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VOLATILITY OF BORSA İSTANBUL-100 INDEX AROUND THE FOOD-BEVERAGE SECTOR INDEX AND THE TECHNOLOGY SECTOR INDEX

ABSTRACT

In this study, ARCH-class models are estimated by using chosen daily data on stock exchange market. Volatility of stock market returns of the Borsa İstanbul-100 (BIST-100) Index around The Food-Beverage Sector Index and The Technology Sector Index is analyzed by estimating the volatility equation between the years of 2003 and 2012 and for 2608 observations. The reason of referring to the Food-Beverage Sector Index as one out of two independent variables is because the food and beverage sector all around the world are expected being less affected by fluctuations in economy. They carry characteristics of being obligatory good in some aspects. The reason of referring to the Technology Sector Index as another independent variable is because technology sector has been developing day by day via globalization and smart devices besides all of the world in Turkey as well. As a result of the analyses made, it is ascertained that there is a relationship between the BIST-100 Index volatility and both The Food-Beverage Sector Index return volatility, and also The Technology Sector Index return volatility.

Keywords: Bist-100 Index, The Food-Beverage Sector Index, The Technology Sector Index, Volatility, ARCH-Class Models

BORSA İSTANBUL-100 ENDEKSİNİN YİYECEK-İÇECEK SEKTÖRÜ ENDEKSİ VE TEKNOLOJİ SEKTÖRÜ ENDEKSİ KARŞISINDAKİ VOLATİLİTESİ

ÖZET

Bu çalışmada, borsadaki, seçilmiş günlük veriler kullanılarak ARCH-sınıfı modellerin tahminlemesi yapılmıştır. Borsa İstanbul-100 Endeksi kar rakamlarının Yiyecek-İçecek Sektörü Endeksi ve Teknoloji Sektörü Endeksi kar rakamları karşısındaki volatilitesi, 2003-2012 yılları arasındaki 2608 gözlem değeri için volatilite denkleminin tahmin edilmesi suretiyle analiz edilmiştir. Yiyecek-İçecek Sektörü Endeksi'nin iki bağımsız değişkenden biri olarak olarak kullanılmasının sebebi, yiyecek-içecek sektörünün, tüm dünya üzerinde, bazı yönlerden zorunlu mal olması özelliğinden ötürü ekonomideki dalgalanmalardan az etkilenmesi beklenen bir sektör olması; Teknoloji Sektörü Endeksi'nin diğer değişken olarak kullanılma nedeni ise teknoloji sektörünün, tüm dünyanın yanı sıra, Türkiye'de de, küreselleşme ve akıllı cihazlardan ötürü günden güne gelişen bir sektör olmasıdır. Yapılan analizler sonucunda, hem Yiyecek-İçecek Sektörü Endeksi kar volatilitesinin, hem de Teknoloji Sektörü Endeksi kar volatilitesinin, Borsa İstanbul-100 Endeksi kar volatilitesi ile bir ilişkisi olduğu saptanmıştır.

Anahtar Kelimeler: Bist-100 Endeksi, Yiyecek-İçecek Sektörü Endeksi, Teknoloji Sektörü Endeksi, Volatilite, ARCH-Sınıfı Modeller

1. INTRODUCTION (GİRİŞ)

The development process of securities lasted centuries (Silber, 2011). The first patterns of securities are based on the concept of debt. Nevertheless, the first introduction of the concept of corporate stock into markets are much later than debt's, that means, any securities. Also, it is obvious that today's modern stock exchange has been revealed more after than any corporation's single stock. Stock exchanges possess many roles in the economy such as increasing capital for businesses, government capital-raising for development projects, barometer of the economy, etc. (Diamond, 1967). That's why, the value of stock exchange in terms of balances among markets and among countries is of great importance. The stock exchange market in operation in Turkey is Borsa İstanbul (BIST). BIST is one of the greatest stock exchanges throughout the world in terms of total value of bonds traded[1].

While classical financial economics study has showed a tendency to stick to the the average of stock market returns, the accent has shifted to stick to the volatility of the returns in question (Brailsford & Faff, 1992). The owner of this accent upon volatility was regulators, practitioners and researchers and other market units. The volatility of financial markets has long been studied by researchers from a variety of academic backgrounds, with the ultimate objective being to uncover its underlying cause and mechanism (Fleming, Kirby, and Ostiek 2006; Wang and Chen, 2012).

2. RESEARCH SIGNIFICANCE (ÇALIŞMANIN ÖNEMİ)

In this paper, volatility of stock market returns of the Borsa İstanbul-100 (BIST-100) Index around Food and Beverage Sector Index and Technology Sector Index will be evaluated. Data for the period between 2003 and 2012 are taken. Measuring the BIST-100 Index as the dependent variable is because that this index is more formal than the BIST-500 Index and more comprehensive than the BIST-30 Index. Using food-beverage and technology indexes as independent variables is because that the food and beverage sector all around the world are expected less affected by fluctuations in economy. Food and beverage sector carries characteristics of being obligatory good in some aspects and the technology sector has been developing day by day via globalization and smart devices besides all of the world in Turkey as well.

This study basically purposes that investors are able to take investion decisions in a little bit more clear ambiances and decision-makers who are present in politics are able to take a little bit concious decision to lead public opinion about ARCH-class models with high volatility thanks to results taking place in the study.

3. LITERATURE REVIEW (KAYNAK TARAMASI)

It was a long time ago that uncertainty variability of financial havings was initially considered (Mandelbrot, 1963; Fama, 1965). Besides, volatility currently obtained an important acting in modern economic theory (Carvalho, Costa & Lopes, 2006). Broad rollings in price locomotions have frankly gotten more common and various observers have put forwards reason of structural alteration for this common raising in volatility (Schwert, 1990). So, the concepts of

[1] Retrieved from http://www.relbanks.com/stock-exchanges/largest-stock-exchanges

level and stationarity as to volatility has been studied by research workers in due course.

Volatility estimations have a lot of implementations just as access in the analysis of market timing decisions, and the meeting of forecasts of variance for access in asset rating models. However, it matters to individuate diverse models in order to arrange the model which submits the most correct estimations (Brailsford & Faff, 1992). Further, because high effectuating power of volatility of financial markets upon policies, volatility forecasts might be seen as barometer for the sensibility of financial markets (Poon & Granger, 2003).

Heteroscedasticity is usually adapted with cross-sectional data. Nonetheless, time series are often showed up in the homoscedastic modelling. There is a proof for some sorts of data about that the disturbance variances in time-series models are not much stable, whereas assumably they are (Cragg, 1982). This finding puts forward that in inflation models, estimation errors take place in clusters with a shape of heteroscedasticity in which the variance of the estimation error is dependent upon the size of the last disturbance. Engel, as a pioneer, also put forward that the autoregressive, conditionally heteroscedastic (ARCH) model as an option against the traditional time-series process. Newer studies of financial markets assert that the phenomenon is rather customary.

The most popular models which are able to be applied are ARCH-class models with the purpose of making the series stationary, which their variances are non-constant (Gökçe, 2001). Many researchs were conducted toward analyzing the sincerity of volatility estimations acquired from varied econometric models included the autoregressive conditional heteroscedasticity (ARCH) class models (Bollerslev, 1992). The ARCH model has been testimonied to be useful in researching the inflation volatility (Coulson and Robins, 1985), the term structure of the rate of interest (Engle, Hendry, and Trumbull, 1985), the volatility of stock market returns (Engle, Lilien, and Robins, 1987), and the behavior of foreign exchange markets (Domowitz and Hakkio, 1985; Bollerslev and Ghysels, 1996) to name but a few. A helpful generalizing of the mentioned model is the generalized conditional heteroskedasticity (GARCH) propounded by Bollerslev (1986).

Besides, there has been an expansion about the application of ARCH-class models. Mitchell and Mckenzie (2008) advocates that various ARCH models have been introduced and examined, which obtain these asymmetries. Zakoian's the threshold GARCH (TGARCH) model (1994), exponential GARCH (EGARCH) model of Nelson (1991) and Glosten's (1993) the GJR-GARCH model, Power ARCH (PARCH) model of Ding (1993) are a few of them.

The TGARCH (also namely QRTGARCH hereafter) warrants an asymmetric rebound of conditional volatility to blows without an presumption of renewal dispersion and to forecast the TGARCH, iterative forecast procedures based on state-space presentment are propounded (Park, 2002).

Nelson (1991) submitted an other option to GARCH models by alternating GARCH to exponential GARCH (EGARCH). He introduced the exponential GARCH (EGARCH) model as an effort to acquire the asymmetric effect of renewals on volatility, based on which a lot of tentative researchs have come up (Jane & Ding, 2009). Unlike GARCH, EGARCH is not in need of non-equal limitations on parameters to undertake a positive variance (Lee & Brorsen, 1997).

The GJR-GARCH model is introduced in VaR to analyze whether it is a superior method to review the market risk of financial assets or not (Su, Huang & Lin, 2011).

The PARCH model which forecasts the optimal power term therein the model warrants a power conversion term bearing any positive value and so allows a simply endless sequence of conversions, preferably than enforcing a pattern on the data (McKenzie, Mitchell, Brooks & Faff, 2001).

4. METHODOLOGY (METODOLOJİ)

4.1. Modelling (Modelleme)

As an alternative to very frequently-used traditional time series models, ARCH-class models let variance change as a function of its lagged expectation errors' squares by putting aside constant variance assumption on methods of time series (Harvey, 1991). Hence, in order to combine regression in the estimation process, ARCH-class models are fitted for non-constant variance.

The ARCH model which is the first one of ARCH-class models is denoted by equations as folows (Engel, 1982):

$$R_t = X_t \vartheta + \varepsilon_t$$

$$\varepsilon_t = z_t \sigma_t$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 \quad (1)$$

The generalized ARCH (GARCH) which is expanded by adding of its own last values of the conditional variance is denoted as follows (Bollerslev, 1986):

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \quad (2)$$

The Thresold GARCH (TGARCH) which chokes' effects on volatility are asymmetric has the equation of the conditional variance as follows (Zakoian,1994):

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \gamma_i S_{t-i} \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \quad (3)$$

The exponential GARCH (EGARCH) which allows analyzing the chokes' reactions on the conditional variance is as follows (Nelson, 1991):

$$\log(\sigma_t^2) = \alpha_0 + \sum_{i=1}^{p} \alpha_i \left| \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} - E\left(\frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} \right) \right| + \gamma \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \sum_{j=1}^{p} \beta_j \log \sigma_{t-j}^2 \quad (4)$$

The Power GARCH (PARCH) which powers of data is considered regarding transformation of the data has the equation of the conditional variance as follows Dink etc., 1993):

$$\sigma_t^d = \alpha_0 + \sum_{i=1}^{p} \alpha_i (|\varepsilon_{t-i}| + \gamma_i \varepsilon_{t-i})^d + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^d \quad (5)$$

Besides, as $E(\varepsilon_t) = 0$ and $V(\varepsilon_t) = \sigma_t^2$ are like that, the error term $f(\varepsilon_t)$ has normal probability density function as follows:

$$f(\varepsilon_t) = \frac{1}{\sqrt{2\pi\sigma_t^2}} e^{-\frac{1}{2}\left(\frac{\varepsilon_t^2}{\sigma_t^2}\right)} \quad (6)$$

The most likelihood estimations of unknown parameter vector are derived by maximization of log-probality function and log-probality function which is derived by using the equation of $\varepsilon_t = z_t \sigma_t$ is as follows:

$$L_{normal} = \ln \prod_t \frac{1}{\sqrt{2\pi\sigma_t^2}} e^{-\frac{1}{2}\left(\frac{\varepsilon_t^2}{\sigma_t^2}\right)} = \ln \prod_t \frac{1}{\sqrt{2\pi\sigma_t^2}} e^{-\frac{1}{2}z_t^2} = -\frac{1}{2}\sum_t \left[\ln(2\pi) + \ln(\sigma_t^2) + z_t^2\right] \quad (7)$$

Because ARCH regression model is an iterative estimation process, the model probably includes ARCH effect. So, The effect should be tested. The most appropriate test for this aim is Lagrange Multiplier (LM) test (Davidson and MacKinnon, 1993).

4.2. The Model of the Research (Çalışmadaki Model)

In this study, it is purposed to measure volatility of the daily return amounts of the BIST-100 Index around The Food-Beverage Sector Index and The Technology Sector Index. So, while the BIST-100 Index observations compose dependent variable, The Food-Beverage Sector Index and The Technology Sector Index observations compose independent variables. In light of these, the model is as follows:

$y = \alpha_0 + \alpha_1 x_1 + \alpha_2 x_2 + \varepsilon$ (8)

5. ANALYSIS (ANALİZ)

5.1. The Data and Preliminary Test (Veriler ve Hazırlık Testi)

The BIST-100 Index (1986=1) as the most suitable variable set in stock exhange market is determined and time series attributes and some statistical extents of this index is analyzed. Also, The Food-Beverage Sector Index and The Technology Sector Index include variable sets having potential for being intriguing for many parties. The data set which is used in analysis is collected by the return amounts of 2608 operation days for these indexes for a-ten year. To explain in detail, for three indexes afore-mentioned, data sets between the dates of 01.02.2003 – 12.31.2012 are used. Actually, during so-called ten years, 2490 operation days are present because of holidays in weekdays. However, closing value of last observation is considered as the value of remnant days for using the programme of the e-views with a accurate way.

Daily trade-off rate is formulated as follows:

$Vol_t = \ln (Volume_t / Volume_{t-1})$ (9)

On this Formula, Vol_t is the rate of trade-off on trade volume and $Volume_t$ is daily operation volume.

5.2. Definition of The Model (Modelin Tanımlanması)

The E-Views 6.0 packet programme is used for testing the significancy of the model.

5.3. Findings and Determination of The Model (Bulgular ve Modelin Belirlenmesi)

The time series graph of the indexes is made up of via the programme and indicated on the figure 1.

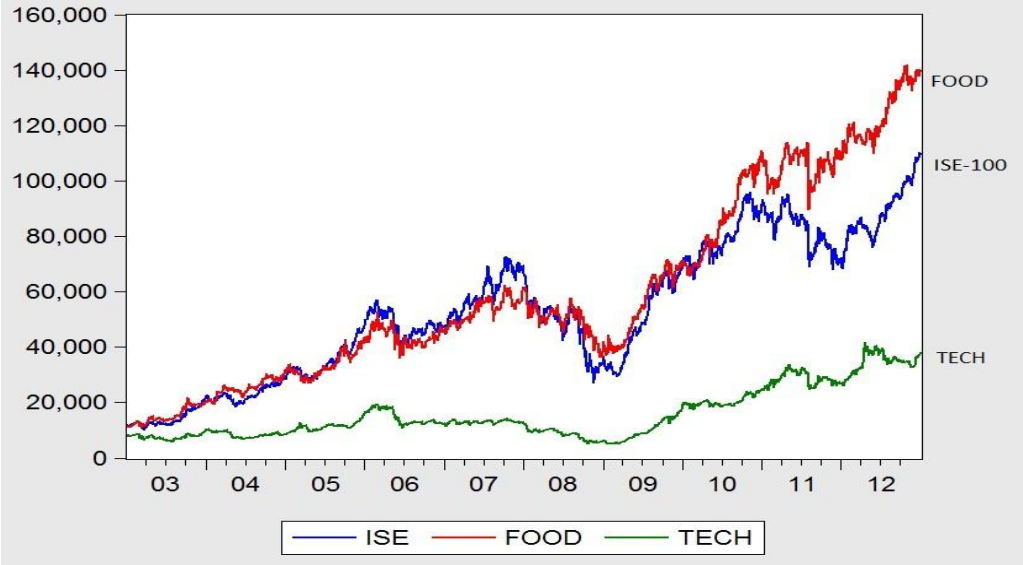

Figure 1. Time series diagram
(Şekil 1. Zaman serisi grafiği)

On the graph, while horizontal axis shows the timeline after the year of 2000, vertical axis shows the volume of the index in TL.

It is mentioned that the least squares (LS) regression model is not efficient at modelling volatility as much ARCH-class model is as because LS regression model is not sensitive enough for data with high frequency. However, the indicator of that ARCH-class model is fitted well to volatility is that the time series has ARCH effect. Morever, ARCH effect is tested with ARCH-Lagrange Multiplier (ARCH-LM) and the test results revealed that there is ARCH effect for both independence variables because probabilities of index parameters are under any value of significance level.

After applying ARCH-LM test, modelling these time series has been made with ARCH-class models. The answer of which ARCH-class model estimates best can be determined with many ways. Firstly, the parameters of the model have to be significant and the model has to be purified from ARCH effect. Also, high log-likelihood is another choice purpose. If these requirements are provided, some criteria are discussed. Criteria such as The Akaike Info Criterion, The Schwarz Criterion and The Hannah-Quinn Criterion, etc. are used for choosing the most available model. Nonetheless, in this study, the most common one, The Akaike Info Criterion is used when parameter significancy and purification from ARCH effect are provided.

In order to ascertain the most available model the ARCH, the GARCH, the TGARCH, the EGARCH, the PARCH models are examined. The table given below shows the details of various ARCH-class models which are examined in the study with varied lag combinations (Table 2).

Table 1. The models and their details
(Tablo 1. Modeller ve detayları)

The Model	**The Details**
ARCH(1)	Only ARCH, with one lag
ARCH(2)	Only ARCH, with two lags
GARCH(1,1)	ARCH and GARCH, both with one lag
TGARCH(1,0,1)	ARCH with one lag and threshold order is one
TGARCH(0,1,1)	GARCH with one lag and threshold order is one
TGARCH(1,1,1)	ARCH and GARCH, both with one lag and thresold order is one
EGARCH(1,0,1)	ARCH with one lag and asymmetric order is one
EGARCH(0,1,1)	GARCH with one lag and asymmetric order is one
EGARCH(1,1,1)	ARCH and GARCH, both with one lag and asymmetric order is one
PARCH(0,1,0), FIX POWER(1)	GARCH with one lag, fix power is one
PARCH(1,0,1), FIX POWER(1)	ARCH with one lag, asymmetric order is one, fix power is one
PARCH(1,1,0), FIX POWER(1)	ARCH and GARCH, both with one lag, fix power is one
PARCH(1,1,1), FIX POWER(1)	ARCH and GARCH, both with one lag, asymmetric order is one fix power is one

Table 2. The models and their details
(Tablo 2. Modeller ve detayları)

The Model	**α0 (P-value)**	**α1 (P-value)**	**α2 (P-value)**	**β1 (P-value)**	**Asymmetry (P-value)**	**Power (P-value)**	**R-squared**	**F-statistic**	**P-value of ARCH (α=0.05)**	**Akaike Criterion Value**
ARCH (1)	37839034 (0.00)	0.51 (0.00)	N/A	N/A	N/A	N/A	0.90	6084.13	0.00	20.41
ARCH (2)	40306979 (0.00)	0.77 (0.08)	-0.74 (0.49)	N/A	N/A	N/A	0.90	4888.96	0.00	20.43
GARCH (1,1)	37427920 (0.)	0.97 (0.00)	N/A	-0.66 (0.00)	N/A	N/A	0.90	4653.28	0.00	20.26
TGARCH (1,0,1)	37839146 (0.00)	0.54 (0.00)	N/A	N/A	-0.08 (0.73)	N/A	0.90	4871.72	0.00	20.41
TGARCH (0,1,1)	34548803 (0.00)	N/A	N/A	1.43 (0.00)	-0.80 (0.00)	N/A	0.52	571.94	0.00	20.38
TGARCH (1,1,1)	37427855 (0.00)	1.13 (0.00)	N/A	-0.30 (0.24)	-0.67 (0.00)	N/A	0.90	3909.14	0.00	20.25
EGARCH (1,0,1)	16.38 (0.00)	1.20 (0.00)	N/A	N/A	0.00 (0.72)	N/A	0.90	4913.98	0.00	20.30
EGARCH (0,1,1)	0.17 (0.00)	N/A	N/A	0.01 (0.00)	0.99 (0.00)	N/A	0.87	3416.72	0.00	20.52
EGARCH (1,1,1)	15.48 (0.00)	1.41 (0.00)	N/A	0.04 (0.30)	0.08 (0.00)	N/A	0.91	4231.07	0.00	20.27
PARCH **(0,1,0/1)**	34548872 (0.00)	N/A	N/A	-1.00 (0.00)	N/A	N/A	N/A	N/A	0.00	33.14
PARCH (1,0,1/1)	57581453 (0.83)	1.03 (0.00)	N/A	N/A	0.01 (0.73)	2.64 (0.00)	0.89	3432.53	0.00	19.79
PARCH (1,1,0/1)	37416974 (0.00)	-30.92 (0.00)	N/A	-0.53 (0.00)	N/A	N/A	N/A	N/A	0.00	34.93
PARCH (1,1,1/1)	57581453 (0.83)	0.71 (0.00)	N/A	0.36 (0.00)	0.01 (0.84)	3.02 (0.00)	0.89	3083.86	0.00	19.77

5.4. Test Results (Test Sonuçları)

In terms of submitting that ARCH-class models are proper to estimate the model, ARCH-LM test is applied and according to the output, ARCH effect is determined and to exert ARCH-class models as the estimation models are considered proper just as assumed theoretical. Then, ARCH-class models are dealt with as estimation method.

The most proper model has to be purified from ARCH effect and model's variables have to be significant. All of the models afore-mentioned in the study is purified in the level of 0.05 as seen on the

Figure 3. However, among all of the models afore-mentioned in the study, only several of model's variables cover the requirement of being significant.

ARCH(1), GARCH(1,1), EGARCH(0,1,1), TGARCH(0,1,1), PARCH(0,1,0/1), PARCH(1,1,0/1) models are these so-called several models. Because ARCH, GARCH and TGARCH models don't meet the requirements of that variables of the models in question have to be in positive way, these models are not proper. Also, because the Akaike Info Criterion values of PARCH models in question are very high, these models are not available neither. So, the only model remained, EGARCH(0,1,1) is chosen the most proper model for the study. The average estimation model comes out from the information above is as below:

bist-100 index= 7438.69 + 0.82 (food index) - 0.52 (tech index) + ε (10)

This average equation show that the volatility of the daily return amounts of the BIST-100 Index has a positive relationship with the daily return amounts of The Food-Beverage Sector Index and has a negative relationship with The Technology Sector Index between the years of 2003 and 2012.

As ARCH-class models are concerned, variance equation is more determinant than average equation. Variance equation of the model is as follows:

$$\log(\sigma_t^2) = \alpha_0 + \sum_{i=1}^{p} \alpha_i \left| \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} - E\left(\frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} \right) \right| + \gamma \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \sum_{j=1}^{p} \beta_j \log \sigma_{t-j}^2$$

α_0 = 0.16 ; α_1 = 0.00 ; γ = 0.01 ; β_1= - 0.99 (11)

Also, since the most proper model is EGARCH in the study, it might be stated that there is positive leverage effect in the this time series. It means, positive shocks in the market are more effective than negative shocks for this time series.

During equation modelling, many different non-constant variance models with various lag distributions are evaluated and EGARCH(0,1,1) model is decided as the most suitable one. It is supported that the model is available for representing the variables with determination coefficient of the model. Adjusted determination coefficient of the model which is 0.87 expresses that independent variables states dependent variable quite successfully.

6. CONCLUSION (SONUÇ)

In this paper, the time series features of the daily return amounts of Borsa İstanbul are researched and the methodology of conditional non-constant variance is used for modelling the series.

When market volatility for the indexes in the study is evaluated, it is obvious that the indexes' volatility motives are affected by each other and exhibit positive or negative correlation. The main reason of this is that the volatility of the market has a tendency to decrease regarding good news and to increase regarding bad ones. Nonetheless, there are always a small amount of lag before the reaction in question because of the characteristic attribute of Borsa İstanbul. In other words, leverage effect commonly participated in financial literature. In the research, it is revealed that there is a positive leverage effect which can be explained with the state of that positive shocks in the market are more effective than negative shocks for the time series in the study.

Morever, even though a conclusion is reached to, the readers must be well aware of that it is almost impossible to state a model completely explain the future of stock exchanges and that they have to

stand uncertainty of residual part which is always much for stock exchanges. In this study, resudial part is approximately 13 percent. So, the results which have come out from the model can be defined as a prediction with 13 percent lapse rate. Although the model includes uncertainty like in this example, investors are able to take investion decisions in a little bit more clear ambiances and decision-makers who are present in politics are able to take a little bit concious decision to lead public opinion thanks to studies alike.

Lastly, despite relationships are determined between the variables, causality between the variables is ignored. Causality notion is of importance since it hinders for free variables having same tendency to be mistakely assumed have a significant correlation. Thus, measuring causality between the variables might be the subject of a further research.

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