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The relationships among interest rate, exchange rate and stock price: A BEKK - MGARCH approach

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Abstract: This paper employs a BEKK-MGARCH model approach to generate the conditional variances of monthly stock exchange prices, exchange rates and interest rates for Turkey. For the sample period 2002:M1-2009:M1, before the effects of global economic crisis hit Turkey, the results indicate a significant transmission of shocks and volatility among these three financial sectors.

Keywords: BEKK-MGARCH Model, Volatility Transmission, Conditional Variance

1. Introduction

In recent years, stock markets have become an important part of many countries' economies. This increasing importance of stock markets has motivated economists to predict stock prices and financial returns. In addition, the estimation of stock market fluctuations is an important practice among investors and policymakers.

It is especially important to obtain information on how various sectors are affected by changes in a country's macroeconomic variables. Policymakers, decision makers and investors should attach more importance to how different factors may affect the stock market and its volatility over time. In addition, exchange rates and interest rates are significant financial and economic factors that affect the stock market. Interest rates are considered as one of the most significant determinants of stock prices. Interest rates indirectly affect stock prices and their volatility and represent one of the most important factors directly affecting economic growth. Exchange rate volatility is another major source of macroeconomic uncertainty that affects the decisions of policymakers and investors. Exchange rates are also sensitive to stock market movements.

The evaluation of the relationship between stock prices and exchange rates is important due to its impact on monetary and fiscal policies. The literature features many empirical studies on the causal relations among these macroeconomic variables.

There is a robust literature using a wide range of economic methods to analyse the relationships between macroeconomic variables and stock prices in different economies.

Maysami and Koh [1] examine the impacts of the interest rate and exchange rate on stock returns and report that the exchange rate and interest rate have a significant negative relationship with stock prices. Wu [2] finds evidence supporting a positive and negative relationship between the exchange rate and stock prices, respectively,with real interest rates. Berument and Günay [3] examine the effect of exchange rate volatility on interest rates within the uncovered interest rate parity condition for Turkey. They find a positive relationship between exchange rate volatility and the interest rate with data from 1986:M12-2011:M01. Kim [4] finds that the stock price index is negatively related to the exchange rate using monthly data for the 1974:01-1998:12 period in the US. Erdem et al. [5] study the relationship between the interest rate, exchange rate, stock exchange, industrial production and money supply(M1) for the period 1991:M01-2004:M01 with EGARCH model for Turkey. They find that inflation and the interest rate are factors affecting stock exchange price volatility for Turkey. Furthermore, they report no relationship between industrial production and the volatility of any variables. Tabak [6] analyses the dynamic relation between stock prices and the exchange rate in the Brazilian economy. He concludes that there is no long-term relationship between these macroeconomic variables. Ozair [7] examines the causal relationship between stock prices and exchange rates in the US by using quarterly data from 1960 to 2004. The results of the study show no causality relationships and no co-integration between these two financial variables. Akay and Nargeleçekenler [8] investigate the relationships between financial volatility in stock prices and stock prices and the exchange rate in Turkey by using the ARCH and GARCH models. The authors indicate that financial volatility increased during the economic crisis. Ayvaz [9] examines the relationship between stock prices and foreign exchange rates by using time series analysis for the period 1991:01-2004:12. He shows the existence of a long-term co-integration relationship between exchange rates and the ISE-100 index. Çifter and Ozun [10] examine the impact of interest rate on stock returns using wavelet analysis with a Granger Causality Test. The authors indicate that the bond market has a long-term effect on the stock market. Sevuktekin and Nargeleçekenler [11] find positive and bidirectional causality between the exchange rates and stock prices in Turkey by using monthly data from 1986 to 2006. Hyde [12] investigates the response of the stock market to interest rate and exchange rate volatilities in four major European economies:France, Germany, Italy and the UK. Dizdarlar and Derindere [13] examine the effects of fourteen macroeconomic variables on the ISE-100 index using multiple regression analysis with monthly data for the period 2005:01-2007:12. The authors indicate that the exchange rate and the ISE-100 index are negatively related. Demireli [14] predicts the relationship between the ISE-100 index and the money supply(M2), inflation rate, interest rate, exchange rate and industrial production index by applying the unit root test, regression analysis, a correlation matrix and the VAR model. The findings of the study indicate that volatility in the ISE-100 index and the foreign exchange rate has a positive relationship. Vardar et al. [15] investigate the impact of the interest rate and the exchange rate on the Istanbul Stock Exchange using daily data over the period 2001-2008 and univariate GARCH models. They find that the interest rate and exchange rate as economic risk factors have predictive power for stock returns. Açıkalın et al. [16] examine the relationships between returns on the Istanbul Stock Exchange (ISE) and macroeconomic variables of the Turkish economy. They employ co-integration tests and the VEC model on quarterly data for the period 1991-2006 in Turkey. This study shows unidirectional relationships between macro indicators such as GDP and the exchange rate. Raghavan and Dark [17] reveal evidence of unidirectional return and volatility spillover effects from the US dollar/Australian dollar exchange rate to the Australian stock prices index. İpekten and Aksu [18] attempt to estimate short- and long-term effects of changes in the Dow Jones index, the exchange rate, the interest rate and the price of gold on the ISE index for the period 1999:01-2011:11 using a bound test. The results of this study indicate that the changes in foreign stock markets have both short- and long-term effects on ISE. Aydemir and Demirhan [19] analyse the causal relationships between stock prices and exchange rates by using data from 2001:02-2008:01. The results reveal the existence of a bidirectional causal relationship between the exchange rate and stock prices. Büyükşalvarcı [20] investigates the effects of some macroeconomic variables (such as consumer price index, oil price, exchange rate and money supply) on the ISE 100 index using multiple regression analysis for the period 2003:01-2010:03 in Turkey. Yıldız and Ulusoy [21] examine the effect of exchange rate volatility on the Turkish stock market using monthly data for the period 1987-2010. They find no significant relationship between volatility of exchange rate and Turkish stock returns. Zia and Rahman [22] attempt to analyze the dynamic relationship between stock market index and exchange rate data over the period January 1995 to January 2010 in Pakistan. Their findings show no causality between exchange rate and stock prices. Anlas [23] explores the relationship between exchange rates and the Istanbul stock exchange rate by employing monthly data from January 1999 and November 2011. The study indicates that changes in the value of US dollars and Canadian dollars are positively related to changes in the ISE-100. In addition, this study shows that fluctuations in domestic interest rates and the Saudi Arabian riyal have a negative impact on the index.

However, the empirical studies that have attempted to test the relationships between the stock market, the interest rate and the exchange rate yield mixed results. It is not clear whether there is a causal relationship between these variables. Therefore, the relationships and dynamic interactions among macroeconomic variables have a major importance for macroeconomic policy.

The economy and finance literatures continue to suffer from a lack of studies using the multivariate GARCH to examine relationships between these macroeconomic variables and their volatilities.

The objective of the paper is to investigate the relationships among some macroeconomic variables such as interest rate, stock market prices and the exchange rate with a BEKK-MGARCH modeling approach. In addition, the paper contributes to the literature as an additional study on volatility spillovers and the comovements of these macroeconomic variables.

The remainder of the paper is organised as follows. Section 2 concerns the theory. In Section 3, we describe the data used in the study and the basic statistics. In addition we discuss the empirical findings. Finally, Section 4 presents concluding remarks.

2. The Model

The Autoregressive Conditional Heteroscedasticity (ARCH) process proposed by Engle [24] and the generalised ARCH (GARCH) process proposed by Bollerslev [25] are well-known univariate volatility models[1]. When conditional volatilities vary over time, G(ARCH) models may be used to capture dynamic clustering behaviour. Several extensions of ARCH have been examined in recent years to capture time-varying conditional variances and covariances. Multivariate GARCH (MGARCH) models present a natural analytical framework for possible interaction within the conditional mean and time-varying conditional variance of two or more financial series[2]. In recent years, univariate and multivariate GARCH models have become popular models in the theoretical and empirical financial economics and econometrics literatures.

The first MGARCH model for the conditional covariance matrices was the VECH (Vector Multivariate GARCH) proposed by Bollerslev, Engle and Wooldridge [33]. Because it is difficult to impose a positive definiteness of the variance-covariance matrix in this model, Bollerslev, Engle and Wooldridge [33] developed a simplified so-called Diagonal VECH Model. The number of parameters reduced to (p+q+1)(N(N+1)/2) and the model ensured the positive definiteness of the variance-covariance matrix. The disadvantage of the Diagonal VECH Model is that it cannot capture the interaction between different variances and covariances[3].

Engle-Kroner[35] proposed the Baba-Engle-Kraft-Kroner (BEKK) model, which may be evaluated as a restricted VECH model. This parameterisation easily imposes the positivity of H_t(conditional variance-covariance matrix). Moreover, the BEKK parameterisation of H_t may reduce the number of parameters to be estimated. The BEKK model is used to model volatility transmission among returns of Stock Exchange Prices, Exchange Rates and Interest Rates. The following mean equations are estimated for each financial sector's returns and the other sector returns lagged by one period:

$$R_t=d+SR_{t-1}+\varepsilon_t \quad , \tag{1}$$

where R_t is an nx1 vector of monthly returns at time t for each sector (Stock Exchange, Exchange Rate, Interest Rate), $\varepsilon_t/I_{t-1}\sim N(0,H_t)$ is an nx1 vector of random errors for each sector at time t, and I_{t-1} represents the market information that is available at time t-1 with its corresponding nxn conditional variance-covariance matrix, H_t. The diagonal elements S_{ij} of matrix S are the respective financial sector's returns lagged by one period, whereas out-diagonal elements S_{ij} represent the mean spillover effect across sectors. d is a 3x1 vector of constants.

$$\varepsilon_t=\sqrt{H_t}\,v_t\,,\ v_t\sim \text{i.i.d } N(0,1) \tag{2}$$

The BEKK model accepted as the most general and flexible MGARCH model may be expressed as follows [4]:

$$H_t=CC'+A\varepsilon_{t-1}\varepsilon'_{t-1}A'+BH_{t-1}B', \tag{3}$$

Where C is a 3x3 lower triangular matrix of constants, and A is a 3x3 square matrix that shows how conditional variances are correlated with past squared errors. The elements of matrix A measure the effects of shocks or "news" on the conditional variances. The 3x3 square matrix B shows how past conditional variances affect the current levels of conditional variances and the degree of volatility persistence in conditional volatility among the sectors.

The parameter matrices are as follows:

$$C=\begin{vmatrix} c_{rsep,rsep} & 0 & 0 \\ c_{rer,rsep} & c_{rer,rer} & 0 \\ c_{rir,rsep} & c_{rir,rer} & c_{rir,rir} \end{vmatrix}$$

$$A=\begin{vmatrix} a_{rsep,rsep} & a_{rsep,rer} & a_{rsep,rir} \\ a_{rer,rsep} & a_{rer,rer} & a_{rer,rir} \\ a_{rir,rsep} & a_{rir,rer} & a_{rir,rir} \end{vmatrix}$$

$$B=\begin{vmatrix} b_{rsep,rsep} & b_{rsep,rer} & b_{rsep,rir} \\ b_{rer,rsep} & b_{rer,rer} & b_{rer,rir} \\ b_{rir,rsep} & b_{rir,rer} & b_{rir,rir} \end{vmatrix}$$

$$\varepsilon_t=\begin{vmatrix} \varepsilon^2_{rsep} & \varepsilon_{rsep,rer} & \varepsilon_{rsep,rir} \\ \varepsilon_{rer,rsep} & \varepsilon^2_{rer} & \varepsilon_{rer,rir} \\ \varepsilon_{rir,rsep} & \varepsilon_{rir,rer} & \varepsilon^2_{rir} \end{vmatrix}$$

The elements of the variance-covariance matrix H_t, depend only on past values of itself and past values of $\varepsilon_t\varepsilon'_t$, indicating that the variances depend solely on past squared residuals, and the covariances depend solely on past covariances. The conditional variance for each equation, ignoring the constant terms, may be expanded for the trivariate BEKK-GARCH(1,1) as follows:

$$\begin{aligned} h_{11,t+1} &= a_{11}^2\varepsilon_{1,t}^2+2a_{11}a_{12}\varepsilon_{1,t}\varepsilon_{2,t}+2a_{11}a_{31}\varepsilon_{1,t}\varepsilon_{3,t}+\\ &a_{21}^2\varepsilon_{2,t}^2+2a_{21}a_{31}\varepsilon_{2,t}\varepsilon_{3,t}+a_{31}^2\varepsilon_{3,t}^2+b_{11}^2h_{11,t}+\\ &2b_{11}b_{12}h_{12,t}+2b_{11}b_{31}h_{13,t}+b_{21}^2h_{22,t}+\\ &2b_{21}b_{31}h_{23,t}+b_{31}^2h_{33,t} \end{aligned} \tag{4}$$

$$\begin{aligned} h_{22,t+1} &= a_{12}^2\varepsilon_{1,t}^2+2a_{12}a_{22}\varepsilon_{1,t}\varepsilon_{2,t}+2a_{12}a_{32}\varepsilon_{1,t}\varepsilon_{3,t}+\\ &a_{22}^2\varepsilon_{2,t}^2+2a_{22}a_{32}\varepsilon_{2,t}\varepsilon_{3,t}+a_{32}^2\varepsilon_{3,t}^2+b_{12}^2h_{11,t}+\\ &2b_{12}b_{22}h_{12,t}+2b_{12}b_{32}h_{13,t}+b_{22}^2h_{22,t}+\\ &2b_{22}b_{32}h_{23,t}+b_{32}^2h_{33,t} \end{aligned} \tag{5}$$

[1] For detailed information, see Engle[24], Bollerslev[25], Nelson[26], Zakoian[27] and Glosten et al.[28].

[2] McAleer provides an extensive review; see McAleer, M.[29], Bollerslev, Engle&Nelson[30], Bera Higgens[31], Bauwens, Laurent&Rombouts [32].

[3] See Wei[34].

[4] Let describe the residual vector ε_t as $\varepsilon_t=(\varepsilon_{rsep,t}, \varepsilon_{rer,t}, \varepsilon_{rir,t})'$ $(\varepsilon_t|\Omega_{t-1})\sim N(0,H_t)$, where Ω_{t-1} is the information set up to t-1.

$$
\begin{aligned}
h_{33,t+1} &= a_{13}^2\varepsilon_{1,t}^2 + 2a_{13}a_{23}\varepsilon_{1,t}\varepsilon_{2,t} + 2a_{13}a_{33}\varepsilon_{1,t}\varepsilon_{3,t} + \\
& a_{23}^2\varepsilon_{2,t}^2 + 2a_{23}a_{33}\varepsilon_{2,t}\varepsilon_{3,t} + a_{33}^2\varepsilon_{3,t}^2 + b_{13}^2 h_{11,t} + \\
& 2b_{13}b_{23}h_{12,t} + 2b_{13}b_{33}h_{13,t} + b_{23}^2 h_{22,t} + \\
& 2b_{23}b_{33}h_{23,t} + b_{33}^2 h_{33,t}
\end{aligned} \tag{6}
$$

Equations (4), (5), and (6) show how shocks and volatility are transmitted across sectors and over time. We maximised the following likelihood function assuming that errors are normally distributed:

$$L(\theta) = -T\ln(2\pi) - \frac{1}{2}\sum_{t=1}^{T}\left(\ln\left|H_t\right| + \varepsilon_t^{'} H_t^{-1}\varepsilon_t\right), \tag{7}$$

Where θ is the estimated parameter vector and T is the number of observation.

3. Empirical Results

To investigate the relationships between conditional volatilities, the monthly data used in this paper were obtained from the database of the Central Bank of the Republic of Turkey. The data consist of Interest Rate (IR), Exchange Rate (ER) and Stock Exchange Price (SEP) information for the period 2002:01-2009:01 in Turkey. In addition, by taking the natural logarithm, the series are converted to return series as follows [5]:

RIR=log(IR/IRt-1)*100
RER=log(ER/ERt-1)*100
RSEP=log(SEP/SEPt-1)*100

Fig. 1 shows the returns, from which it is clear that there is clustering of returns and hence in the volatilities.

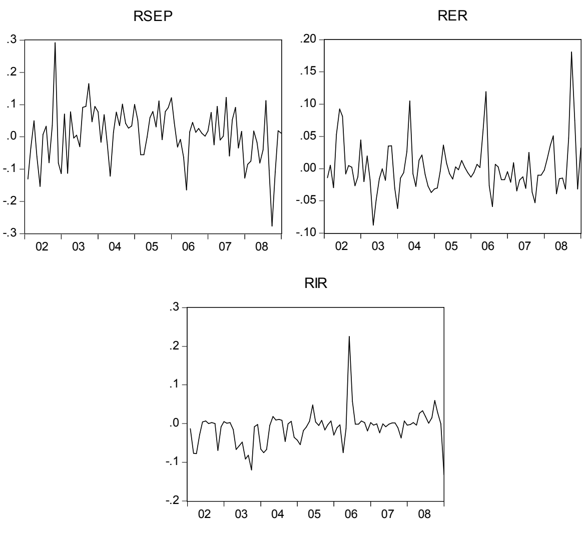

Fig.1. *Returns to SEP, ER, IR*

[5] RSEP, RER and RIR denote returns of the Stock Exchange Prices, Exchange Rates and Interest Rates, respectively.

Table 1 presents the descriptive statistics for each return series. According to Table 1, statistics of skewness indicate a lack of normality in the distribution of the return series, whereas kurtosis statistics indicate that all return series are more heavily peaked than the normal distribution. In particular, RER and RIR exhibit excessive kurtosis. In addition, the Jarque-Bera (JB) normality tests reject the null hypothesis of a normal distribution.

Table 1. *Descriptive Statistics of Returns of Stock Exchange Prices, Exchange Rate, Interest Rate.*

Statistics	RSEP	RER	RIR
Mean	0.007937	0.001802	-0.011473
Median	0.014786	-0.006829	-0.002477
Maximum	0.292163	0.180752	0.224834
Minimum	-0.277267	-0.087823	-0.131968
Std. Dev.	0.084373	0.041189	0.044028
Skewness	-0.229958	1.524937	1.198689
Kurtosis	4.510006	6.932222	12.10261
Jarque-Bera	8.720737	86.67437	310.1174
Prob.	0.012774	0.000000	0.000000

Table 2. *The Results of Unit Root Tests for the Returns*

	Test Statistics	
Variables	**ADF**	**PP**
RSEP	-7,514269**	-7,509613**
RER	-6,822918**	-5,961153**
RIR	-5,434035**	-5,325417**

(** denotes ADF and PP test statistics for rejection of the null hypothesis of a unit root at the 5% significance level. Mackinnon critical values of ADF and PP tests are -2,897 at the 5% significance level.)

As shown in Table 2, the ADF (Augmented Dickey Fuller) and the PP (Phillips Perron) test statistics are significant at the 5% level, indicating that all variables are stationary at level. According to Table 2, we must use the Johansen Co-integration Test because RSEP, RER and RIR are integrated at the same level. Prior to the test, we construct an initial VAR model to determine the lag order of the co-integration test. The VAR lag order selection criteria are indicated in Table 3.

In Table 3, the values of LogL, LR, FPE, AIC, SC and HQ information criteria indicate that one lag order is appropriate.

The Johansen Co-integration Test has been applied to reveal the long-run behaviour of the variables of interest[6] .

[6] The Johansen Co-integration Test has been implemented (with intercept (no trend) in CE and no intercept in VAR.

The test results are shown in Table 4.

Table 3. *VAR Lag Order Selection Criteria*

Lag	LogL	LR	FPE	AIC	SC	HQ
0	374.0045	NA	1.15e-08	-9.763277	-9.671275	-9.726508
1	**394.2932**	**38.44172**	**8.58e-09***	**-10.06035***	**-9.692337***	**-9.913273***
2	397.1858	5.252331	1.01e-08	-9.899626	-9.255608	-9.642246
3	407.0240	17.08733*	9.90e-09	-9.921683	-9.001657	-9.553996
4	413.9537	11.48880	1.05e-08	-9.867203	-8.671169	-9.389210
5	416.0270	3.273632	1.27e-08	-9.684922	-8.212879	-9.096622
6	423.0415	10.52171	1.36e-08	-9.632671	-7.884621	-8.934066
7	429.8667	9.698930	1.47e-08	-9.575439	-7.551381	-8.766527
8	432.8457	3.998231	1.76e-08	-9.416993	-7.116927	-8.497776

Table 4. *The Johansen Cointegration Test Results*

Hypothesis					
H_0	**H_1**	**Eigenvalue**	**Trace Stat.**	**5% Critical**	**p value**
r=0	r>0*	0,371554	90,73664	35,19275	0,0000
r=1	r>1*	0,303714	52,64727	20,26184	0,0000
r=2	r>2*	0,244251	22,9635	9,164546	0,0001
Hypothesis					
H_0	**H_1**	**Eigenvalue**	**Max.Eigen Value Stat.**	**5% Critical**	**p value**
r=0	r>0*	0,371554	38,08937	22,29962	0,0002
r=1	r>1*	0,303714	29,68352	15,89210	0,0002
r=2	r>2*	0,244251	22,96375	9,164546	0,0001

Table 5. *Parameter Estimates for the VECM(1)BEKK-MGARCH(1,1) Model*

Conditional Mean Equations

$$D(RSEP)=0{,}003664-\underset{(0{,}009120)\quad(0{,}004164)}{0{,}013450}(RSEP_{t-1}-73{,}793RER_{t-1}-24{,}841RIR_{t-1}-0{,}13767)-\underset{(0{,}128854)}{0{,}210132}DRSEP_{t-1}-\underset{(0{,}249040)}{0{,}298162}DRER_{t-1}-\underset{(0{,}328432)}{0{,}331793}DRIR_{t-1}$$

$$D(RER)=0{,}00003+\underset{(0{,}002906)\ (0{,}001476)}{0{,}008356}(RSEP_{t-1}-73{,}793RER_{t-1}-24{,}841RIR_{t-1}-0{,}13767)-\underset{(0{,}034398)}{0{,}09797}DREP_{t-1}+\underset{(0{,}128192)}{0{,}027403}DRER_{t-1}-\underset{(0{,}086838)}{0{,}00267}DRIR_{t-1}$$

$$D(RIR)=-0{,}001519+\underset{(0{,}003605)\quad(0{,}001132)}{0{,}003879}(RSEP_{t-1}-73{,}793RER_{t-1}-24{,}841RIR_{t-1}-0{,}13767)+\underset{(0{,}048789)}{0{,}003733}DRSEP_{t-1}+\underset{(0{,}079487)}{0{,}334737}DRER_{t-1}+\underset{(0{,}178159)}{0{,}067810}DRIR_{t-1}$$

		Conditional Variance Equations	
	RSEP	RER	RIR
ω	0,000868	0,000438**	0,000518**
	(0,000888)	(0,000191)	(0,000219)
	[0,97750]	[2,289335]	[2,368912]
α	0,641100**	0,809598**	0,909953**
	(0,159550)	(0,184828)	(0,212208)
	[4,018177]	[4,380279]	[4,288017]
β	0,704589**	0,316603	0,412109**
	(0,138985)	(0,310771)	(0,212027)
	[5,069523]	[1,018765]	[1,953664]
LogL	430,3906		
Avg. LogL	1,749555		
AIC	-9,911965		
SC	-9,207559		
HQ	-9,629157		

According to the results of the Johansen Co-integration Test, the Trace and the Maximum Eigenvalue Statistics display three co-integration relations. Therefore, the VECM(1) system has been used in initial analysis. Table 5 denotes the results of the VECM(1)BEKK-GARCH(1,1) model.

The estimation results of the multivariate GARCH model with diagonal BEKK parameterisation for each mean equation are reported in Table 5. Furthermore, it contains the coefficients, standard errors( ), z-statistics[ ], log-likelihood and information criteria of conditional mean and variance equations for the trivariate BEKK-GARCH(1,1) model as well.

As shown in Table 5, the α_i value of the short-run volatility persistence is positive and significant for RSEP, RER and RIR. Furthermore, the GARCH β effects are significant only for RSEP and RIR, whereas RER exhibits high short-run persistence at 0.809598. The reported results in Table 5 demonstrate that all series exhibit time-varying conditional variance, which may be successfully modelled using the BEKK-GARCH (1,1) model.

In other words, the conditional variances equations effectively capture the volatility and cross-volatility spillovers among these three sectors. From the empirical results, we conclude that there is strong evidence of ARCH and GARCH effects. Moreover, the coefficients of the GARCH effect, which shows the influence of h^2_{t-1} (the older information about residuals), and the ARCH effect, which shows the relationship of the value variation of the present time to the value variation of the previous time, are high.

In this study, to assess the model, we evaluated Ljung-Box statistics at 4, 8 and 12 lags for levels and squares of standardised residuals for the estimated VECM(1) BEKK-GARCH(1,1) model. Table 6 provides the results.

Table 6. *Residual Diagnostics of VECM(1) BEKK-GARCH(1,1)*

	RSEP Equation	RER Equation	RIR Equation
Q(4)	7,7216	2,4016	5,2621
Q(8)	9,0453	6,7587	6,4182
Q(12)	10,274	13,201	8,9310
$Q^2(4)$	2,3420	1,3867	6,4647
$Q^2(8)$	4,4132	5,1315	8,1874
$Q^2(12)$	8,5641	9,7806	10,121
Critical Value (at 5% significance level)			
	Q(4)	Q(8)	Q(12)
	9,488	15,507	21,026

According to Table 6, Ljung-Box Q statistics denote that the model is adequate for describing the conditional heteroscedasticity of the series. In other words, the results indicate that the model is statistically appropriate.

In Fig. 2, we plot conditional covariances for RSEP-RER (cov_r1r2); RSEP-RIR(cov_r1r3) and RER-RIR(cov_r2r3) of the VECM(1) BEKK-GARCH(1,1) model.

Fig. 2 shows that the conditional covariances for RSEP-RER and RSEP-RIR are negative, whereas that for RER-RIR is positive. Moreover, the conditional covariances confirm that the co-movements between RSEP, RER and RIR are similar over the period of study.

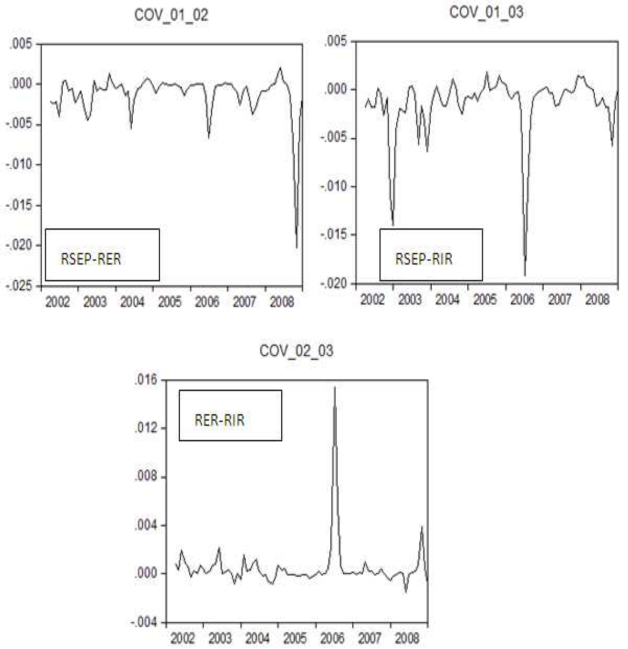

Fig.2. *Estimated Conditional Covariances for VECM(1) BEKK-GARCH(1,1) Model*

In addition, Fig. 3 presents conditional variances for RSEP (Var_r1), RER(Var_r2) and RIR(Var_r3) for the BEKK-GARCH(1,1) model.

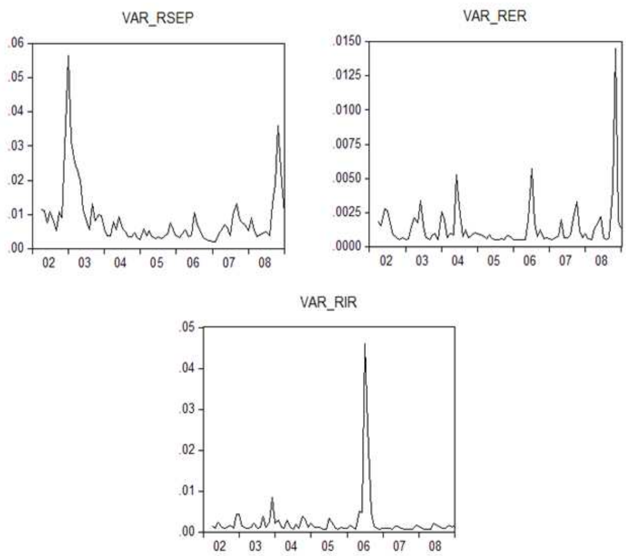

Fig.3. *Estimated Conditional Variances for BEKK-GARCH(1,1) Model*

Fig. 3 appears to suggest that all conditional variances are highly unstable. The conditional variances show spillover effects to be continuous in the long term. Furthermore, this situation is supported by the conditional correlations between RSEP, RER and RIR for the VECM(1) BEKK-GARCH(1,1) model.

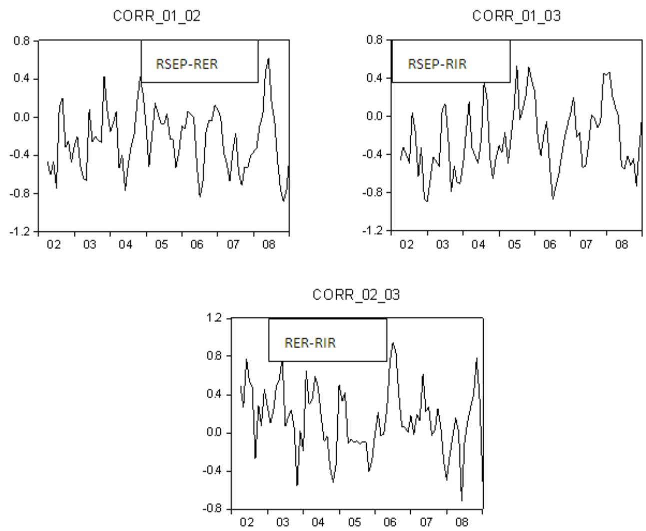

Fig.4. *Estimated Conditional Correlations for VECM(1) BEKK-GARCH(1,1) Model*

According to Fig. 4, the conditional correlation between RSEP and RER tends to fluctuate around -0.47. This finding suggests a positive(negative) change in the RSEP leads to a negative(positive) change in the RER generally. Moreover, the conditional correlation between RSEP and RIR tends to fluctuate around -0.45. This finding also implies that a positive(negative) change in the RSEP leads to a negative(positive) change in the RIR. Finally, the conditional correlation between RER and RIR tends to fluctuate approximately 0.49. This finding implies also that a positive(negative) change in the RSEP leads to a positive(negative) change in the RIR.

4. Concluding Remarks

This paper examined the transmission and spillovers of volatility and shocks among some important macroeconomic variables, such as stock exchange prices, exchange rates and interest rates by using the BEKK-MGARCH approach on monthly data from 2002 to 2009 for Turkey. Generally, our results show a significant transmission of shocks and volatility among all of these variables. The estimated coefficients from the equations of the conditional mean return indicate that all variables are significantly integrated reacting to information that influences not only the mean returns but their volatility as well.

The magnitude and persistence of the coefficients of the variance equations indicate that all variables exhibit strong ARCH and GARCH effects. In other words, current and old news have a significant impact on conditional volatility.

This study indicates that variables do interact with each other through shocks and volatility. This finding points to the presence of cross-market hedging and sharing of common information by investors in these sectors. This result suggests that investors keep a close eye on all sectors because "news" impacting a certain sector will eventually impact all sectors through their interdependence. Consequently, forecasting the transmission and spillover of volatility between these three financial sectors is important for policymakers, decision makers and investors.

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