12	14-04-03			16-02-01			09-05-00			08-12-00		
13	26-09-03			12-03-01			17-11-00			16-02-01		
14	01-12-03			27-04-01			12-03-01			26-02-01		
15	18-01-08			06-12-01			19-07-01			06-12-01		
16	10-04-08			01-11-02			11-09-01			13-06-02		
17	25-06-08			16-04-03			06-12-01			19-03-03		
18	10-09-08			26-09-03			01-11-02			20-07-04		
19	01-12-08			02-12-03			25-03-03			26-07-04		
20	20-05-09			14-06-04			26-09-03			11-03-05		
21				06-03-06			01-12-03			28-04-05		
22				14-03-06			14-06-04			12-10-05		
23				11-05-06			06-07-07			14-10-05		
24				26-05-06			05-09-08			11-05-06		
25				20-07-06			01-12-08			28-07-06		
26				26-02-07			08-06-09			26-06-07		
27				15-03-07						18-01-08		
28				15-01-08						12-02-08		
29				18-03-08						10-09-08		
30				10-09-08						24-11-08		
31				24-11-08						05-03-09		
32				20-02-09								

Note: IT, K-1, and K-2 stand for ICSS algorithm of Inclan Tiao (1994), Kappa-1, and Kappa-2 procedures, respectively. For instance, time point of volatility shift detected by Kappa-2 procedure for the ISE-IND index is on March 25, 2003.

Table 4: EGARCH(1,1) Model without dummy variables

Index	**β**	**Ξ**	**LLH**	**ARCH(1)** **ARCH(4)**	**Q(12)** **Q(20)**	**Half-live Shock**
ISE-100	0.9782* (0.0052)	-0.0277* (0.0097)	7431.75	7.4799* 14.9090*	25.956** 31.731**	31.45
ISE- IND	0.9719* (0.0057)	-0.0379* (0.0114)	8014.24	11.4633* 15.0847*	32.218* 35.661**	24.32
ISE-FIN	0.9756* (0.0058)	-0.0244** (0.0101)	7017.77	7.3601* 12.961**	22.869** 27.752	28.06
ISE-SRV	0.9693* (0.0061)	-0.0379* (0.0118)	7664.82	28.4131* 31.5988*	36.459* 39.787*	22.23

Note: β is coefficient of the GARCH term and it is a measure of volatility persistence in EGARCH model. ξ is asymmetry term. LLH stands for log likelihood. ARCH(.) refers to ARCH-LM tests. The Q(12) and Q(20) are the Ljung–Box test statistics with 12 and 20 degrees of freedom based on the residuals respectively; SE are reported in the parentheses below corresponding parameter es timates.

Table 5: EGARCH(1,1) Model with dummy variables

Index	β	Ξ	Pers. Decline	LLH	ARCH(1) ARCH(4)	Q(12) Q(20)	Half-live Shock
PANEL-A: ICSS algorithm							
ISE-100	0.6909* (0.0584)	-0.0769* (0.0213)	**0.2873**	7505.08	0.3623 5.0395	17.724 28.380	1.87
ISE- IND	0.4971* (0.0780)	-0.1115* (0.0227)	**0.4748**	8156.18	0.7486 4.1395	15.172 22.371	0.99
ISE- FIN	0.5976* (0.0863)	-0.0683* (0.0235)	**0.3780**	7121.56	0.4908 6.9369	15.553 21.698	1.35
ISE-SRV	0.5830* (0.0699)	-0.0395*** (0.0226)	**0.3863**	7831.01	0.5605 3.1371	8.332 17.807	1.28
PANEL-B: κ-1							
ISE-100	0.8256* (0.0363)	-0.0663* (0.0173)	**0.1526**	7481.17	1.7896 7.1139	20.562*** 33.383**	3.62
ISE- IND	0.8475* (0.0238)	-0.0803* (0.0174)	**0.1244**	8062.74	2.0799 3.0624	12.652 21.654	4.19
ISE- FIN	0.8904* (0.0229)	-0.0445* (0.0150)	**0.0852**	7045.22	1.7495 6.6539	16.935 22.483	5.97
ISE-SRV	0.8580* (0.0251)	-0.0547* (0.0171)	**0.1113**	7697.48	16.8688* 20.1527*	24.066** 27.002	4.53
PANEL-C: κ-2							
ISE-100	0.9132* (0.0175)	-0.0555* (0.0142)	**0.0650**	7457.78	2.1099 7.2280	17.243 24.241	7.63
ISE- IND	0.9065* (0.0151)	-0.0733* (0.0152)	**0.0654**	8044.24	4.3456** 6.2717	22.412** 27.663	7.06
ISE- FIN	0.9097* (0.0192)	-0.0451* (0.0143)	**0.0659**	7040.86	1.9942 5.1528	13.596 18.055	7.32
ISE-SRV	0.8749* (0.0217)	-0.0582* (0.0164)	**0.0944**	7694.58	18.0196* 21.2754*	25.574** 28.248	5.19

Note: β is coefficient of the GARCH term and it is a measure of volatility persistence in EGARCH model. ξ is asymmetry term. LLH stands for log-likelihood. ARCH(.) refers to ARCH-LM tests. The Q(12) and Q(20) are the Ljung–Box test statistics with 12 and 20 degrees of freedom based on the residuals respectively. SE are reported in the parentheses below corresponding parameter estimates. Dummies are determined according to three tests, Inclan Tiao, Kappa-1 and Kappa-2 respectively.