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THE IMPACT OF THE EXCHANGE RATE VOLATILITY ON THE STOCK RETURN VOLATILITY IN TURKEY

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Abstract

This research investigates the impact of the Turkish Lira to U.S. Dollar (TRY/USD) exchange rate volatility on the Borsa Istanbul 100 Index (BIST100) return volatility, in particular by providing insight into possible volatility spillover effects between TRY/USD exchange rates and BIST100 returns. For studying the impact of the TRY/USD exchange rate volatility on the BIST100 return volatility, a simple Ordinary Least Squares (OLS) model and a novel Bivariate Asymmetric Quadratic GARCH (BAQ-GARCH) model are employed on the daily data during the period over July 2005 - April 2020. Evidence from this study shows that there is a positive impact of the TRY/USD exchange rate volatility on the BIST100 return volatility. The benefit of the BAQ-GARCH model, which is used to examine volatility spillover effects, is that it can capture the impact of good and bad news separately and reveal the interaction between the assets while taking into account asymmetric effects. This research can be helpful to better understand the structure of the BAQ-GARCH model and the volatility spillover interactions by interpreting the BAQ-GARCH model's parameter estimates. The results of the BAQ-GARCH model indicate that there are negative bidirectional asymmetric volatility spillover effects. The negative asymmetric spillover means that bad news in TRY/USD exchange rates and bad news in BIST100 returns increase the next day's volatility of BIST100 returns and the negative shocks will increase the volatility more than positive shocks. The economic interpretation of this is that bad news of a weakening Turkish Lira appears to have more impact on BIST100 returns than news of a rise in Turkish Lira. These empirical findings can be used by policymakers to create financial stability, and by investors to diminish investment risks while making decisions.

Keywords: Stock Price Volatility, U.S. Dollar to Turkish Lira Exchange Rate Volatility, Bivariate Asymmetric Quadratic GARCH, Volatility Spillover

1. Introduction

Turkish Lira to U.S. dollar (TRY/USD) exchange rates have been highly volatile since 2016 following a failed coup, which makes the TRY/USD pair one of the most volatile currency pairs. The impacts of the exchange rate volatility on the stock returns have been the research topic in the literature because foreign exchange and stock markets can interact. The exchange rate would affect international trade, which in turn would affect the profit of firms and thus their stock prices. Besides, the exchange rate volatility affects economic activities and therefore it influences the monetary policy decisions. Exchange rates are also important for investors and portfolio managers who are seeking ways of increasing their returns with relatively low risk therefore, the diversified portfolios with international stocks and securities are in trend. However, including international market stocks in the portfolio is attached to the currency risk. Exchange rates are determinant in calculating the profits of foreign investors, therefore if exchange rates are highly volatile, there may be uncertainty and lack of confidence in the stock market investments. The purpose of this research is to identify the impact of TRY/USD exchange rate volatility on the Borsa Istanbul 100 Index (BIST100) return volatility, in particular by providing insight into possible volatility spillover effects between TRY/USD exchange rates and BIST100 returns. For this research, Turkey is selected because Turkey is among the fastest-growing emerging markets which received international portfolio investments, especially in the last ten years. However, Turkey suffered financial outflows starting with 2014 and political turbulence in 2016 following a failed coup. Therefore, the study of stock and exchange markets interdependencies in a period including financial and political turbulences would contribute to the understanding of the dynamics between stock and exchange markets. It is interesting to analyze an emerging country with dynamic models on recent data because most of the time, an emerging country misses a developed financial market to mitigate exchange rate risks.

The relationship between stock returns and exchange rates has been investigated over the past few decades. In general, there are two approaches to investigate the impact of exchange rate volatility on the stock return volatility. The first approach is based on the Ordinary Least Squares (OLS) model and Generalized Autoregressive Conditional Heteroscedastic (GARCH) model developed by Bollerslev (1986). For this approach, first of all, the GARCH model is employed to determine the volatilities and then the OLS model is used to analyze the impact of the exchange rate volatility on the stock return volatility. The studies of both Mechri *et al.* (2018) and Kasman *et al.* (2011) estimated volatilities by using GARCH models. However, the GARCH model assumes that volatility responses to positive and negative news from previous periods equally. This assumption is usually not true with financial asset returns. Instead, it is often observed that volatility increases when negative asset returns are observed, this effect is known as the leverage effect. To account for the leverage effect, the Glosten, Jagannathan, and Runkle (GJR)-GARCH model (1993) is used for estimating the volatilities of both TRY/USD exchange rates and BIST100 returns.

The first approach based on the OLS model provides a static estimation of the impact of the TRY/USD exchange rate volatility on the BIST100 return volatility, however, the relationship between the volatilities of financial series' returns is dynamic in nature. To account for the dynamic nature of the series, another approach which investigates the volatility spillover effects between the exchange rates and stock returns is followed in many studies (Erdem *et al.* 2005; Mwambuli *et al.* 2016; Mozumder *et al.* 2015; Kanas, 2000) by carrying out the Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH) model. However, the EGARCH model also captures most of the asymmetry, there is evidence that the variability of the conditional variance implied by the EGARCH is too high (Engle and Ng, 1993). Therefore, it is decided to use a bivariate asymmetric quadratic GARCH (BAQ-GARCH) model introduced by Schmidbauer and Rosch (2008) which accounts for the leverage effect to study the volatility spillover effects. Interpreting the results from the applications of the BAQ-GARCH model is not easy because of its rather complicated model structure. In order to understand the empirical results derived from this model better, it is very important to interpret the estimated parameters. The contribution of this paper is that there is no such extensive study related to GJR-GARCH and BAQ-GARCH models to analyze the impact of exchange rate volatility on the stock returns volatility.

The remainder of this paper is organized as follows: Section 2 gives an overview of the existing literature. The description of the data is reported in Section 3. In Section 4, the different econometric models are presented. In Section 5, the empirical results of the different econometric models are presented and discussed. Finally, Section 6 provides conclusions.

2. Literature review

Figure 1 demonstrates the behavior of the exchange rate of Turkish Lira against the U.S. Dollar during the past 10 years, which reflects the economic and political situation in Turkey. The Turkish Lira value has declined remarkably especially since 2016 following a failed coup. It is inevitable to expect that these remarkable declines interact with the stock returns. The impacts of the exchange rate volatility on the stock return volatility have been the research topic in the literature because the foreign exchange market and the stock market can interact. International portfolio investment involves the exchange rate, and therefore, change in the exchange rate can affect the stock price (Leung *et al.* 2017).

Figure 1. TRY/USD conversion rates of between 2005 and 2020

In the following first subsection, empirical studies that have investigated the impact of exchange rate volatility on the stock return volatility using the first approach based on the OLS and GARCH estimation models will be presented. In the second subsection, the second approach that has investigated the volatility spillover effects between stock returns and exchange rates will be presented.

2.1. The first approach: studies based on OLS and GARCH estimation models

Mechri *et al.* (2018) analyzed the impact of exchange rate volatility on the stock return volatility focusing on two emerging markets: Tunisia and Turkey. The GARCH(1,1) is used to determine the volatilities of all series and the multiple regression is applied to analyze the impact of the volatilities of inflation rates, interest rates, exchange rates, and oil prices on the stock return volatility. They used the monthly data because of the availability of macro-economic variables. A positive effect of the exchange rate volatility on the stock return volatility is found for both countries. The explanation for Turkey is the political instability in Turkey from early 2016, which is reflected in a fall of Turkish Lira and high volatility. Also, oil price, interest rate, and gold price volatilities are added in the OLS model as control variables and they all have a significantly positive effect on stock return volatility.

Kasman *et al.* (2011) studied the effects of interest rate and foreign exchange rate changes on Turkish banks' stock returns using the OLS and GARCH estimation models. The daily data is used during the period over 27 July 1999 - 9 April 2009. Their results indicate that exchange rate and interest rate fluctuations have a negative and significant impact on the bank stock return. They also analyzed the impact of exchange rate volatility on the bank stock return volatility. Their results indicate that interest rate and exchange rate volatilities have a positive impact on the bank stock return volatilities.

Kennedy and Nourzad (2016) investigated the effect of the volatility of the exchange rate of the U.S. exchange on the stock market volatility applying the GARCH(1,1) model on the weekly data for the period from January 1999 to January 2010. They specified a regression model that includes also monetary announcements, money supply fluctuations, terrorist attacks, negative equity market returns, bear markets, and derivatives variables as control variables. They concluded that the exchange rate volatility has a significantly positive effect on the stock return volatility.

2.2. The second approach: studies investigate the volatility spillover effects

The findings on the dynamic linkage between stock returns and exchange rate volatilities are mixed: symmetric, asymmetric, unidirectional, bidirectional, or no volatility spillover effects from one market to another market. There is extensive research focusing on different countries, however, the main focus is Turkey in the literature review of this paper. The EGARCH model is widely used to investigate the volatility spillover effects between stock return and exchange rate volatilities, therefore firstly papers employing the EGARCH model will be presented.

Erdem *et al.* (2005) investigated the volatility spillover effects between exchange rates and stock returns by employing the EGARCH model on the monthly data from January 1991 to January 2004 about Turkey. Their findings show that there is a positive volatility spillover from exchange rate to the stock market. Mwambuli *et al.* (2016) investigated the volatility spillover effects between Turkish stock returns and stock exchange rates by making use of the EGARCH model too on the daily data during the period over 2005 - 2015 and their results indicate that there are volatility spillover effects from exchange rates to stock prices for full sample. Mozumder *et al.* (2015) employed the EGARCH model to examine the volatility spillover effects between stock prices and exchange rates in three developed (Ireland, the Netherlands, and Spain) and three emerging (Brazil, South Africa, and Turkey) economies by dividing the data into four periods: full sample, pre-crisis, in-crisis and post-crisis periods. For the full sample period, they found symmetric spillover effects from stock returns to exchange rates in the Netherlands and Turkey and negative asymmetric spillover effects[1] from exchange rates to stock returns in Brazil. The results for the pre-crisis period indicate that there are no volatility spillover effects. The results for the period of the financial crisis indicate that there are negative asymmetric volatility spillover effects from stock returns to exchange rates in Ireland, the Netherlands, and Turkey; symmetric volatility spillover effects from stock returns to exchange rates in South Africa; negative is bi-directional, and asymmetric spillover effects in Brazil. The results for the post-crisis period indicate that there are positive, asymmetric volatility spillover effects[2] between the markets only in Ireland.

Panda and Deo (2014) studied the volatility and asymmetric transformation effect in Indian stock and foreign exchange markets by employing the EGARCH model. Their study focused on the 2008 financial crisis period and analyzed data for the two sub-periods namely pre-crisis and post-crisis periods on the daily data during the period over April 2004 - April 2012. Their findings indicate that the post-crisis period comprised the highest bidirectional volatility and asymmetric spillover effects between these two markets compared to the pre-crisis period.

Some studies employed BEKK-GARCH models instead of the EGARCH model. Akkas and Sayilgan (2016) studied the volatility spillovers between stock and foreign exchange markets about Turkey by employing a bivariate VAR-GARCH-BEKK model on the daily data during the period over January 2002 - December 2015. They divided data into four periods: the full sample, pre-crisis, in-crisis, and post-crisis periods. They found that there are bidirectional volatility spillover effects between the stock return and exchange rate volatilities except for the

[1] The negative asymmetric spillover means that bad news has a more impact on the volatility than good news.

[2] The positive asymmetric spillover means that good news has a more impact on volatility than bad news.

in-crisis period. For the in-crisis period, they found the unidirectional volatility spillovers effects from the exchange market to the stock market. Turkyilmaz and Balibey (2013) employed the BEKK-GARCH model similar to the model used by Akkas and Sayilgan (2016) on the monthly data during the period over 2002 to 2009. They found bidirectional volatility spillover effects among stock returns, exchange rates and interest rates in Turkey.

Another study in reference to Turkey based on the different models is by Yildiz and Ulusoy (2011). They used the squared residuals from the Autoregressive Moving Average (ARMA) on the monthly data during the period over 1987-2010 to estimate exchange rate volatility and then tested against Turkish stock returns. They found no evidence of volatility transmission between the stock market and foreign exchange market which is a contradiction to the findings of Akkas and Sayilgan (2016).

Kanas (2000) investigated volatility spillovers between stock returns and exchange rate changes for six developed countries, namely the US, the UK, Japan, Germany, France, and Canada, by using the EGARCH model. Symmetric volatility spillovers are found from the stock returns to the exchange rates in all countries except Germany.

Manasseh *et al.* (2019) studied stock prices and exchange rate interactions by employing the VAR-GARCH model on monthly data from January 2000 to October 2014. The empirical evidence of the VAR-GARCH model indicates a significant mean spillover effect from the stock market to the exchange market but not a mean spillover from the exchange market to the stock market. The variance equation results indicate the existence of a bidirectional volatility effect between the markets.

Qin *et al.* (2018) studied the volatility spillover effects between the RMB foreign exchange markets and the stock markets by employing daily returns of the Chinese RMB exchange rates and the stock markets in China and Japan during the period in 1998–2018 by using the DBEKK-GARCH-M model. Their results show that there are the bidirectional spillover effects between the foreign exchange market and the stock markets in both countries. Their results also show that the average co-volatility spillover effects among the markets in Japan and China are generally negative.

The literature review shows clearly that the findings on volatility spillover effects between exchange rates and stock returns are mixed. The results vary from an emerging to a developed country, also depending on the methodology and period of data used. Therefore, analyzing the effects of volatility spillovers between exchange rates and stock returns based on the BAQ-GARCH model on an up-to-date dataset can give new insights.

3. Data

In this section, the calculation of the returns, descriptive statistics, and diagnostic tests are given. The daily closing prices of TRY/USD and BIST100 are obtained from investing.com. The Borsa Istanbul 100 Index is a capitalization-weighted index that tracks the performance of 100 companies selected from the national market, real estate investment trusts, and venture capital investment trusts. The TRY/USD pair is selected because the U.S. Dollar is the most dominant currency of international trade in Turkey. BIST100 and TRY/USD daily closing prices are acquired over the period from July 2005 to April 2020, which yields a total of 3811 observations. BIST100 and TRY/USD returns are calculated as follows:

$$R_{s,t} = log\left(\frac{B_t}{B_{t-1}}\right)100\% \text{ and } R_{E,t} = log\left(\frac{E_t}{E_{t-1}}\right)100\%$$

where S_t and E_t are the closing prices at time *t* for BIST100 and TRY/USD prices respectively, log is defined as the natural logarithm.

Both series have a mean close to zero and exhibit positive skewness, suggesting a slight prevalence of positive returns (Table 1). These characteristics have been considered in the specification of the volatility models in the Methodology Section.

Table 1. Descriptive statistics

	Observations	Mean	Median	Min.	Max.	Std. Dev.	Kurtosis	Skewness
BIST100	3811	-0.0004	0.0004	-0.1479	0.0794	0.0164	6.8427	-0.3418
EXR	3811	0.0003	0.0008	-0.1106	0.1213	0.0093	20.2133	-1.0704

Assuming exchange rates and stock returns have normal distribution is a very strong assumption because it is commonly known in finance that returns often have fat-tailed distributions. To check the normality, the Jarque-Bera normality test is carried out. Both series are not normally distributed because the null hypothesis of a normal distribution is strongly rejected in all cases on the Jarque-Bera normality test (Table 2).

The null hypothesis is that there is no autocorrelation in the returns is tested by the Ljung-Box test (Ljung and Box, 1978). The returns of BIST100 do not appear to show significant autocorrelation whereas the exchange rate returns appear to show autocorrelation at a 5% significance level (Table 2). To account for the autocorrelation identified in TRY/USD rates, the return of the previous period which is called the AR effect is included in the mean equation of the GARCH model of the TRY/USD exchange rates. AR(1)-GARCH(1,1) model of the TRY/USD exchange rates are tested for autocorrelation in the mean equations making use of the Ljung-Box test. The results of the Ljung-Box test indicate that there is no autocorrelation left in the residuals (Table 2).

The squared residuals are tested for ARCH effects not captured by the variance equation using the Li-Mak test (Li and Mak, 1994). The null hypothesis is that there is no heteroscedasticity in the residuals of the estimation. The Li-Mak test results indicate that there is no heteroscedasticity (Table 2). After these diagnostic tests, it is decided to use the AR(1)-GJR-GARCH model for TRY/USD exchange rates and the GJR-GARCH model for BIST100 returns.

Moreover, to be able to say more about the distributions of the series, kurtosis and skewness tests are performed besides the normality test. The excess kurtosis describes the tail shape of the data distribution. Positive excess kurtosis would indicate a fat-tailed distribution and is said to be leptokurtic. As shown in Table 2 there is a presence of excess kurtosis in both series on the kurtosis test. The skewness is a measure of symmetry. Negative skewness indicates that the mean of the returns is less than the median, and the returns' distribution is left-skewed. There is a presence of negative skewness in both series on the skewness test. To account for the non-normality and the skewness, the skewed student-t distribution is used.

The augmented Dickey–Fuller test (ADF) tests the null hypothesis that a unit root is present in the series. Hence, the conclusion based on the ADF is that the series of all returns do not have a unit root and are therefore assumed to be stationary (Table 2).

Table 2. Diagnostic tests

Test	Jarque-Bera	Box – Ljung[1]	Box – Ljung[2]	Li-Mak	Kurtosis	Skewness	ADF
BIST100	0.00*	0.11*		0.52*	0.00*	0.00*	0.00*
EXR	0.00*	0.02**	0.17 *	0.48*	0.00*	0.00*	0.00*

Note: ***, ** and * denote the significance at a 10%, 5% and 1% level, respectively and otherwise insignificant. p-values are given in the table for each test. 1: Based on the GARCH(1,1) model, 2: Based on the AR(1)- GARCH(1,1) model.

Log Returns of BIST100 and TRY/USD series are given in Figure **2** and Figure 3. Larger volatilities are observed around the year 2008 because of the global financial crisis which caused high volatilities in both series. Another remarkable volatility in the exchange rates is observed on the 12th of August of 2018. The Turkish Lira added to its steep losses, hitting a record low after President Donald Trump announced that he was doubling metals tariffs on Turkey. Another remarkable volatility in the stock returns is observed in 2020 which is due to the Covid-19 pandemic. As the novel Coronavirus (COVID-19) spread from a regional crisis in China to a global pandemic, drove the tremendous surge in stock-market volatility around the world. Other high degrees of volatilities in TRY/USD and BIST100 series are due to economic slowdowns and increased political uncertainties. Time-varying volatility and also volatility clustering indicate the suitability of a GARCH model to estimate volatilities.

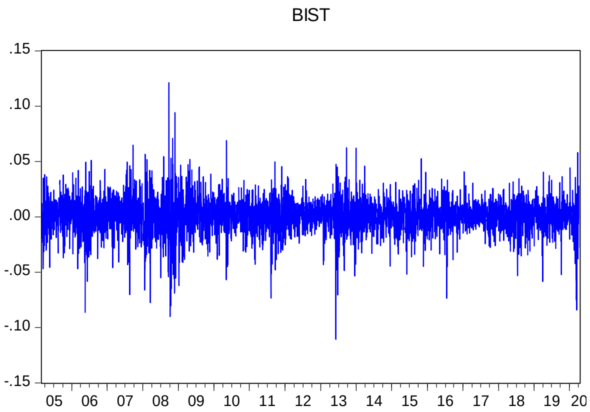

Figure 2. Log Returns of BIST100

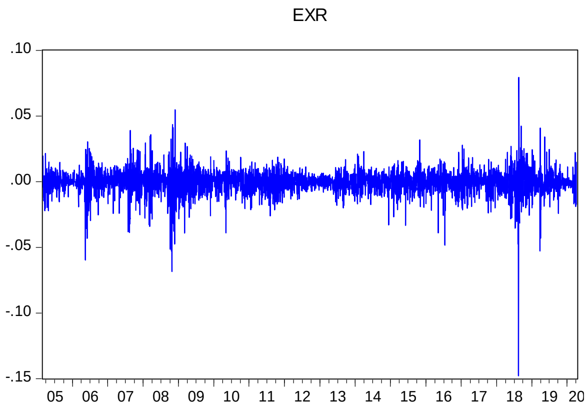

Figure 3. Log Returns of exchange rates

4. Methodology

This section contains the econometric models. The first subsection explains the models of the first approach based on the OLS and GJR-GARCH estimation models. The second subsection explains the models of the second approach which investigates the volatility spillover effects between the exchange rate and stock return volatilities based on the BAQ-GARCH model.

4.1. The first approach: OLS and GARCH estimation models

For the first approach, first of all, the exchange rate and the stock return volatilities have to be calculated. The volatilities are estimated by employing GJR-GARCH models which will be explained in the next subsection.

4.1.1. The GJR-GARCH model

In the literature, the GARCH(1,1) model is commonly used to analyze the effect of exchange rate volatility on the stock return due to the time-varying nature of the volatility of returns and the clustering as explained in the data section. Engle (1982) introduced autoregressive conditional heteroscedasticity (ARCH) models for estimating the conditional variance with dynamic properties. Bollerslev (1986) developed the General ARCH (GARCH) model, which is an autoregressive moving average model based on the weighted average of past squared residuals. The basic GARCH model assumes that the volatility responses to negative and positive news from the previous periods equally. This assumption is usually not true with financial returns. Instead, the volatility increases when negative asset returns are observed, this effect is known as the leverage effect. To incorporate the leverage effect, the asymmetric GJR-GARCH model is developed by Glosten *et al.* (1993). The mean equation is the same as the GARCH(1,1) model. A leverage variable and an indicator variable added in the variance equation of the GARCH(1,1) model. The mean and variance equations of GJR-GARCH(1,1) model are given as follows:

$$r_t = \mu + \varepsilon_t \text{ with} \epsilon_t = \sigma_t Z_t,\ \ Z_t \sim N(0,1) \tag{1}$$

$$\sigma_t^2 = \omega + (\alpha + \gamma I_{t-1})\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{2}$$

I_{t-1} is 1 when the return of the period $t-1$ is below the mean return and I_{t-1} is 0 when the return of the period $t-1$ is above the mean return. This allows for the volatility to react differently to bad news and good news. The requirement for the persistence of the variance equation can be given as $\alpha + \beta + 0.5\gamma < 1$. There is no requirement for γ to be positive, however, it is required that $\alpha + \gamma > 0$ such that the coefficient of ε_{t-1}^2 is always positive. The significance of the γ term is checked to verify whether the symmetric or asymmetric model is the best to estimate the volatilities.

For the estimation of the stock return volatility the GJR-GARCH(1,1) model is used because no autocorrelation identified in the BIST100 returns. For the estimation of the exchange rate volatility, the AR(1)-GJR-GARCH(1,1) model is used because as explained in the data section, autocorrelation identified in exchange rates. To account for the autocorrelation identified in the returns, the return of the previous period is included in the mean equation of the model which is an AR(1)-GJR-GARCH(1,1) model. Taking into account the AR effect, the mean equation is adjusted as follows:

$$r_t = \mu + \varphi r_{t-1} + \varepsilon_t \text{ with } \epsilon_t = \sigma_t Z_t,\ \ Z_t \sim N(0,1) \tag{3}$$

$$\sigma_t^2 = \omega + (\alpha + \gamma I_{t-1})\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{4}$$

where r_{t-1} one day lagged of the returns to account for the autocorrelation and φ is the corresponding coefficient. The conditional variance equation of the AR(1)-GJR-GARCH model is the same as the conditional variance equation of the GJR-GARCH model.

4.1.2. The OLS regression model

The OLS regression model is the simplest method and commonly used to determine whether there is a significant effect of exchange rate volatility on stock return volatility. In this method, the conditional variance of each of the series is estimated based on the GJR-GARCH models. The measured volatilities are the estimated conditional standard deviations determined as the square root of the estimated variances of the series. The natural logarithm of the volatilities is used to minimize the presence of large variations in the magnitude of volatilities in both series. Only the influence of the previous day's volatilities is included in the model to lessen a spurious interpretation of the relationship. The OLS regression model is presented as:

$$\ln(\sigma_{1,t}) = \alpha + \beta_1 \ln(\sigma_{1,t-1}) + \beta_2 \ln(\sigma_{2,t-1}) + \varepsilon_{1,t} \tag{5}$$

$\sigma_{1,t}$ and $\sigma_{1,t-1}$ are the estimated conditional standard deviations of the stock returns at time period t and $t-1$ respectively. β_1 is the coefficient of the estimated conditional standard deviation of the stock returns at time period $t-1$. $\sigma_{2,t-1}$ is the estimated conditional standard deviation of exchange rates at time period $t-1$ and β_2 is the corresponding coefficient. The $\varepsilon_{1,t}$variable is an error term assumed to be independently and identically distributed with mean zero and constant variance and α is a constant. This model gives an indication of any significant overall effect of exchange rate volatility on stock market volatility. To get more insight into the interaction between the stock returns and exchange rates and to account for the dynamic nature of the series, it is better to study the spillover effects by employing the BAQ-GARCH model which will be explained in the following subsection.

4.2. The second approach: the BAQ-GARCH model

The BAQ-GARCH model is a combination of the multivariate Baba, Engle, Kraft, and Kroner (BEKK) GARCH and the univariate GJR-GARCH models. The BAQ-GARCH model can be seen as an extension of the univariate GJR-GARCH model because the univariate GJR model captures the asymmetrical nature of time series and has one dimension. The BAQ-GARCH model can be seen as a generalization of the bivariate BEKK model because this model does not capture the asymmetrical nature of time series but has two dimensions. The combination of the univariate GJR and the bivariate BEKK models is the bivariate BAQ-GARCH model which allows for asymmetry in the volatility specification found in both series and has two dimensions.

The GJR-GARCH model is already explained and the BEKK-GARCH model will be explained in this section to understand the BAQ-GARCH model better.

4.2.1. The BEKK-GARCH model

The BEKK model is a bivariate GARCH model formalizes a multivariate volatility specification that incorporates cross-equation dynamics. The BEKK model optimizes the two GARCH processes simultaneously, making it a bivariate GARCH model. The big advantage of using the BEKK model is that it ensures that the variance-covariance matrix is positive-definite (Lutkepohl and Kratzig, 2004). The mean and variance equations for the bivariate BEKK-GARCH(1,1) are given as follows:

$$R_t = M + \varepsilon_t \tag{6}$$

$$\sum_t = C'C + A'\varepsilon_{t-1}\varepsilon_{t-1}'A + B'\sum_{t-1}B \tag{7}$$

These equations are similar to the equations of univariate models; univariate model equations have single variables whereas the BEKK-GARCH model equations have vectors and matrices.

$$R_t = \begin{bmatrix} r_{1,t} \\ r_{2,t} \end{bmatrix}, \mathrm{M} = \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix}, \varepsilon_t = \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \end{bmatrix}$$

$$\sum_t = \begin{bmatrix} \sigma_{1,t}^2 & \sigma_{12,t} \\ \sigma_{21,t} & \sigma_{2,t}^2 \end{bmatrix}, C = \begin{bmatrix} c_{11} & c_{12} \\ 0 & c_{22} \end{bmatrix}, A = \begin{bmatrix} a_1 & a_{12} \\ a_{21} & c_1 \end{bmatrix}, B = \begin{bmatrix} b_1 & b_{12} \\ b_{21} & b_2 \end{bmatrix}$$

Vector R_t contains the returns of BIST100 and TRY/USD at time *t*. *M* is the vector of constants for the long-run mean. ε_t is the vector of innovations formulated as $\epsilon_t = \sum_t^{1/2} v_t$ where v_t is identically and independently distributed having a multivariate distribution with mean zero and the identity matrix for a covariance matrix. Innovations are assumed to be symmetrically distributed, but they are allowed to be correlated across both series. $\sum_t$ is the conditional covariance matrix of the process. C is an upper triangular matrix and $C'C$ is the intercept matrix. A is coefficient matrix of the ARCH processes that show the spillover of lagged innovations and B is coefficient matrix of the GARCH processes that show the spillover of lagged conditional variances between the series. The conditional variance of BIST100 returns, the conditional variance of TRY/USD exchange rates, and the covariance equations are given as follows:

$$\sigma_{1,t}^2 = c_{11}^2 + a_1^2\varepsilon_{1,t-1}^2 + 2a_1a_{21}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{21}^2\varepsilon_{2,t-1}^2 + b_1^2\sigma_{1,t-1}^2 + 2b_1b_{21}\sigma_{12,t-1} + b_{21}^2\sigma_{2,t-1}^2 \tag{8}$$

$$\sigma_{2,t}^2 = c_{12}^2 + c_{22}^2 + a_2^2\varepsilon_{2,t-1}^2 + 2a_2a_{12}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{12}^2\varepsilon_{1,t-1}^2 + b_2^2\sigma_{2,t-1}^2 + 2b_2b_{12}\sigma_{21,t-1} + b_{12}^2\sigma_{1,t-1}^2 \tag{9}$$

$$\begin{aligned}\sigma_{12,t} = c_{11}c_{12} + a_1a_{12}\varepsilon_{1,t-1}^2 + (a_{12}a_{21} + a_1a_2)\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{21}a_2\varepsilon_{2,t-1}^2 + b_1b_{12}\sigma_{1,t-1}^2 \\ +(b_{12}b_{21} + b_1b_2)\sigma_{12,t-1} + b_2b_{21}\sigma_{2,t-1}^2\end{aligned} \tag{10}$$

The purpose of this research is to reveal the impact of exchange rate volatility on the stock return volatility in terms of volatility spillovers. The conditional variance of BIST100 returns $(\sigma_{1,t}^2)$ depends on the variables of both series that make it possible to study the volatility spillover effects.

4.2.2. The BAQ-GARCH model

The BAQ-GARCH model is preferred to the BEKK-GARCH model because of the asymmetric effects found in both series (Table 4). The BAQ-GARCH model is based on the BEKK-GARCH model by using the same idea as the univariate GJR-GARCH model through the addition of a leverage matrix and a weighting function that determines the direction of leverage effect

(Schmidbauer and Rosch, 2008). The mean and variance equations for the bivariate BAQ-GARCH(1,1) are given as follows:

$$R_t = M + \varepsilon_t \tag{11}$$

$$\sum_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'\sum_t B + S_w.\Gamma'\varepsilon_{t-1}\varepsilon'_{t-1}\Gamma \tag{12}$$

The additional matrix of the BAQ-GARCH model is Γ matrix which represents the leverage effects and is defined as follows:

$$\Gamma = \begin{bmatrix} \gamma_{11} & \gamma_{12} \\ \gamma_{21} & \gamma_{22} \end{bmatrix}$$

S_w is a weight function defined as:

$$S_w(\varepsilon_1, \varepsilon_2) = \begin{cases} 0.5 - \dfrac{cos\left(\frac{\pi}{4}+w\right).\varepsilon_1 + sin\left(\frac{\pi}{4}+w\right).\varepsilon_2}{2\sqrt{\varepsilon_1^2+\varepsilon_2^2}}, & \text{if}(\varepsilon_1^2 + \varepsilon_2^2) \neq 0 \\ 0, & \text{if}(\varepsilon_1^2 + \varepsilon_2^2) = 0 \end{cases} \tag{13}$$

The S_w weighting function is included in the model instead of an indicator function (I_{t-1}) to account for the leverage effect. The S_w value is determined by the sign and magnitude of innovations of both variables. The expected value of the $S_w(\varepsilon_{t-1})$ function is equal to 0.5 under the assumption of a symmetric distribution of the innovations. The parameter w in the weight function S_w determines the angle for which the (mean corrected) return vector *(ε_1; ε_2)* leads to an excess impact on next period's volatility (Schmidbauer and Rosch, 2008).

The stationarity requirements for the variance system of equations of the univariate GARCH model is $\alpha + \beta + 0.5\gamma < 1$. For the BEKK model the eigenvalues of the sum of Kronecker products of the ARCH and GARCH coefficient matrices $(\mathrm{A} \otimes \mathrm{A} + \mathrm{B} \otimes \mathrm{B})$ must be between 0 and 1 (Tsay, 2010). The extension of this requirement in case of the BAQ-GARCH model is the addition of the 0.5γ term to the stationarity requirement of the univariate case. Thus, for the stationarity of the BAQ-GARCH model, the eigenvalues of $(\mathrm{A} \otimes \mathrm{A} + \mathrm{B} \otimes \mathrm{B} + 0.5(\Gamma \otimes \Gamma))$ must be between 0 and 1. The BAQ-GARCH model equations including Γ matrix and tS_w:

$$\begin{aligned}\sigma_{1,t}^2 = {} & c_{11}^2 + (a_1^2 + S_w(\varepsilon_{t-1})\gamma_1^2)\varepsilon_{1,t-1}^2 + 2(a_1 a_{21} + S_w(\varepsilon_{t-1})\gamma_1\gamma_{21})\varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ & +(a_{21}^2 + S_w(\varepsilon_{t-1})\gamma_{21}^2)\varepsilon_{2,t-1}^2 + b_1^2\sigma_{1,t-1}^2 + 2b_1 b_{21}\sigma_{12,t-1} + b_{21}^2\sigma_{2,t-1}^2\end{aligned} \tag{14}$$

$$\begin{aligned}\sigma_{12,t} = {} & c_{11}c_{12} + (a_1 a_{12} + S_w(\varepsilon_{t-1})\gamma_1\gamma_{21})\varepsilon_{1,t-1}^2 + (a_{21}a_2 + S_w(\varepsilon_{t-1})\gamma_2\gamma_{21})\varepsilon_{2,t-1}^2 \\ & +\left((a_{12}a_{21} + a_1 a_2) + S_w(\varepsilon_{t-1})(\gamma_{12}\gamma_{21} + \gamma_1\gamma_2)\right)\varepsilon_{1,t-1}\varepsilon_{2,t-1} + b_1 b_{12}\sigma_{1,t-1}^2 \\ & +(b_{12}b_{21} + b_1 b_2)\sigma_{12,t-1} + b_2 b_{21}\sigma_{2,t-1}^2\end{aligned} \tag{15}$$

$$\begin{aligned}\sigma_{2,t}^2 = {} & c_{12}^2 + c_{22}^2 + (a_2^2 + S_w(\varepsilon_{t-1})\gamma_2^2)\varepsilon_{2,t-1}^2 + 2(a_2 a_{12} + S_w(\varepsilon_{t-1})\gamma_2\gamma_{12})\varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ & +(a_{12}^2 + S_w(\varepsilon_{t-1})\gamma_{12}^2)\varepsilon_{1,t-1}^2 + b_2^2\sigma_{2,t-1}^2 + 2b_2 b_{12}\sigma_{21,t-1} + b_{12}^2\sigma_{1,t-1}^2\end{aligned} \tag{16}$$

In the equations, numerous terms added and therefore the coefficient of each of the squared innovations and cross terms have an additional leverage variable. The diagonal elements of Γ have impacts on own-leverage effects and the non-diagonal elements have impacts on cross-leverage effects.

Table 3. Lag selection

Lag	AIC	BIC	HQ	p-value
0	-17.734	-17.734	-17.734	0.000
1	-17.753	-17.746	-17.750	0.000
2	-17.753	-17.740	-17.748	0.043
3	-17.770	-17.750	-17.763	0.000
4	-17.775	-17.749	**-17.766**	0.000
5	-17.775	-17.742	-17.763	0.115
6	-17.774	-17.735	-17.760	0.172
7	-17.775	-17.729	-17.759	0.035
8	-17.774	-17.721	-17.755	0.469
9	-17.774	-17.715	-17.753	0.075
10	-17.774	-17.708	-17.750	0.139
11	-17.773	-17.701	-17.747	0.391
12	-17.772	-17.694	-17.744	0.134
13	-17.773	-17.687	-17.742	0.066

Given the presence of autocorrelation in the BIS100 returns, the optimal lag structure has to be determined. The Akaike information criterion (AIC), Bayesian (Schwarz) information criterion (SIC), and Hannan and Quinn criterion (HQ) are used for the determination of the optimal lag structure. The optimal numbers of lags for the BAQ-GARCH model are 7 (AIC), 3 (SIC), and 4 (HQ). The scores of each criterion can be found in Table 3. The AIC provides a much higher lag and it is not consistent as the sample size increases towards infinity. The SIC penalizes complicated models more heavily. Using SIC results in more parsimonious specifications with fewer parameters than HQ and AIC if there are differences in the orders chosen by the three criteria. HQ estimates the order consistently as the sample size increases towards infinity (Lutkepohl and Kratzig, 2004). Therefore, it is decided to implement 4 lags in the system of the mean. The BAQ-GARCH model after the lag order selection:

$$R_t = M + \beta_1 R_{t-1} + \beta_2 R_{t-2} + \beta_3 R_{t-3} + \beta_4 R_{t-4} + \varepsilon_t \tag{17}$$

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B + S_w.\Gamma'\varepsilon_{t-1}\varepsilon'_{t-1}\Gamma \tag{18}$$

5. Results

The structure of the results section is in line with the structure of the methodology section. The first subsection contains the estimations obtained from the first approach based on the OLS and GJR-GARCH models. The second subsection contains the results obtained from the second approach based on the BAQ-GARCH model.

5.1. The first approach: OLS and GARCH estimation models

5.1.1. The GJR-GARCH model

The results of the estimations are given inTable 4. The presence of asymmetry explained in the methodology section is accounted by adding leverage effect in the GJR-GARCH model. The requirement for the persistence of the variance equation to be less than one is met for both series since $\alpha + \beta + 0.5\gamma = 0.9980 < 1$ for the exchange rates and $\alpha + \beta + 0.5\gamma = 0.9848 < 1$ for the stock returns. Note that the sign of γ is negative meaning that stock returns experience an opposite or negative leverage effect. The requirement that $\alpha + \gamma > 0$ such that the coefficient of ε_{t-1}^2 is always positive is met for both series since $\alpha + \gamma = 0.0378 > 0$ for the exchange rates and $\alpha + \gamma = 0.0303 > 0$ for the stock returns. The γ term is significant at 1% level verifying that the asymmetric model is the best specification for the estimation of the volatility models of exchange rates and the stock returns.

As stated in the methodology section, the GJR-GARCH model is employed to estimate the volatilities. The Jarque-Bera test is carried out on the residuals of the volatility estimations and none of the residuals has a normal distribution and the skewness estimators are significant, therefore, the skewed student-t distribution is used for estimating the volatilities.

Table 4. GJR-GARCH models results

Return	μ	ar1	ω	α	β	γ	skew
BIST[1]	0.00113		0.0000070*	0.13539*	0.89822*	-0.09762*	0.994095*
EXR[2]	-0.00001	0.01574	0.000001**	0.18790*	0.88892*	0.15760*	0.967235*

Note: ***, ** and * denote the significance at a 10%, 5% and 1% level, respectively. 1: Based on GJR-GARCH(1,1) model, 2: Based on AR(1)-GJR-GARCH(1,1) model.

5.1.2. OLS regression model

The estimated volatilities are determined as the square root of the estimated conditional variances based on the GJR-GARCH models. Estimated volatilities are used in the regression model given by the equation (5). The estimates of the OLS model are given in Table 5. The results show a small positive influence of TRY/USD exchange rate volatility on BIST100 returns volatility, which is interpreted as a 0.008% increase in BIST100 volatility when there is a 1% increase in the TRY/USD exchange rate volatility of the previous day. The main influence in determining BIST100 returns volatility in the estimation is from the previous period's volatility of the BIST100 returns, which is interpreted as a 0.961% increase in BIST100 returns volatility when there is a 1% increase in the BIST100 returns volatility of the previous day. The Ljung-Box test result indicates that there is no autocorrelation in the residuals of the model. The squared residuals are tested for remaining ARCH effects making use of the Breusch-Pagan test (Breusch, 1978). The Breusch-Pagan test result indicates that there is no heteroscedasticity in the residuals of the model at a 5% significance level.

Table 5. OLS model results

Variable	Coefficient
C	-0.124*** (0.000)
$\ln(\sigma_{s,t-1})$	0.961*** (0.000)
$ln(\sigma_{E,t-1})$	0.008** (0.020)
R-squared:	0.936
Breusch-Pagan test p-value	0.404
Box-Ljung test p-value	0.077

Note: ***, ** and * denote the significance at a 1%, 5% and 10% level, respectively. Dependent variable is $\ln(\sigma_{s,t})$. p-values are presented in parentheses.

The results are consistent with the findings of Mechri *et al.* (2018). However, Mechri *et al.* (2018) added more explanatory variables. It is decided to restrict the number of variables to study the interaction between TRY/USD exchange rate volatility and BIST100 returns volatility based on a fully specified multivariate model. The next subsection gives the results of the estimation of a fully specified multivariate model namely the BAQ-GARCH model.

5.2. The second approach: BAQ-GARCH model

The estimations of the BAQ-GARCH model for each matrix are given in Table 6. All components of the *A*, *B* and *Γ* matrices are highly significant. These matrix values are used to construct the variance and covariance equations as specified in the Methodology Section.

Table 6. BAQ-GARCH model results

Matrix	Matrix component	Estimates	p-value
A	a_{11}	-0.264	0.000
	a_{12}	-0.088	0.000
	a_{21}	0.426	0.000
	a_{22}	-0.272	0.000
B	b_{11}	-0.696	0.000
	b_{12}	0.049	0.000
	b_{21}	-0.368	0.000
	b_{22}	-0.926	0.000
C	c_{11}	0.007	0.000
	c_{12}	0.000	0.058
	c_{21}	0.000	1.000
	c_{22}	0.000	1.000
Γ	γ_{11}	-0.337	0.000
	γ_{12}	0.078	0.001
	γ_{21}	-0.463	0.000
	γ_{22}	-0.383	0.000
	w	0.9187	0.0000

There are obviously asymmetric effects between BIST100 returns and TRY/USD exchange rate volatility because parameter *w* and all parameters of matrix Γ are significantly different from zero. There are bidirectional volatility spillover effects between the BIST100 returns and TRY/USD exchange rates because a_{12}, a_{21}, b_{12} and b_{21} values are significantly different from zero. To check this finding, the null hypotheses of absence of cross market volatility spillover effects are tested by means of the Wald test. There is no volatility spillover effect from the stock market to the foreign exchange market is tested by the hypothesis H_{01}. There is no volatility spillover effect from the foreign exchange market to the stock market is tested by the hypothesis H_{02}. Both hypotheses are rejected based on the Wald tests (Table 7).

Table 7. Wald test

The null hypothesis	p-value
$H_{01}: a_{12} = b_{12} = 0$	0.00
$H_{02}: a_{21} = b_{21} = 0$	0.00

These findings are in line with the findings of Panda and Deo (2014) and Qin *et al.* (2018) because they found bidirectional and asymmetric volatility spillover effects between stock and exchange markets whereas these findings are contradictory to findings of Erdem *et al.* (2005), Mozumder *et al.* (2015), and Kanas (2000) because they found unidirectional volatility spillover effects.

The stationarity condition of the BAQ-GARCH model is that the eigenvalues of the sum of Kronecker products of the ARCH and GARCH coefficient matrices must be between 0 and 1. This condition is satisfied since the eigenvalues are strictly between 0 and 1 as represented in **Error! Reference source not found.**.

Table 8. The eigenvalues

Eigenvalues	Estimates
Λ_{11}	0.97
Λ_{12}	0.68
Λ_{21}	0.68
Λ_{22}	0.85

The model parameter estimates of the BIST100 returns variance (19), the TRY/USD exchange rates variance (20), and the covariance of BIST100 returns and TRY/USD exchange rates (21) equations will be interpreted to analyze the magnitude of the asymmetric volatility spillover effects. For all equations, the impact of the shocks depends on the value of the S_w function for each period.

$$\begin{aligned}\sigma_{1,t}^2 &= (0.070 + S_w(\varepsilon_{t-1})0.114)\varepsilon_{1,t-1}^2 + (-0.225 + S_w(\varepsilon_{t-1})0.312)\varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ &+(0.181 + S_w(\varepsilon_{t-1})0.214)\varepsilon_{2,t-1}^2 + 0.484\sigma_{1,t-1}^2 + 0.512\sigma_{12,t-1} + 0.136\sigma_{2,t-1}^2\end{aligned} \tag{19}$$

$$\begin{aligned}\sigma_{2,t}^2 &= (0.074 + S_w(\varepsilon_{t-1})0.146)\varepsilon_{2,t-1}^2 + (0.048 - S_w(\varepsilon_{t-1})0.059)\varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ &+(0.008 + S_w(\varepsilon_{t-1})0.006)\varepsilon_{1,t-1}^2 + 0.858\sigma_{2,t-1}^2 - 0.090\sigma_{21,t-1} + 0.002\sigma_{1,t-1}^2\end{aligned} \tag{20}$$

$$\begin{aligned}\sigma_{12,t} &= -0.026 + (0.023 - S_w(\varepsilon_{t-1})0.026)\varepsilon_{1,t-1}^2 + (-0.116 + S_w(\varepsilon_{t-1})0.177)\varepsilon_{2,t-1}^2 \\ &+ (0.034 - S_w(\varepsilon_{t-1})0.036)\varepsilon_{1,t-1}\varepsilon_{2,t-1} - 0.082\sigma_{1,t-1}^2 - 0.034\sigma_{12,t-1} + 0.645\sigma_{2,t-1}^2\end{aligned} \tag{21}$$

The research question of this paper is the impact of the TRY/USD exchange rate volatility on BIST100 returns volatility, therefore, the main focus will be the interpretation of the BIST100 returns variance equation, however, it is clear from the equation of BIST100 returns variance that the covariance between the two series has a significant impact on the BIST100 returns volatility indicating the importance of the covariance equation's interpretation. The TRY/USD exchange rates variance equation will be explained to understand the interaction between the volatilities of two series' returns better.

5.2.1. The BIST100 returns variance equation

The variance equation of the BIST100 returns is predominantly derived from the GARCH effects: the variance of itself (0.484) and the covariance between the series (0.512). There is also a contribution of the variance of TRY/USD exchange rates (0.136).

The ARCH effects in the variance equation for the BIST100 are mainly derived from the short-term volatility of TRY/USD exchange rates $(0.181 + S_w 0.214)$ that varies between 0.181 and 0.395 since S_w is between 0 and 1.

All squared coefficients positively affect the BIST100 returns variance in the next period. The interpretation of the non-diagonal elements is important to understand the dynamics between the markets: The value of $b_1 b_{21}(0.512)$ indicates that an increase in the covariance increases the BIST100 return variance in the next period. The coefficient of the cross innovations $\gamma_1\gamma_{21}$(0.312) indicates that when two series have simultaneous negative shocks, these negative shocks will increase the next day's BIST100 return volatility.

These results indicate that there is a positive impact of the TRY/USD exchange rate volatility on the BIST100 returns volatility which is in line with the findings of the OLS model, however, the impact of the TRY/USD exchange rate volatility based on the BAQ-GARCH model is significantly higher than the impact found based on the OLS model. This shows the importance of using a dynamic model to study the volatility impacts. There is also a significant positive impact of the covariance on the BIST100 returns volatility. The $\gamma_1\gamma_{21}$ value indicates that there are negative asymmetric spillover effects meaning that bad news in TRY/USD exchange rates and bad news in BIST100 returns increase the volatility of BIST100 returns. Another important indication is that the negative shocks will increase the volatility more than positive shocks. The magnitude and persistence of the coefficients of the variance equation indicate that all variables exhibit ARCH and very strong GARCH effects implying that current and old news has a significant impact on the BIST100 returns volatility. These results show that markets interact with each other through shocks and volatility.

5.2.2. The TRY/USD exchange rates variance equation

The effects in the variance equation of the TRY/USD exchange rates are mainly derived from its own long-term volatility (0.858). The value of $b_2 b_{12}(-0.09)$ indicates that an increase in the covariance very slightly decreases the next day's TRY/USD exchange rates variance. The coefficient of the cross innovations $\gamma_2\gamma_{12}(-0.059)$ indicates that when two asset returns have simultaneous negative shocks, these negative shocks have less impact on the next day's TRY/USD exchange rates variance. These results indicate that the volatilities of the BIST100 returns have much less effect on the TRY/USD exchange rate volatility compared to the effect of TRY/USD exchange rate volatility on the BIST100 returns volatility.

5.2.3. The BIST100 and TRY/USD covariance equation

The effects in the covariance equation are mainly derived from the long-term volatility of TRY/USD exchange rates (0.645). In this subsection, the interpretations of the non-diagonal estimated parameters based on matrices *A*, *B* and Γ will be given respectively.

The value of $a_1 a_{12}$ (0.023) indicates that a shock to the BIST100 returns has a positive effect on the next day's covariance. The value of $a_{21} a_2 (-0.016)$ indicates that a shock to the TRY/USD exchange rates affects the next day's covariance negatively. The value of $a_{12} a_{21} + a_1 a_2 (0.034)$ indicates that there is an increase in covariance when there are shocks to both returns.

The value of $b_1 b_{12} (-0.034)$ indicates that an increase in the BIST100 returns variance decreases the next day's covariance very weakly. The value of $b_2 b_{21} (0.341)$ indicates that an increase in the TRY/USD exchange rates variance increases the next day's covariance. The sum of $b_{12} b_{21} + b_1 b_2 (0.627$)indicates that an increase in the covariance strongly ups the next day's covariance.

The value of $\gamma_1 \gamma_{21}$(-0.026) indicates that a negative shock to the BIST100 returns affects the covariance slightly. The interpretation of $\gamma_2 \gamma_{21}$(0.177) is that a negative shock to the TRY/USD exchange rates increases the covariance. The sum of $\gamma_{12} \gamma_{21} + \gamma_1 \gamma_2 (0.093$) indicates that when two asset returns have simultaneous negative shocks, these negative shocks clearly increase the next day's covariance.

These results indicate that there is a significant impact of TRY/USD exchange rate volatility on the covariance. The $\gamma_1 \gamma_{21}$ value indicates that there are negative asymmetric spillover effects implying that bad news in TRY/USD exchange rates and bad news in BIST100 returns increases the covariance. The negative shocks will increase the covariance more than positive shocks. One of the main mechanisms behind the asymmetry for the high leverage in the variance equation for the BIST100 returns is covariance asymmetry. Negative shocks increase the conditional covariance substantially. Also, the results of the covariance equation show the significant impact of the exchange rate volatility on the stock return volatility in Turkey. This impact can be also seen from the BAQ-GARCH model volatility and covariance graphs (Figure 4) that the volatilities have a very similar pattern revealing the contribution of TRY/USD exchange rates to the BIST100 returns. The contribution was the most prominent during the financial crisis of 2008 and just after the announcement of President D. Trump about doubling metals tariffs on Turkey in 2018.

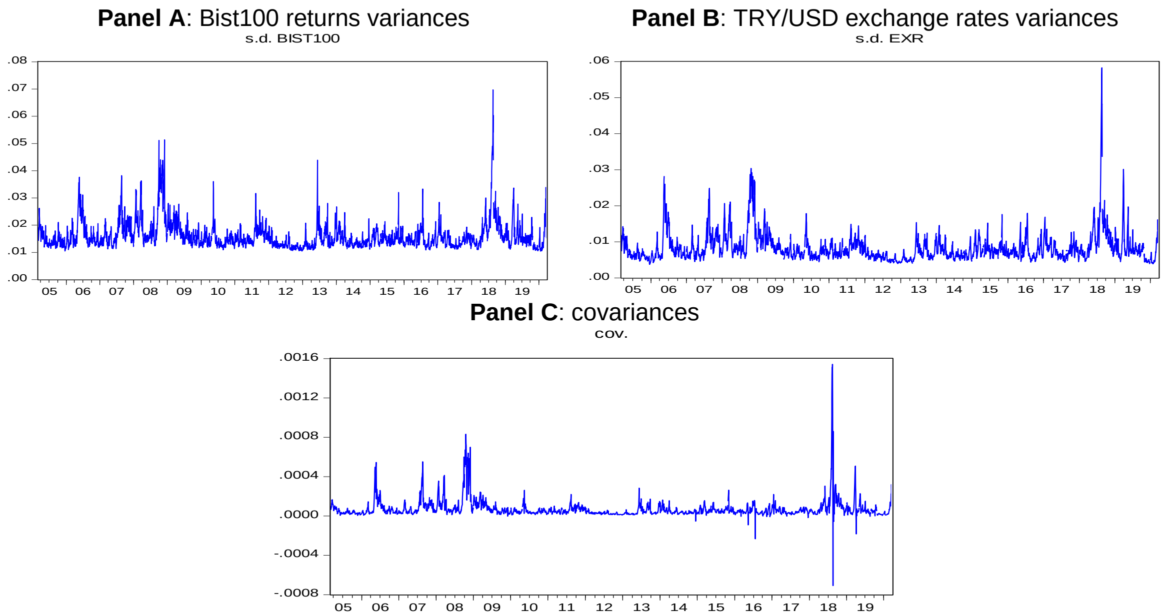

Figure 4. BAQ-GARCH model volatility, correlation, and covariance estimations

6. Conclusion

This research aimed to identify the impact of the TRY/USD exchange rate volatility on the BIST100 return volatility, in particular by providing insight into possible volatility spillover effects between TRY/USD exchange rates and BIST100 returns. BIST100 and TRY/USD daily closing prices are acquired over the period from July 2005 to April 2020.

Asymmetric volatility effects are investigated by employing the GJR-GARCH model and its results indicate that asymmetric volatility effects are present in both TRY/USD exchange rates and BIST100 returns. Accordingly, models to account for asymmetric effects were implemented to investigate the impact of the exchange rate volatility on the stock return volatility.

Two approaches are followed to study the research topic. The first approach is based on the OLS and GJR-GARCH estimation models: the GJR-GARCH model is employed to estimate the volatilities of the time series and then the OLS model is used to analyze the impact of the TRY/USD exchange rate volatility on the BIST100 return volatility. The results of the OLS model indicate that there is a small positive impact of TRY/USD exchange rate volatility on BIST100 return volatility.

The second approach investigates the volatility spillover effects between stock returns and exchange rates by employing the BAQ-GARCH model to account for asymmetric effects. The benefit of employing the BAQ-GARCH model is that it is able to capture the impact of good and bad news separately. The estimates of the variance equation for the BIST100 returns based on the BAQ-GARCH model indicate that there is a positive impact of TRY/USD exchange rate volatility on the BIST100 return volatility which is in line with the findings of the OLS model, however, the impact of the TRY/USD exchange rate volatility based on the BAQ-GARCH model is significantly more than the impact found based on the OLS model. This shows the importance of using a dynamic and better specified econometric model to understand the degree of the impact. The highly significant estimates of the BAQ-GARCH model indicate clearly that there are negative, bidirectional asymmetric volatility spillover effects. The negative asymmetric spillover effect means that bad news in TY/USD exchange rates and bad news in BIST100 returns increase the next day's volatility of BIST100 returns and the negative shocks will increase the volatility more than positive shocks. Economic interpretation is that bad news of a weakening Turkish Lira appears to have more impact on the stock prices than news of a rise in Turkish Lira. This can be explained by fear related speculative activity; investors who invested in stocks in Turkey fear for the further weakness of the Turkish Lira which affects their investment decisions. Fear controlled investment decisions have consequences for the volatility of stocks. Another explanation is that an emerging economy as Turkey misses a developed financial market to mitigate exchange rate risks.

The findings of the volatility spillover effects indicate that Turkish stock and foreign exchange markets are interrelated which implies that lagged information from the foreign exchange market can be used to forecast the changes in the stock market. This is also an indication of inefficient markets where the foreign exchange market has significant predictive power on the stock market. This interaction has important implications for portfolio managers and investors because including both assets in the same portfolio is risky. Policymakers should take into account the interaction between the markets before implementing their exchange rate policies for financial stability. This research can be extended by studying the interaction between the stock and foreign exchange markets not only within one country but also across other countries.

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