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VOLATILITY STRUCTURE OF STOCK PRICE INDEX AND EXCHANGE RATES: CASUALITY ANALYSIS FOR TURKEY

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ABSTRACT

Volatility in finance is used as a concept of uncertainty, change and fluctuation as well as a measure of risk. Recently, rapid rises and falls of exchange rates and BIST Stock Index unfold the concept of volatility. The purpose of the study is to reveal the volatility structure of Turkish stock exchange market and exchange rates and also to determine the relationship between the stock exchange index and exchange rates. In the studies conducted in the field of finance, there is usually a one-way or two-way relationship between stock markets and exchange rates. However, there is no consensus on the structure of this relationship. The aim of this study is to determine the relationship between stock price index and exchange rates. Two hypothesis will be tested in the study: Is there a cointegration relationship (long-term equilibrium) and causality between the exchange rate and stock prices in Turkey? ARCH family models which are widely used in literature are tested using BIST 100 index, EURO/TL selling rate and USD/TL selling rate. Results of the study show that there is volatility in all of the series. Furthermore, causality test show that the value of the variables are linked each other.

Key Words: Financial Market, Exchange Rates, Stock Market Prices, BIST 100 Index
Jel Codes: E32; O14; O40.

DÖVİZ KURU VE BORSA ENDEKSİ VOLATİLİTE YAPISI: TÜRKİYE İÇİN NEDENSELLİK ANALİZİ

ÖZ

Finans alanında volatilite genellikle risk ölçü birimi olarak kullanılmakla birlikte aynı zamanda belirsizlik, değişim, oynaklık anlamlarına da gelmektedir. Özellikle son zamanlarda Türkiye'de döviz kurları ve borsa İstanbul'da yaşanan hızlı artış ve düşüşler volatilite kavramının önemini bir kez daha gözler önüne sermiştir. Bu çalışmanın amacı, Türkiye'de hisse senedi piyasaları ve döviz kurlarının volatilite yapısını ortaya koymaktır. Finans alanında yapılan çalışmalarda genellikle, hisse senedi piyasaları ile döviz kurları arasında tek yönlü ya da çift yönlü olabilecek bir ilişki tepit edilmiştir. Ancak, bu ilişkinin yapısı hakkında tam bir fikir birliği bulunmamaktadır. Bu çalışmada hisse senedi endeksi ve döviz kurları arasındaki ilişkinin belirlenmesi amaçlanmaktadır. Çalışmada iki hipotez test edilmektedir: Türkiye'de döviz kurları ve hisse senedi fiyatları arasında bir eşbütünleşme (uzun dönemli denge) ve nedensellik ilişkisi var mıdır? Çalışmada volatilitenin tespit edilebilmesi için literatürde yaygın bir şekilde kullanılan ARCH ailesi modelleri kullanılarak, BIST 100 endeksi ve EURO/TL Satış Kuru ile USD/TL satış kurlarına ait veriler kullanılmıştır. Çalışmanın sonucunda tüm serilerde

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volatilite tespit edilmiştir. Nedensellik analizi sonuçlarında tüm serilerin birbirlerinin Granger anlamda nedeni olduğu görülmüştür.

Anahtar Kelimeler: Finansal Piyasalar,, Döviz Kurları, Hisse Senedi Fiyatları, Borsa İstanbul 100 Endeksi
Jel Kodları: E32; O14; O40.

Introduction

Exchange rates are a determinant of the foreign investors' profit as well as the domestic investors. The highest trading volume among financial markets is in foreign exchange market[2]. Exchange rates have a wide range of effects on economy starting from the international capital flows to real economic activities and policy support instruments. If the exchange rate diverges from the equilibrium point in real terms, competition power of the economy diminishes and policy makers intervene the economy. Exchange rate volatility play an active role both in the fiscal policy decisions and the monetary policy decisions which affects the economic activities and economic stability. In addition, exchange rates are determinant in calculating the profits of the foreign investors in an economy. If exchange rates are highly volatile, there may be uncertainty and lack of confidence in the stock market investments. Increasing volatility of stock prices causes more risk in stock exchange markets. Thereby, volatility affects the investment behavior to a great extent. If the returns of the domestic stocks increase, investors demand more domestic assets and less foreign assets, as a result domestic currency appreciate. This change, named stock oriented model-portfolio model, indicates a negative relationship between stock exchange prices and exchange rates (Frankel, 1993). Conversely, a second model, traditional-flow oriented model, determining the relationship between exchange rate and stock prices defines a positive relationship. The changes of exchange rate change the competitiveness of a company, which then affects revenue or cost of funds of the company and have an impact on the company's stock price (Dornbusch and Fischer, 1980).

As a result of these wide effects, estimating the values of the financial assets dominate the financial market operations. Uncertainty of the financial markets can be measured using the volatility of the financial variables. Thus, before detecting the uncertainty, volatility has to be measured. Volatility of the variables such as interest rates, exchange rates, inflation, stock exchanges, wages or production costs are a measure of bias from the expected values of

[2] Exceeding $5.1 trillion per day according to Bank of International Settlement data (https://www.bis.org/publ/rpfx16.htm?m=6%7C381%7C677).

parameters (Bolgün and Akcay, 2009: 353). In other words, volatility is defined, the statistical measure of price changes of a financial asset (Butler, 1999: 190). Volatility shows the fluctuations in the financial series and it includes the uncertainty in the financial markets. Mandelbrot (1963) emphasizes that big changes in the returns of financial assets are followed by other big changes and small changes in the returns of financial assets are followed by small changes that are defined as volatility clustering.

Therefore, volatility is the main concern of various financial theories (portfolio theories, capital asset pricing model (CAPM), risk management). Volatility in stock prices has also been the focus of investors as a determinant of their investment returns. Exchange rates determine the profit of the international investors, thus the volatility of exchange rates play an important role in investment decisions. Most of the time, high volatility shows high risk investment, especially in the periods of financial crisis for the variables. In order to reveal the volatility properties of stock returns and exchange rates, the mean and the standard deviation of the series should be evaluated. If the standard deviation is high, the series has high volatility, and if the standard deviation is low, series has low volatility.

Volatility calculation employs standard error index, historical volatility and expected volatility approach. These traditional approaches assume that the change in volatility is constant over time and change in the volatility is independent from the previous changes of the volatility. But, for the time series models, this assumption is extended to stand a variance with dynamic properties. Engle (1982) introduced autoregressive conditional heteroscedasticity (ARCH) models estimating the dynamic properties of the conditional variance. Afterwards; Bollerslev (1986) developed General ARCH (GARCH) model, which is an autoregressive moving average model based on the weighted average of past squared residuals. In this study, ARCH/GARCH models will be used to determine the relationship between stock prices and exchange rates. In a world with limited resources, investors try to gain the maximum return using the limited resources with optimum efficiency. In order to make the best decision, investors must reach and analyze all the available information. Especially in the developing economies, asset prices move quickly against unexpected situations. In order to determine the relationship between stock prices and exchange rates, two hypothesis will be tested: Is there a cointegration relationship (long-term equilibrium) and causality between the exchange rate and stock prices in Turkey. Hereby, this paper contributes to the literature by analyzing the relationship between the volatility of Turkish stock market and exchange rates using symmetric and asymmetric ARCH -GARCH models.

In the following section, a literature review will be presented. Then, model specification and model will be discovered. In the last section empirical results will be concluded.

Literature Review

Both directional and bidirectional evidence between the variables are found in the literature. Some empirical evidence shows causation from exchange rate to stock market prices (Abdalla and Murinde, 1997, Erbaykal and Okuyan, 2007, Yusuf and Rahman, 2012, Olugbenga, 2012). On the contrary, some empirical evidence shows causation from stock market prices to exchange rate (Erbaykal and Okuyan, 2007, Yusuf and Rahman, 2012, Pan et.al. 2007, Lin, 2012).

Moreover there are some evidence of no causality between stock market prices and exchange rate (Asaolu and Ogunmuyiwa, 2011, Zia and Rahman, 2011, Zhao 2010). In addition, bidirectional causality are also found in some studies (Erbaykal and Okuyan, 2007; Yusuf and Rahman, 2012, Bahmani et.al., 1992; Doong et al., 2005, Zhao 2010, Singh et al., 2010).

Schwert (1989) analyze the stock market volatility changes, real and nominal macroeconomic volatility using monthly data from 1857 to 1987. The paper tests the relationships between stock volatility and other variables. It is concluded that economic series (including financial asset returns) are more volatile during recessions. In addition, it is suggested that macroeconomic volatility cannot be used to predict stock and bond return volatility. Nevertheless, financial assets volatility is more explanatory to predict future macroeconomic volatility. In addition a relationship is found between trading activity and stock volatility.

Bollerslev and Mikkelsen (1996) discuss the structure of stock market volatility with an EGARCH model to characterize the long run determinants of US stock market volatility. Conditional variance of Standard and Poor’s 500 composite index is used to reveal the model including the market integration process.

Morley and Pentegost (2000) test the relationship for G-7 countries with the data from January 1982 to January 1994 using time series modelling and found that stock prices and exchange rates have no common trends, instead they move in common cycles. They emphasize that stock markets and exchange rates are linked with a common cyclical pattern rather than a common trend.

Kim (2003) investigates the relationship between dollar exchange rate and stock prices using cointegration method and finds that the S&P 500 stock price is negatively related to the real exchange rate. The data used include monthly series covering January 1974 to December 1998 and determine a long term relationship between the variables in U.S financial markets.

Yang and Doong (2004) employs a GARCH model to measure the volatility of stock markets and foreign exchange markets for G7 countries. Results of the study show that movements of stock prices are a determinant of future values of exchange rates. Besides, changes in exchange rates are not determinant of the future volatility of stock prices. It is concluded in the analysis that there is information flow between the two markets and the two markets are integrated.

Phylaktis and Ravazzolo (2005) investigate the linkages between stock prices and exchange rates in the short run and in the long run using Granger Causality Method. The study reveals that stock market and foreign exchange market are related positively linked by US stock market as a conduit. In addition, foreign exchange restrictions and financial crisis are important determinants in these linkages.

Vygodina (2006) tests the effects of size and international exposure of the US firms based on the relationship between stock prices and exchange rates in the firm size over a period 1987–2005 using Granger causality methodology. It is found that the characteristics of the relationship varies over time. In the study, some turning points are used to emphasize the result that causality relation between stock prices and exchange rates changes over time. Final results support this hypothesis, with changes in exchange rate being significant in determining changes in large-cap stock prices for the periods 1995–2000 and 2003–2005 and changes in large-cap stock prices leading changes in exchange rates for the period 2000–2003.

Diebold and Yılmaz (2008) analyze the connection between macroeconomic fundamentals and asset return volatility. Volatility of GDP is mentioned by standard deviation of GDP and stock market volatility is measured by the major stock index series from the IMF's International financial statistics and DataStream of the Standard and Poor's emerging market database and the world federation of exchanges. A positive relationship is found between stock return and GDP volatilities. A higher volatility is found in developing countries and a lower volatility in industrial countries.

Agrawal (2010) investigates the volatility of Indian Rupee/USD exchange rate and stock returns of India. Findings of Granger Causality test support a negative correlation and also a uni-directional relationship from stock returns to exchange rate.

Kumar (2013) searches IBSA countries stock returns and exchange rate volatility with a multivariate GARCH model with time varying variance covariance BEKK model originated by Diebold and Yılmaz (2008). Results confirm returns and volatility spillovers within IBSA countries.

Mozumder et. al. (2015) use E-Garch model to examine the volatility spillover effects between stock prices and exchange rates in 3 developed (Ireland, Netherlands, Spain) and 3 emerging countries (Brazil, South Africa and Turkey). Results of the study show asymmetric volatility spillover effects between the variables in both the developed and the emerging countries during financial crisis. Findings reveal that the markets are inefficient and one market has significant predictive power on the other.

There are also empirical studies on the volatility relationship between exchange rate volatility of Borsa Istanbul. Gökçe (2001) examines the volatility of Istanbul Stock Exchange Market returns by using ARCH models using daily data of stock exchange values. The model shows a positive relationship between stock exchange volatility and stock exchange return. It is found that the volatility of the variables is continuously high and fluctuating over time. It is also proved that there is a positive relationship between market returns and volatility but this relationship rapidly changes according to the good and bad news in the market. This tendency of rapid movements is a characteristic structure of Istanbul Stock Exchange Market.

Similarly, Kalaycı (2005) employes a GARCH model to determine the conditional volatility in Istanbul Stock Exchange Market. The conditional variance is used for a multiple regression analysis together with macroeconomic variables (interest rate of Treasury Bills, consumer price index, money supply, dollar exchange rate and industrial production index). The study shows that only inflation and money supply effect the volatility. It is concluded that Istanbul Stock Exchange Market is not sufficiently effective and speculative movements are dominating.

Ayvaz (2006) tests the relationship between BIST 100 index and exchange rates for Turkish economy for 1991-2004 period with time series analysis based on monthly data. The results indicate that there is a bi-directional causality among exchange rate and stock price indexes.

Aydemir and Demirhan (2009) investigate the causal relationship between stock prices and exchange rates, using Turkish data from 2001 to 2008. The results of the study shows that there is bidirectional causal relationship between exchange rate and all stock market indices. While the negative causality exists from national 100, services, financials and industrials indices to exchange rate, there is a positive causal relationship from technology indices to exchange rate. On the other hand, negative causal relationship from exchange rate to all stock market indices is determined.

Elmas and Esen (2011) examine the relationship between the local stock market indexes and exchange rate (USD) using the Engle-Granger (1987), Johansen (1988, 1995) and JohansenJuselius (1990) cointegration methods and find a Granger causality from exchange rates to stock price index supporting the traditional model.

Contrary results supporting the portfolio model are found by Berke (2012). It is stated that when the exchange rates increase, stock prices tend to decrease and a negative relationship is seen for the Turkish economy between 2002-2012.

On the other hand, Çiçek (2014) analyzes intermarket price and volatility spillover effects among Istanbul Stock Exchange 100 Index, Turkish government debt securities, and foreign exchange using Multivariate EGARCH Model and the results of the study shows there is no long run relationship among three markets.

Veli A. (2015) examines the stock market integration between Brazil, India, Indonesia, South Africa and Turkey economies from November 2000 to December 2013. A long run relationship is found between the countries in the financial markets. In addition, granger causality analysis shows causality relationship in the short run. The study concludes that portfolio diversification and arbitrage profit can be ensured in stock exchange markets of these countries.

Data Description and Methodology

Data Set

This study aims to determine the volatility properties of stock returns and exchange rates and reveal the casual relationship between the stock return and exchange rate for Turkish economy using daily data of Euro, USD and BİST 100 index between the periods of 03.01.2005-03.05.2018. The data has been taken from Electronic Data Delivery system of Central Bank web site. In the study, firstly, stationarity of data and ARMA structure are tested. Secondly, volatility is measured by using GARCH model. Finally, Granger causality test is applied to analyze the causality between exchange rate volatility and stock price volatility. Return series are calculated using the formula $100 * \ln\left(r_t / r_{t-1}\right)$. Graphics of the series are given below:

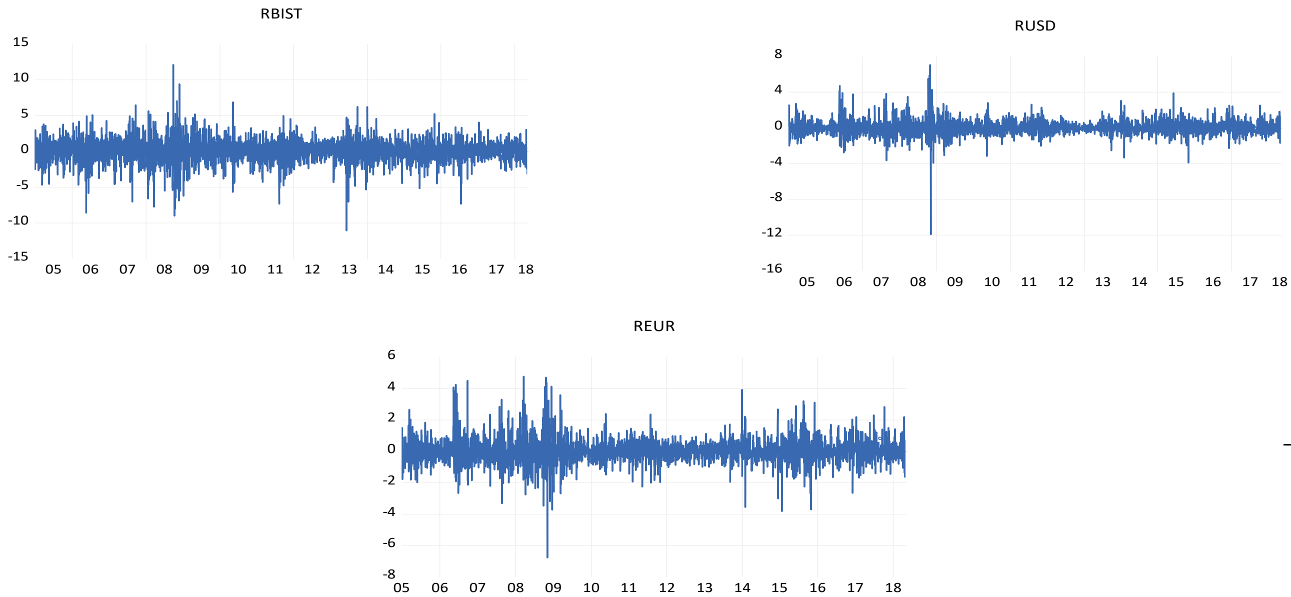

Figure 1. The time series graphics of the variables

When we look at the graphs of the series, we can see the volatility clustering defined by Mandenbrot (1963), Time series graphs show that big changes in data are followed by other big changes and small changes in data are followed by small changes. Therefore, heteroscedasticity is tested to see the volatile structure of the series.

Table 1: Descriptive Statistics

	RBIST100	**REUR**	**RUSD**
Mean	0.041193	0.029721	0.033515
Median	0.077922	0.000000	-0.015338
Maximum	12.12721	4.770852	7.042900
Minimum	-11.06379	-6.771848	-11.93484

Std. Dev.	1.648825	0.785569	0.826631
Skewness	-0.288440	0.366776	-0.125484
Kurtosis	6.820507	9.129243	21.17509
Sum	138.2435	99.74282	112.4779
Sum Sq. Dev.	9120.981	2070.431	2292.535
Observations	3356	3356	3356

Firstly, to see the normality of the series, skewness and kurtosis values are examined. When we look at the skewness and kurtosis values, kurtosis statistic should be 3 and skewness statistic should be 0 in order to accept that the series are normally distributed (Gujarati, 1999: 143). All of the series are fat tailed and therefore the series are not normally distributed. Brooks (2008) states that the financial time series are not distributed normally in general. Distribution of the financial assets are generally more pointed in the mean when we compare with the normally distributed series. In other words, these type of series have fat tail. As big changes is followed by big changes and small changes are followed by small changes, when there is volatility clustering, we can say that the price changes are not independent from each other. There properties of the series refer to the use of ARCH-GARCH models which reveals unbiased results.

When we look at the properties of the series in Table 1, we can see that result. Fat tail of the series show that the series display extreme and big movements and sharp points show that the edge points are high. These properties indicates that the series show volatility.

Unit Root Tests

Most of the financial data series show non-stationary properties. Stationary test such as Augmented Dickey Fuller and Philips Perron Tests must be done before the analysis here with there will be no spurious regression problem. Unit root test results are given in the table 2

Table 2: Unit Root Test Results

	ADF (Augmented Dickey-Fuller) Test		PP (Philips-Perron) Test	
Series	**Constant**	**Constant and Trend**	**Constant**	**Constant and Trend**
RBIST	-56.35293(0.0001)	-56.34746(0.0000)	-56.35531(0.0001)	-56.35121(0.0000)

REURO	-55.03134(0.0001)	-55.06697(0.0000)	-55.00563(0.0001)	-55.06697(0.0000)
RUSD	-56.41985(0.0001)	-56.45493(0.0000)	-56.40838(0.0001)	-56.44079(0.0000)

Values in parenthesis are p values.

PP and ADF test the null hypothesis that a unit root is present in a time series sample. According to both tests, null hypothesis is rejected as the calculated values exceed the critical table values (p values are smaller than 1%). Series are stationary at 1 % significance level according to both ADF and PP tests.

Unit root tests show that all the series are integrated at level, therefore, ARMA structure of the series are tested in the second place. ARMA structure of the series according to Schwarz Information criteria taking p and q values as 10 are shown in table 3. When we analyze table 3, most efficient ARMA structure for Stock Istanbul Index and exchange rate index is AR (0) and MA (0). The most efficient combination for euro index is AR (0) MA (1).

Table 3. ARMA Structure of the Series

Series	**ARMA Structure**	**BIC Coefficient**
RBIST	ARMA(0,0)	-5.367472
REURO	ARMA(0,1)	-6.851545
RUSD	ARMA(0,0)	-6.749297

After detecting ARMA structure of the series according to the selection criteria, residuals derived from the series are tested for homoscedasticity with ARCH LM test. Results of the test are shown in the table 4.

Table 4: ARCH LM Test Results

Series	**Lag value**	**F Statistic**	**Observed R^2**	**Result**
RBIST	1	47.77226	47.12965 (0.0000)	H_0 is rejected.
	2	52.94221	102.7349 (0.0000)	
	5	57.74207	266.2604 (0.0000)	
	10	37.95578	341.9184 (0.0000)	
	1	85.45068	83.37801 (0.0000)	
	2	70.11421	134.7197 (0.0000)	

REURO	5	62.78910	287.5375 (0.0000)	H_0 is rejected.
	10	36.91866	333.5063 (0.0000)	
RUSD	1	78.50266	76.75353 (0.0000)	H_0 is rejected.
	2	43.19241	84.29050 (0.0000)	
	5	79.38838	355.4933 (0.0000)	
	10	55.50325	477.4495 (0.0000)	

H_0 hypothesis for the LM test is there is no heteroscedasticity. When we look at the table 4, observed $R^2 < \chi^2$ condition is not satisfied when ARCH LM test statistics for different lag values are tested. As a result, we can reject the null hypothesis and conclude that there is heteroscedasticity and ARCH effect in the series. Consequently, ARCH-GARCH models must be used in order to determine the volatility structure of the series.

Autoregressive Conditional Heteroscedasticity (ARCH) Model

ARCH model was introduced by Engle (1982) modelling the conditional variance and conditional heteroscedasticity. ARCH model enables the individual modelling of the conditional mean and conditional variance of a series simultaneously. According to the ARCH model, shocks are one of the deterministic component of the financial returns without autocorrelation but dependent. Volatility models can reveal this dependency. Dependency of error terms can be defined by the past forms of themselves as the quadratic functions.

ARCH model defines the conditional variance and conditional mean as follows (Çil Yavuz, 2015: 437-438):

$$\mu = E(r_t|F_{t-i}) \tag{1}$$

$$\sigma_t^2 = Var(r_t|F_{t-i}) = E[(r_t - \mu)^2|F_{t-i}] = E[(\varepsilon_t)^2|F_{t-i} \tag{2}$$

The term F_{t-i} (t-1) shows the past information to t-i period. Hence, conditional standard deviation (σ_t) is a function of past information of r_t:

$$\sigma_t = \xi(r_{t-1}, r_{t-2}, \dots.) \tag{3}$$

Generalized Autoregressive Conditional Heteroscedasticity (GARCH) Model

The GARCH model was firstly defined by Bollerslev (1986) including the lagged conditional variance terms in the auto regression model. The GARCH model defines the variance of the ARCH model with an ARMA structure having a more flexible lag structure and giving better long term results (Bozkurt, 2007: 6):

GARCH (p,q)

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i e_{t-i}^2 + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2 \quad (4)$$

$$\sigma_t^2 = \alpha_0 + \alpha(L) e_t^2 + \beta(L) \sigma_t^2 \quad (5)$$

in the model,

$$p \geq 0, q > 00 \quad (6)$$

$$\alpha_0 > 0, \alpha_i \geq 0, i = 1, \dots \dots .., q. \quad (7)$$

$$\beta_i \geq 0, i = 1, \dots \dots .., p. \quad (8)$$

If p=0, p=q=0 in the ARCH model. Hence, it shows that error terms are white noise. Conditional variance is defined both by the lagged values of the error terms and the lagged values of the variance. For this reason, β and α coefficients should not have negative values in order to maintain stability and autocorrelation of the error terms (Bollerslev et al., 1992: 7,8).

GARCH model is developed in various ways. Within the GARCH framework, EGARCH (Exponential GARCH), TGARCH (Threshold GARCH) models are developed.

EGARCH model defines the conditional variance as a logarithmic function including asymmetric effects (Nelson, 1991: 354):

$$\log(h_t) = \omega + \sum_{j=1}^{p} \beta_j \log(h_{t-j}) + \sum_{i=1}^{q} \alpha_i \frac{|\varepsilon_{t-i}|}{\sqrt{h_{t-i}}} + \sum_{i=1}^{q} \gamma_i \frac{\varepsilon_{t-i}}{\sqrt{h_{t-i}}} \quad (9)$$

This equation enables to distinguish the negative and positive volatility effects of shocks. EGARCH measures whether the upward and downwards movements in the financial markets cause the same effect on the predictability of future volatilities of the financial assets. In predicting the volatility, downward movements are more effective than the upward movements (leverage effect) indicating that bad news have more effects on financial asserts than good news on the values of the financial assets (Çil Yavuz, 461-462).

On the other hand, TGARCH model is defined as (Zakoian, 1994: 934):

$$h_t = \alpha_0 + \sum_{i=1}^{q}(\alpha_i \varepsilon_{t-i}^2 + y_i D_{t-i} \varepsilon_{t-i}^2) + \sum_{i=1}^{p} \beta_i h_{t-i} \quad (10)$$

Positive and negative news are treated asymmetrically in the T-ARCH model. γ is the asymmetry (leverage) term. If $\gamma = 0$, the model can be defined as the standard GARCH form. If the shock is positive, the effect on volatility is α_1, but if the news is negative, the effect on volatility is $\alpha_1+\gamma$. If γ is significant and positive, negative shocks have a larger effect on h_t than positive shocks (Hill et al., 2011: 527).

The GARCH model defines the conditional variance of the time series upon squared residuals of the process (Bollerslev, 1986: 311). Thus, the heteroscedasticity property of the time series can be imported into a more dynamic model (Engle and Granger., 1987: 264). Exchange rate data shows volatility clustering that means that large changes tend to be followed by large changes of either sign and periods of tranquility alternate with the periods of high volatility.

EMPIRICAL RESULTS

In this part of the study, ARCH (p), GARCH (p,q), TGARCH (p,q) and EGARCH (p,q) models are analyzed. Results of the tests are given below.

GARCH Results

In the proceeding part of the study, volatility structure of the series are tested using ARCH (p), GARCH (p, q), TGARCH (p, q) and EGARCH (p, q) models. First of all, most efficient volatility model is chosen and then volatility of the series are determined. In order to choose the most efficient model, model parameters must be significant and satisfy the constraint conditions. Initial volatility model, variance equation of the conditional heteroscedasticity model doesn't require fulfilling the positive coefficient conditions, thus all the parametric values of the EGARCH model is defined as logarithmically (Alexander, 2008: 133). Moreover, the coefficients must be have positive values and the sum of coefficients must be smaller than one. Otherwise, volatility in the series is permanent and estimation is not efficient. When we decide among the models, the lowest value of Akaike Information Criteria (AIC), Schwarz

Bayesian Information Criteria (SBIC) and the highest value of likelihood value and Theil's Inequity Coefficient (TIC) are preferred. In this step, when the criteria give different results, the lowest Theil's Inequity Coefficient is evaluated. Models matching these criteria are given in the table 5.

Table 5: Volatility Models

Series		BIST100	EURO	USD
Parameters	Model	GARCH(2,1)	EGARCH(2,3)	EGARCH(3,1)
α_0		9.79E-06	-0.656956	-0.460248
α_1		0.082108	0.219101	0.159166
α_2		0.019645	0.059901	-0.024818
α_3				0.069793
β_1		0.862976	0.632605	0.969098
β_2			-0.000434	
β_3			0.322830	
γ_1			0.148375	0.076250
AIC(Akaike Onformation Criteria)		-5.534140	-7.145008	-7.083678
SBIC(Shwarz Bayesian Information Criteria)		-5.525029	-7.128608	-7.070922
Log Likelihood		9296.821	12005.47	11900.49
TIC(Theil Inequality Coefficient)		0.940400	0.952087	0.960122

When we look at table 5, the most efficient model for BIST 100 is GARCH (2, 1), the most efficient model for EURO is EGARCH (2, 3), and the most efficient model for USD is EGARCH (3, 1). Conditional heteroscedasticity models for exchange rate series measure the asymmetrical response of the volatility of the series. When we analyze the models, γ_1 parameter derived from the EGARCH models is statistical significant, hence, has asymmetrical effects on volatility. In addition to this, positive γ_1 coefficient shows positive shocks on exchange rates (an increase in Exchange rate, in other words depreciation of TL) has more increasing volatility effects of the series than the negative shocks (a decrease in exchange rate, in other words appreciation of TL) (Kayral, 2017: 10; Kula and Baykut, 2017: 132-133).

All of the models in table are statistically significant not withstanding that the residuals should be tested for the remainder of any ARCH effect in the second place. For this purpose, residuals derived from each model are tested for ARCH effects with ARCH LM test. Results of the test show that there is no ARCH effect reminder in the series. We can conclude that heteroscedasticity problem is eliminated for all the series.

In the last part of the study, causality between the volatility series are tested.

Granger Causality Test

The Granger Causality Test measures the degree and direction of the relationship between two variables. In this study, this test is employed to present the causality relationship between stock price index and exchange rates. Such in all the time series analysis, in order to analyze the causality relationship between the series derived from GARCH model should be stationary. For this reason, series derived from GARCH model are tested for stationary. Results of the ADF and PP tests indicate that none of the series have unit root at 1 % significance level, therefore all of the series are stationary.

Table 6. Granger Causality Test Results

Hypothesis	F Statistics	P Value	Direction Of Causality
H_{01}: Euro volatility does not granger cause Stock Prices (BIST100) volatility	2.45853	0.0118	Euro ⟷ BIST100
H_{02}: Stock Prices (BIST100) volatility does not granger cause Euro volatility	21.7647	1.E-32	
H_{03}: USD volatility does not granger cause Stock Prices (BIST100) volatility	3.69281	0.0003	USD ⟷ BIST100
H_{04}: Stock Prices (BIST100) volatility does not granger cause USD volatility	31.5968	3.E-48	
H_{05}: USD volatility does not granger cause Euro volatility	11.1339	1.E-15	USDV ⟷ EUROV
H_{06}: Euro volatility does not granger cause USD volatility	3.93694	0.0001	

Results of the causality test are given in table 6. When we look at the table 6, volatility of the exchange rates granger causes BIST100 stock prices at 1 % significance level. At the same time, volatility of BIST100 stock prices granger causes the volatility of exchange rates. Moreover, Euro and USD exchange rates granger cause each other mutually. We can see the causality effects in Figure 2.

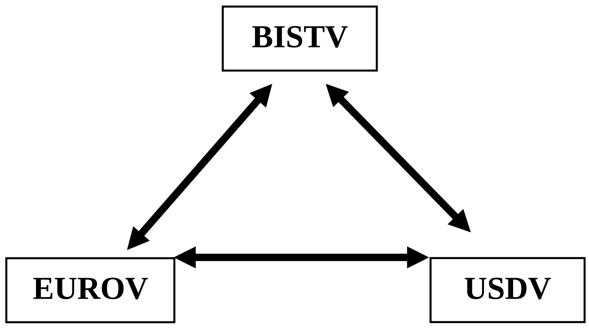

Figure 2. Causality between the Series

CONCLUSION

The relationship between exchange rates and stock prices is discussed in the literature but the direction of causality is unresolved in both theory and empirics. Although some empirical studies reveals the causality relation, many other studies show no causality between these two variables. Furthermore, direction of causality differ from one economy to another because of the economic policies of countries or data and method used in the studies. This paper examines the relationship between the stock prices and exchange rate for Turkish Economy for the period 03.01.2005 to 03.05.2018 using daily data. Properties of the data show that there is ARCH effect in the series, thus the volatility structure of the series are tested using ARCH (p), GARCH (p,q), TGARCH (p,q) and EGARCH (p,q) models in the study. The most efficient model for BIST 100 series is GARCH (2, 1), the most efficient model for EURO series is EGARCH (2, 3), and the most efficient model for USD series is EGARCH (3, 1). In order to see the causality relationship between the volatility of stock exchange prices and exchange rates, Granger Causality Test is used. The results of the Granger Causality Test show that volatility of the exchange rates granger causes BIST100 stock prices at 1 % significance level, volatility of

BIST100 stock prices granger causes the volatility of exchange rates and Euro and USD exchange rates granger cause each other mutually.

Findings of the study support the conclusions of Erbaykal and Okuyan, 2007; Yusuf and Rahman, 2012, Bahmani et.al. 1992; Doong et al., 2005, Zhao 2010, Singh et al., 2010. Ayvaz (2006) finds also bi-directional causality relationship between BIST 100 index and exchange rates for Turkish economy for 1991-2004 period. Congruently, Aydemir and Demirhan (2009) emphasize the bidirectional causal relationship between stock prices and exchange rates for Turkish economy from 2001 to 2008.

Capital flows are an important factor for developing countries. In order to make investment decision in an environment of uncertainty, foreign investors have to consider all the economic variables as well as their relationship to each other. Risky economic conditions lead to a decrease notably in international capital flows. Results of the study show that a volatility in the exchange rates will cause a volatility in stock prices, and vice versa, volatility in the stock prices will lead to volatility in the exchange rate. Investors can use information about exchange rate to predict the behavior of the stock market and can also use the information about stock market to make decisions about exchange rate volatility. Moreover, policy makers can design an economic policy using these variables together or individually.

References

Abdalla I. and Murinde V., (1997). “Exchange Rate and Stock Price Interactions in Emerging Financial Markets: Evidence on India, Korea, Pakistan and Philippines”, *Applied Financial Economics*, 7, pp. 25 – 35.

Agrawal, G., Srivastav, A. K., and Srivastava, A. (2010). “A Study of Exchange Rates Movement and StockMarket Volatility”, *International Journal of Business and Management*, 5(12), pp. 62-73.

Akel, V. (2015), “Kırılgan Beşli Ülkelerinin Hisse Senedi Piyasaları Arasındaki Eşbütünleşme Analizi”, *International Journal of Management Economics & Business*, 11(24), s.75-96.

Alexander, C. (2008), *Market Risk Analysis, Value at Risk Models*, John Wiley & Sons.

Ashaolu T.O and Ogunmuyiwa M. S (2011), “An Econometric Analysis of the Impact of Macro Economic Variables on Stock market movement in Nigeria”, *Journal of Business Management* 3(1) pp. 72-78.

Bahmani-Oskooee, M., and Sohrabian, A. (1992), “Stock Prices and The Effective Exchange Rate of the Dollar”, *Applied Economics*, 24, pp. 459–464.

Bolgün, K. E., and Akçay, M. B. (2009). *Risk Yönetimi: Gelişmekte Olan Türk Finans Piyasasında Entegre Risk Ölçüm ve Yönetim Uygulamaları*, Scala Press, İstanbul.

Bollerslev, T. (1986), "Generalized Autoregressive Conditional Heteroskedasticity", *Journal of Econometrics,* 37, pp. 307-327.

Bollerslev, T., Chou, R. Y., and Kroner, K. F. (1992) "ARCH Modeling In Finance: A Review Of The Theory and Empirical Evidence", *Journal Of Econometrics*, 52(1-2), pp. 5-59.

Bollerslev, T., and Mikkelsen, H. O. (1996), "Modeling and Pricing Long Memory In Stock Market Volatility", *Journal Of Econometrics*, 73(1), pp. 151-184.

Bozkurt, H. (2007), *Zaman Serileri Analizi*, Ekin Kitapevi, Ankara.

Brooks, C. (2008), *Introductory Econometrics for Finance*, 2nd Edition, Cambridge University Press, UK.

Butler, C. (1999), *Mastering Value at Risk, A Step-By-Step Guide to Understanding and Applying Var*, Financial Times Pitman Publishing, Market Editions, London.

Çil Yavuz, N. (2015), *Finansal Ekonometri*, 2. Baskı, Der Yayınları, İstanbul.

Diebold, F. X., and Yilmaz, K. (2008), "Macroeconomic Volatility and Stock Market Volatility, Worldwide (No. w14269). National Bureau of Economic Research.

Doong, S.-C., Yang, S.-Y., and Wang, A. T. (2005), "The Emerging Relationship and Pricing of Stocks and Exchange Rates: Empirical Evidence from Asian Emerging Markets", *Journal of American Academy of Business,* Cambridge, 7, (1), 118-123.

Dornbusch, R., and Fischer, S. (1980). Exchange Rates and The Current Account. *The American Economic Review,* 70(5), 960-971.

Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. Econometrica: Journal of the Econometric Society, 987-1007.

Engel, R.F. and Granger, C.W.J. (1987), "Co-integration and Error Correction Representation, Estimation and Testing", *Econometrica*, 55(2), pp. 251-276.

Erbaykal, E., and Okuyan, H. A. (2007). Hisse Senedi Fiyatları ile Döviz Kuru İlişkisi: Gelişmekte Olan Ülkeler Üzerine Ampirik Bir Uygulama", *BDDK Bankacılık ve Finansal Piyasalar Dergisi*, 1(1), 77-89.

Gujarati, D. N. (1999). Temel Ekonometri (Çev. Ümit Şenesen, Gülay Günlük Şenesen). Birinci Basım, İstanbul: Literatür Yayınları.

Frankel, J. A. (1984). Tests of Monetary and Portfolio Balance Models of Exchange Rate Determination. In Exchange rate theory and practice (pp. 239-260). University of Chicago Press.

Gökçe, A. (2001), "İstanbul Menkul Kıymetler Borsası Getirilerindeki Volatilitenin ARCH Teknikleri ile Ölçülmesi", *Gazi Üniversitesi İktisadi ve İdari Bilimler Dergisi*. 1, 35-58.

Hill, R. C., Griffiths, W. E., and Lim, G. C. (2011), *Principles of Econometrics,* Fourth Edition, John Wiley & Sons, Inc.

Kalaycı, Ş. (2005), "Borsa ve Ekonomide Volatilite İlişkisi: İMKB'de Bir Şartlı Varyans Analizi", *Süleyman Demirel Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi*, 10(1), 241-250.

Kayral, İ. E. (2017). "Türkiye'de Döviz Kuru Volatilitelerinin Modellenmesi", *Politik Ekonomik ve Finansal Analiz Dergisi*, 1(1), 1-15.

Kim, K. H. (2003), "Dollar Exchange Rate and Stock Price: Evidence From Multivariate Cointegration and Error Correction Model," *Review of Financial Economics*, 12(3), 301-313.

Kula, V., ve Baykut, E.(2017), "Bist Şehir Endekslerinin Volatilite Yapısı", *Uluslararası Katılımlı 21. Finans Sempozyumu*, 18-21 Ekim 2017, 121-138.

Kumar, M. (2013), "Returns and Volatility Spillover Between Stock Prices and Exchange Rates: Empirical Evidence From IBSA Countries", *International Journal of Emerging Markets*, 8(2), 108-128.

Lin, Chien-Hsiu. (2012), "The Comovement Between Exchange Rates and Stock Prices in The Asian Emerging Markets", *International Review of Economics and Finance*, 22, p. 161-172.

Mandelbrot, B. (1963), "The Variation of Certain Speculative Prices", *The Journal of Business of the University of Chicago*, 36, 394-419.

Morley, B., and Pentecost, E. J. (2000), "Common Trends And Cycles In G-7 Countries Exchange Rates and Stock Prices", *Applied Economics Letters*, 7(1), 7-10.

Mozumder, N., De Vita, G., Kyaw, S., and Larkin, C. (2015), "Volatility Spillover Between Stock Prices and Exchange Rates: New Evidence Across The Recent Financial Crisis Period", *Economic Issues Journal Articles*, Economic Issues, vol. 20(1), pages 43-64, March.

Nelson, D. (1991), "Conditional Heteroskedasticity in Asset Returns: A New Approach." *Econometrica*, 59(2), 347-70.

Olugbenga, A. A. (2012) "Exchange Rate Volatility and Stock Market Behavior: The Nigerian Experience", *European Journal of Business and Management*, 4(5), 31-39.

Pan, M.-S., Fok, R. C.-W., and Liu, Y. A. (2007), "Dynamic Linkages between Exchange Rates and Stock Prices: Evidence from East Asian Markets", *International Review of Economics and Finance*, 16, 503-520.

Phylaktis, K., and Ravazzolo, F. (2005), "Stock Prices and Exchange Rate Dynamics", *Journal of International Money and Finance*, 24(7), 1031-1053.

Robert, E. (1982), "Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation", *Econometrica*, 50(4), 987-1007.

Schwert, G. W. (1989), "Why Does Stock Market Volatility Change Over Time?", *The Journal Of Finance*, 44(5), 1115-1153.

Singh, P., Kumar, B., and Pandey, A. (2010), "Price and Volatility Spillovers Across North American, European and Asian Stock Markets", *International Review of Financial Analysis*, 19(1), 55-64.

Vygodina, A. V. (2006), "Effects Of Size and International Exposure of the US Firms on the Relationship between Stock Prices and Exchange Rates", *Global Finance Journal*, 17(2), 214-223.

Yang, S. Y., and Doong, S. C. (2004), "Price and Volatility Spillovers between Stock Prices and Exchange Rates: Empirical Evidence from the G-7 Countries", *International Journal of Business and Economics*, 3(2), 139.

Yusuf, M., and Rahman, H. A. (2012), "The Granger Causality Effect Between the Stock Market and Exchange Rate Volatility in the Asean 5 Countries", *IEEE Symposium on In Business, Engineering and Industrial Applications (ISBEIA)*, pp. 754-759). IEEE.

Zakoian, J.M. (1994), "Threshold Heteroskedasticity Models", *Journal of Economic Dynamics and Control*, 15: 931-955.

Zhao, H. (2010), "Dynamic Relationship Between Exchange Rate and Stock Price: Evidence From China", *Research in International Business and Finance*, 24(2), 103-112.

Zia, Q. Z., and Rahman, Z. (2011) "The Causality Between Stock Market and Foreign Exchange Market Of Pakistan", *Interdisciplinary Journal of Contemporary Research in Business*, 3(5), 906-919.