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Spillover effect in financial markets in Turkey

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ABSTRACT

An increase in the return of an asset in the financial markets may cause the returns of the remaining assets to fluctuate over time because of the arbitrage conditions. This may also create a spillover or contagion between the volatilities of the assets in the financial markets. This study aimed to capture the spillover between financial markets in the Turkish economy and to investigate the effects of global markets on Turkish financial markets, since the spillover may arise from the global financial markets as well as the domestic ones. Employing BEKK parameterization of the multivariate GARCH model between 2006 and 2018, it found a strong mean spillover from global markets to domestic stock and bond markets, from stock and exchange markets to the bond market and from the dollar return to the stock market. For the volatility spillover, the results also supported strong spillover between each market pairs. These findings implied that the Turkish economy is well integrated into global markets and that a fluctuation in volatility in a global or domestic market immediately spreads to other domestic markets, regardless of borders.

1. Introduction

The liberalization of capital movements, improvement in technology levels and the increase in the number of instruments in financial markets have caused financial instruments to rapidly react to new information from both domestic and global markets. According to many economists, arbitrage conditions take place behind these reactions: an increase in the return of an asset may cause the return of the remained assets to change at the same time, which is called mean spillover. Moreover, once the fluctuation in returns has started, it will take some time for it to decelerate, which is called volatility spillover. Since the behaviour of instruments in the financial markets is crucial for the decision-making process of both economic agents and policy makers, it is important to investigate and understand the spillover between instruments in the financial markets.

In the literature, economists generally focused on volatility spillover rather than mean spillover to capture the interdependence between financial markets. It is generally handled in two ways: causality and dynamic correlation. While the first approach focuses on the direction of the spillover, the second just aims to capture whether there is interdependence. Additionally, most early studies of spillover across financial markets covered industrialized countries and most of them investigated the interdependence between foreign exchange and stock markets. Along with globalization, financial market integration has become more important in the finance literature. The global financial crisis showed that the contagion effect should be better studied, especially for emerging markets, to take the right actions to preserve countries from vulnerabilities.

This study focused on both mean and volatility spillover effects for the Turkish economy. The Turkish economy is important in the following ways. First, Turkey is a small, open emerging country that might be affected by global financial markets since its domestic financial markets are well integrated. Second, in recent years, especially after 2013 following the Fed's tapering program, Turkish financial markets have experienced turmoil due to the decreasing value of the Turkish lira and climbing inflation rates. Third, the number of studies regarding the relationship of financial market volatilities is quite limited for the Turkish economy. Therefore, this study employed BEKK-GARCH methodology to capture the spillover between three domestic markets and the interdependence of these three markets with global financial and markets. While investigating the interdependence between the markets, it also searched

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for some submarket details. The empirical analysis, based on daily data on foreign exchange, bond, stock, and global markets, suggested that there is a strong mean spillover from global markets to domestic stock and bond markets, from stock and exchange markets to the bond market, and from the exchange market to the stock market. For volatility spillover, the results support strong spillover between each market. At the submarket level, it also found strong interdependencies between domestic markets besides the spillover from the global markets to domestic markets of Turkey, which are detailed in following subsections.

The remainder of this article is organized as follows. Section 2 describes the BEKK- GARCH methodology, section 3 gives information about the data, section 4 submits the estimation results, and section 5 presents conclusions.

2. Literature review

A significant amount of research has examined the impact of return and volatility spillover on stock prices in different countries using numerous methodologies. In the past, many studies used Granger (1969) causality and Sims (1980) vector autoregressive methods. In recent studies, as in this one, multivariate GARCH models are frequently preferred. Some research focused on return and volatility spillover between developed and developing countries' stock markets, as seen in the study by Sun and Zhang (2009). This article investigates price and volatility spillover for stock markets from the United States to mainland China and Hong Kong (HK) SAR during the subprime crisis by using both multivariate and univariate GARCH models. The price and volatility spillover from the United States are significant for both China and HK.

Some researchers focused on the spillover effect among emerging markets. For example, Kang et al. (2017) investigated spillover across nine emerging CDS markets using the multivariate DECO-GARCH model. Their article used weekly emerging sovereign CDSs for nine countries (Brazil, China, Indonesia, Korea, Malaysia, Philippines, Russia, South Africa, and Thailand), covering the data from January 7, 2005 to July 15, 2016. Their results indicated that the volatility spillover effect rose since the last global financial crisis. Hence, their results supported the contagion effect during market turmoil. The studies that focused on volatility spillover among different type of markets were usually about volatility spillover between stock and foreign exchange markets.

Raghavan and Dark (2005) investigated the return and volatility spillover effects between the US dollar/Australian dollar (USD/AUD) exchange rate and the Australian All Ordinaries Index (AOI) using the unrestricted bivariate VAR-BEKK-GARCH(1,1) model. Their research employed daily data on the USD/AUD and the AOI from January 2, 1995 to December 31, 2004. Their findings supported the existence of unidirectional return and volatility spillover effects from the USD/AUD exchange rate to the AOI. Ely (2015) examined the evidence of mean and volatility spillover between stock and foreign exchange markets in Brazil with a multivariate GARCH-in-mean model. He used daily data from the Brazil index (IBrX-100) and the exchange rate between the Brazilian real and US dollar from February 1999 to December 2014. He found, in parallel with research on emerging markets' exchange rate–stock market spillover effect, that currency market movements affected both stock market returns and volatility.

There are few studies in the literature identifying volatility spillover by using more than two different financial markets. Diebold and Yilmaz (2012) investigated volatility spillover across four US markets: stock, bond, foreign exchange, and commodity. They examined the S&P 500 index, the 10-year Treasury bond yield, the New York Board of Trade US dollar index futures, and the Dow-Jones/UBS commodity index from January 1999 to January 2010. They used their own approach, which produced continuously varying indexes for spillover effect. Their results showed that volatility spillover across each of the four markets was not very different. However, their results demonstrated the importance of volatility spillover from the US stock market to other markets during and after the subprime crisis. Bajo-Rubio et al. (2017) used the methodology of Diebold and Yilmaz (2012) for Turkey. They examined return and volatility spillover between the Turkish stock market and international stock, exchange rate and commodity markets. They conducted their study with two data samples: a full sample from 1999 to 2015 and two subsamples from 2006. The period after 2006 covered the financial crisis. A key message of their study was that there was a spillover effect between all markets and that spillover rose as a result of the financial crisis.

Although it is not rich compared to global-scale studies, there is growing literature on spillover effects in Turkey. Bozma and Başar (2018) analysed volatility transmission between the stock markets of Turkey, Romania, Poland, Hungary and Ukraine by using the daily data from January 2011 to December 2016. The estimations were performed using the BEKK-GARCH model. Their findings indicated that the stock market of Turkey (BIST100) was affected by its own volatility, as well as by volatility in the Polish and Hungarian stock markets. Vardar, Aksoy, and Can (2008) used a GARCH model with daily sector data from 2001 to 2008 to investigate the impact of interest rate and exchange rate movements on the stock market by considering the sectors. Their findings indicated that exchange rates had increased the level of volatility in the stock market, except for the technology sector index. Öztürk (2010) found, using a cross-correlation function (CCF), that there was a bilateral interaction between the same-day returns of the exchange rate and interest rate. Additionally, while the return mean of the exchange rate did not affect the return mean of the interest rate with a one-day lag, a fluctuation in the interest rate did affect the exchange rate negatively with a one-day lag.

Çiçek (2008) examined price and volatility transmissions among the currency, bond, and stock markets of Turkey by using the EGARCH model from January 2004 to April 2008. Although Johansen cointegration analysis suggested there was no long-run relationship between these three markets, there was a significant return and volatility transmission between them in the short run. This result showed that the spillover between bond and stock markets was bidirectional, while that from bond and stock markets to the currency market was unidirectional. It also indicated that, in contrast to expectations, when the interest rate falls, so does the exchange rate. There was no volatility spillover effect from the bond market to the other two markets. However, the bond market was affected by both the stock and currency markets in a negative direction. While interest rate shocks had no effect on exchange rate volatility, stock market shocks had a highly significant and negative effect.

3. Methodology

In financial economics, some problems have solutions with multivariate distributions. Financial contagion is one of these. The literature offers several multivariate GARCH presentations, such as vector GARCH (VECH-GARCH), diagonal vector GARCH (DVECH-GARCH), Baba-Engle-Kraft-Kroner GARCH (BEKK-GARCH) Baba et al., 1989, and diagonal BEKK-GARCH, as developed by Engle and Kroner (1995). Other studies used dynamic conditional correlation GARCH (DCC-GARCH) or constant conditional correlation GARCH (CCC-GARCH), as proposed by Engle (2002) and Bollerslev (1990), respectively.

VECH-GARCH models are not very popular in empirical applications due to the possibility of nonpositive, semidefinite variance-

Table 1
Descriptive statistics of return series of the financial markets.

Data	Symbol	Mean	Median	Max	Min	Std. Dev.	Skew.	Kurt.	JB Test	Obs.
Foreign Exchange Market										
BASKET	$e_{B/£}$	0.0004	0.0000	0.1406	−0.0812	0.0089	1.4214	28.6998	94406.39[a]	3389
USDTRY	$e_{\$/£}$	0.0004	0.0000	0.1482	−0.0766	0.0097	1.4201	24.9804	69362.39[a]	3389
EURTRY	$e_{€/£}$	0.0004	0.0001	0.1341	−0.0853	0.0093	1.0221	22.4298	53898.57[a]	3389
Stock Market										
BIST100	s_{100}	0.0002	0.0007	0.1213	−0.1106	0.0164	−0.2855	6.9395	2237.55[a]	3389
BIST30	s_{30}	0.0002	0.0004	0.1273	−0.1090	0.0175	−0.1479	6.5177	1759.72[a]	3389
BANK	s_{bnk}	0.0000	0.0000	0.1559	−0.1186	0.0218	−0.0784	5.8151	1122.49[a]	3389
SERVICE	s_{srv}	0.0004	0.0009	0.0999	−0.0970	0.0140	−0.3090	6.9519	2259.28[a]	3389
FOOD	s_{food}	0.0003	0.0004	0.0967	−0.1189	0.0168	−0.5406	8.3475	4202.96[a]	3389
METAL	s_{met}	0.0005	0.0011	0.1315	−0.1107	0.0203	−0.1837	6.9508	2223.20[a]	3389
INDUSTRY	s_{ind}	0.0004	0.0012	0.0839	−0.1140	0.0137	−0.8723	9.1153	5710.56[a]	3389
Bond Market										
TR2	b_{2y}	−0.0003	0.0000	0.3425	−0.3102	0.0244	0.7135	37.4418	167793.80[a]	3389
TR5	b_{5y}	0.0001	0.0000	0.1178	−0.1221	0.0180	0.1166	8.2817	3946.89[a]	3389
Global Market										
VIX	g_{vix}	0.0002	−0.0025	0.7682	−0.3506	0.0741	1.0140	10.0264	7552.24[a]	3389

[a] indicates significant at the level of 1%.

covariance combinations. To solve the problem of positive definiteness, the BEKK-GARCH model uses quadratic forms, making it easier to verify the stationary conditions of the covariance process. The diagonal BEKK model was developed to decrease the number of parameters to be estimated. Because of assumptions of constant correlations over time being unrealistic in the CCC-GARCH model, the DCC-GARCH models are much preferable. From an empirical point of view, it does not seem possible to judge appropriately between the two preferred BEKK and DCC models (McAleer, 2010). This study used the bivariate diagonal BEKK-GARCH model proposed by Engle and Kroner (1995) to investigate volatility linkage between financial markets. The BEKK-GARCH model uses a maximum log-likelihood approach for parameter estimation. The success of GARCH models in estimating volatility has motivated many researchers to extend these models to the multivariate dimension (Tse, 2000).

This study started with a bivariate VAR(1)-GARCH(1,1) model that includes each market's returns (r_t) and their first lagged values (r_{t-1}) in VAR form at time t, where r_t equals the natural logarithm of the closing price (P) for each indicator at time t $(r_t = \ln(P_t/P_{t-1})$. In this model, the mean transmissions are measured using the VAR coefficients of the mean equations.

$$\begin{bmatrix} r_{1,t} \\ r_{2,t} \end{bmatrix} = \begin{bmatrix} \alpha_{10} \\ \alpha_{20} \end{bmatrix} + \begin{bmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{bmatrix} \begin{bmatrix} r_{1,t-1} \\ r_{2,t-1} \end{bmatrix} + \begin{bmatrix} \beta_{13} \\ \beta_{23} \end{bmatrix} [z_{t-1}] + \begin{bmatrix} u_{1,t} \\ u_{2,t} \end{bmatrix} \tag{1}$$

$$R_t = \alpha + \beta R_{t-1} + \beta' Z_{t-1} + U_t \tag{2}$$

$$U_t|\Omega_{t-1} \sim N(0, H_t) \tag{3}$$

In the matrix notations (2) and (3), R_t is an $n\,x\,1$ vector of daily returns for the markets at time t, z is a 1x1 vector of exogenous variable at time $t-1$; α is an $n\,x\,1$ constant vector; U_t is an $n\,x\,1$ vector of random errors at time t;and H_t is an $n\,x\,n$conditional variance-covariance matrix, where $n = 2$. Ω_{t-1} represents the

Table 2
Unit root test results.

Data	Symbol	ADF Test Results			PP Test Results		
		None	Constant	Constant & Trend	None	Constant	Constant & Trend
Foreign Exchange Market							
BASKET	$e_{B/£}$	−37.0345[a]	−37.1772[a]	−37.2189[a]	−54.3569[a]	−54.4578[a]	−54.4878[a]
USDTRY	$e_{\$/£}$	−36.8161[a]	−36.9417[a]	−36.9951[a]	−55.7943[a]	−55.8869[a]	−55.9266[a]
EURTRY	$e_{€/£}$	−36.7632[a]	−36.8895[a]	−36.9146[a]	−54.7915[a]	−54.8765[a]	−54.8924[a]
Stock Market							
BIST100	s_{100}	−55.9483[a]	−55.9500[a]	−55.9419[a]	−55.9256[a]	−55.9257[a]	−55.9174[a]
BIST30	s_{30}	−56.2918[a]	−56.2908[a]	−56.2824[a]	−56.2674[a]	−56.2656[a]	−56.2571[a]
BANK	s_{bnk}	−57.2701[a]	−57.2619[a]	−57.2563[a]	−57.2653[a]	−57.2568[a]	−57.2514[a]
SERVICE	s_{srv}	−56.1851[a]	−56.2227[a]	−56.2176[a]	−56.1604[a]	−56.2045[a]	−56.1997[a]
FOOD	s_{food}	−57.2093[a]	−57.2180[a]	−57.2306[a]	−58.1168[a]	−58.2019[a]	−58.3648[a]
METAL	s_{met}	−54.1121[a]	−54.1416[a]	−54.1364[a]	−54.0261[a]	−54.0543[a]	−54.0482[a]
INDUSTRY	s_{ind}	−53.7932[a]	−53.8208[a]	−53.8129[a]	−53.7299[a]	−53.7562[a]	−53.7482[a]
Bond Market							
TR2	b_{2y}	−69.7195[a]	−69.7225[a]	−69.7133[a]	−68.6124[a]	−68.6169[a]	−68.6092[a]
TR5	b_{5y}	−66.1445[a]	−66.1383[a]	−66.1557[a]	−65.6081[a]	−65.6025[a]	−65.6169[a]
Global Market							
VIX	g_{vix}	−45.8192[a]	−45.8133[a]	−45.8065[a]	−73.1463[a]	−73.3715[a]	−73.3572[a]

[a] indicates significant at the level of 1%. Optimal lag selection was made according to the AIC.

Table 3
VAR(1) model estimates between $\mathbf{e}_{\mathbf{B}/£}$ and $\mathbf{s}_{100}$ and ARCH test results.

Depended Variable →	Basket Rate ($e_{B/£,t}$)		BIST100 Index ($s_{100,t}$)
	Eq. 11		Eq. 12
Coefficients			
$\boldsymbol{c}_{10}$	0.0004**	$\boldsymbol{c}_{20}$	0.0003
	(0.0002)		(0.0003)
$\boldsymbol{e}_{\boldsymbol{B}/£,\boldsymbol{t}-1}$ (γ_{11})	0.0896*	$\boldsymbol{e}_{\boldsymbol{B}/£,\boldsymbol{t}-1}$ (γ_{21})	**−0.1325***
	(0.0194)		**(0.0352)**
$\boldsymbol{s}_{100,\boldsymbol{t}-1}$ (γ_{12})	**0.0241****	$\boldsymbol{s}_{100,\boldsymbol{t}-1}$ (γ_{22})	−0.0292
	(0.0104)		(0.0189)
$\boldsymbol{g}_{\boldsymbol{vix},\boldsymbol{t}-1}$ (γ_{13})	−0.0027	$\boldsymbol{g}_{\boldsymbol{vix},\boldsymbol{t}-1}$ (γ_{23})	**−0.0324***
	0.0022		**0.0040**
Diagnostics			
Adj. $\boldsymbol{R}^2$	0.0056		0.0293
F-stat	7.3184		35.0801
AIC	−6.6136		−5.4177
ARCH Test	**378.8072***		**39.6672***

(1) * and ** indicates significant at the level of 1% and 5% respectively.
(2) Standard errors are in parenthesis.

information in the market at time $t-1$, and β is an $n\ x\ n$ parameter matrix for the autoregressive term.

A simple diagonal-BEKK-GARCH specification with order 1 is as follows:

$$\mathrm{H}_t = CC^{'} + A\varepsilon_{t-1}\varepsilon_{t-1}^{'}A^{'} + \ B\mathrm{H}_{t-1}B' \tag{4}$$

For the bivariate case, the diagonal-BEKK-GARCH model can be expressed as follows:

$$\begin{bmatrix} h_{11,t} & h_{12,t} \\ h_{21,t} & h_{22,t} \end{bmatrix} = \begin{bmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{bmatrix} \begin{bmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{bmatrix}^{'} + \begin{bmatrix} a_{11} & 0 \\ 0 & a_{22} \end{bmatrix} \times \begin{bmatrix} \varepsilon_{1,t-1} \\ \varepsilon_{2,t-1} \end{bmatrix} \begin{bmatrix} \varepsilon_{1,t-1} \\ \varepsilon_{2,t-1} \end{bmatrix}^{'} \begin{bmatrix} a_{11} & 0 \\ 0 & a_{22} \end{bmatrix}^{'} + \begin{bmatrix} b_{11} & 0 \\ 0 & b_{22} \end{bmatrix} \times \begin{bmatrix} h_{11,t-1} & h_{12,t-1} \\ h_{21,t-1} & h_{22,t-1} \end{bmatrix} \begin{bmatrix} b_{11} & 0 \\ 0 & b_{22} \end{bmatrix}^{'} \tag{5}$$

where C is a lower triangular matrix and A and B are diagonal $n\ x\ n$ parameter matrices. There are $2.5n^2 + 0.5n$ parameters in the model. If solving the matrix presented in equation (5), one may have the following equations;

$$h_{11,t} = c_{11}^2 + a_{11}^2\varepsilon_{1,t-1}^2 + \ b_{11}^2 h_{11,t-1} \tag{6}$$

$$h_{12,t} = c_{11}c_{21} + a_{11}a_{22}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + b_{11}b_{22}h_{12,t-1} \tag{7}$$

$$h_{22,t} = c_{21}^2 + c_{22}^2 + a_{22}^2\varepsilon_{2,t-1}^2 + b_{22}^2 h_{22,t-1} \tag{8}$$

The conditional covariance matrix cannot be defined negatively by its nature and the conditional covariance matrices are guaranteed to be stationary if:

$$a_{ii} + b_{ii} < 1 \qquad \text{for } \forall i = 1,2 \qquad \text{for Eq. 6 and 8} \tag{9}$$

Table 4
Estimated coefficients of conditional mean return equations for $\boldsymbol{e}_{\boldsymbol{B}/£}$ and $\boldsymbol{s}_{100}$

Depended Variable →	Basket Rate ($e_{B/£,t}$)		BIST100 Index ($s_{100,t}$)
Coefficients	Eq. 13		Eq. 14
α_{10}	0.0001	α_{20}	0.0010*
	(0.0001)		(0.0002)
$\boldsymbol{e}_{\boldsymbol{B}/£,\boldsymbol{t}-1}$ (β_{11})	−0.0333***	$\boldsymbol{e}_{\boldsymbol{B}/£,\boldsymbol{t}-1}$ (β_{21})	**−0.0890***
	(0.0188)		**(0.0313)**
$\boldsymbol{s}_{100,\boldsymbol{t}-1}$ (β_{12})	**−0.0292***	$\boldsymbol{s}_{100,\boldsymbol{t}-1}$ (β_{22})	−0.0395
	(0.0072)		(0.0173)
$\boldsymbol{g}_{\boldsymbol{vix},\boldsymbol{t}-1}$ (β_{13})	−0.0008	$\boldsymbol{g}_{\boldsymbol{vix},\boldsymbol{t}-1}$ (β_{23})	**−0.0256***
	0.0015		**0.0032**
Diagnostics			
LogL			21972.47
Avg. LogL			3.2427
Q(12)			205.4620*
ARCH-LM			0.6917
AIC			−12.9613
SC			−12.9324
Obs.			3389

(1) * and ** indicates significant at the level of 1% and 5% respectively.
(2) Standard errors are in parenthesis.

Table 5
Estimated coefficients for transformed H matrix for $\mathbf{e}_{B/£}$ and $\mathbf{s}_{100}$

	Coefficient of H Matrix
C matrix	
c_{11}	0.00000088*
	(0.0000)
c_{21}	−0.00000077*
	(0.0000)
c_{22}	0.00000395*
	(0.0000)
A matrix	
a_{11}	0.284528*
	(0.0137)
a_{22}	0.209168*
	(0.0132)
B matrix	
b_{11}	0.951994*
	(0.0043)
b_{22}	0.970188*
	(0.0039)
Diagnostics	
LogL	21972.47
Avg. LogL	3.2427
AIC	−12.9613
SC	−12.9324

(1) * indicates significant at the level of 1%.
(2) Standard errors are in parenthesis.

Table 6
Wald test results and stability conditions.

Hypothesis	Value	Std. Err.	Chi-Square
h_{12}	$a_{11}*a_{22}$ = 00.0595[a]	0.0053	123.86
$b_{11}*b_{22}$ = 00.9236[a]	0.0061	22819.87	
$a_{11}*a_{22}+b_{11}*b_{22}=0.9831<1$			

[a] indicates significant at the level of 1%.

$$a_{ii}*a_{jj}+b_{ii}*b_{jj}<1 \quad for\ i=1\ and\ j=2 \quad for\ Eq.\ 7$$

To estimate the parameters of the GARCH family models, a maximum likelihood estimation was employed since the consistency of the maximum likelihood estimators has been proved (Brooks, 2008). Also, Bollerslev and Wooldridge (1992) indicated that if the normality assumption is contravened, then using this method makes the standard errors robust. Therefore, the parameters of the above specifications were estimated by maximizing the log-likelihood function because of the assumption of conditional normality.

The conditional log likelihood function L(θ) is

$$L(\theta)=-\frac{Tk}{2}\ln(2\pi)-\frac{1}{2}\sum_{t=1}^{T}\left(ln|H_t(\theta)|+\varepsilon_t^{'}H_t^{-1}(\theta)\varepsilon_t\right) \tag{10}$$

where T is the number of observations, k is the number of variables (markets) and θ is the vector of all unknown parameters to be estimated. The study tested the null hypothesis with an asymptotically χ^2 $(p-q)$ distributed Ljung-Box Q-statistic. Here, q is the number of explanatory variables.

4. Data

The data used in the analysis was daily figures, as Andersen and Bollerslev (1998) indicated that GARCH models perform better when volatility is measured as the sum of the squares of intra-day changes. To search for return and volatility spillover effects

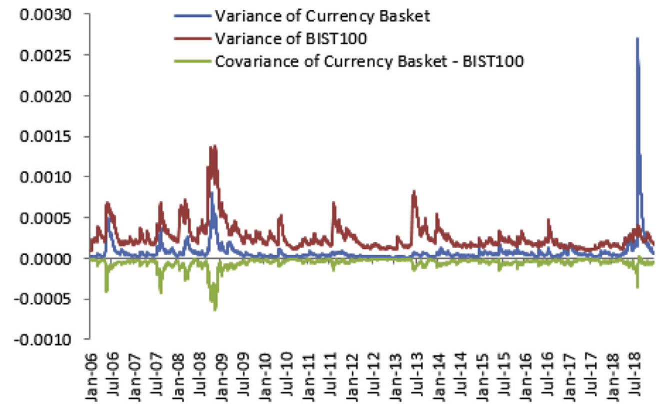

Fig. 1. Currency basket – Bist100 index.

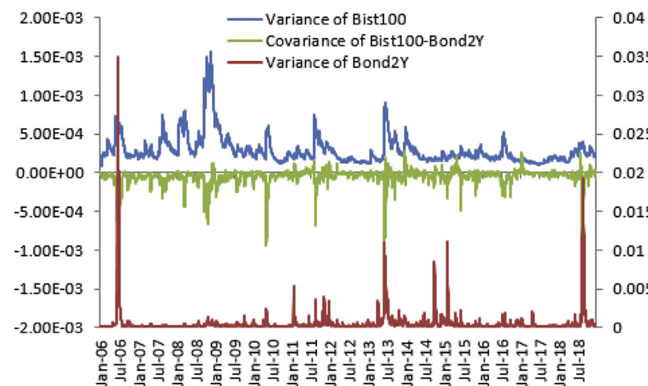

Fig. 2. Bist100 Index-Bond2Y.

between the exchange rate, stock and bond markets, this study used several variables as proxies for the markets in the research. To capture the effect of global developments, it also integrated a global market variable as an explanatory variable to the model. For the foreign exchange market, it used nominal daily spot exchange rates of USD/TRY ($e_{\$/£}$) and EUR/TRY ($e_{€/£}$), as well as a basket rate ($e_{B/£}$) composed of these two currencies ($0.5e_{\$/£}+0.5e_{€/£}$). For the stock market, it used BIST100 (s_{100}) and BIST30 (s_{30}) index values and sectoral-based indexes as banking (s_{bnk}), service (s_{srv}), food (s_{food}), metal (s_{met}), and industry (s_{ind}) sectors. For the bond market, it used two- (b_{2y}) and five-year (b_{5y}) Treasury bond yields. Finally, to represent the global market, it used the global volatility index VIX (g_{vix}) in the analysis.[1] The study obtained all time series from the Reuters data terminal and produced the return series using a formula of $log(P_t/P_{t-1})$. It was particularly preferred to include the floating exchange rate regime with an explicit inflation targeting period and selected the range between January 02, 2006 and December 28, 2018.

Table 1 presents the descriptive statistics of the variables under investigation with market name categories: bond, stock, foreign exchange and global. The mean is close to zero for all series. The standard deviations show that VIX has the highest volatility.

[1] Other potential global market variables are the index that measures the performance of global equities MSCI for emerging markets (MSCI-E), the index that measures the performance of global equities MSCI for the world market (MSCI-W) and the exchange rate of EUR/USD. Since VIX index is constructed from weighted average options prices, it is a good measure of risk-neutral expected volatility and a sensible proxy for variations in risk (Ready, 2017). Therefore, it was preferred to use the VIX index to search for the effect of global markets.

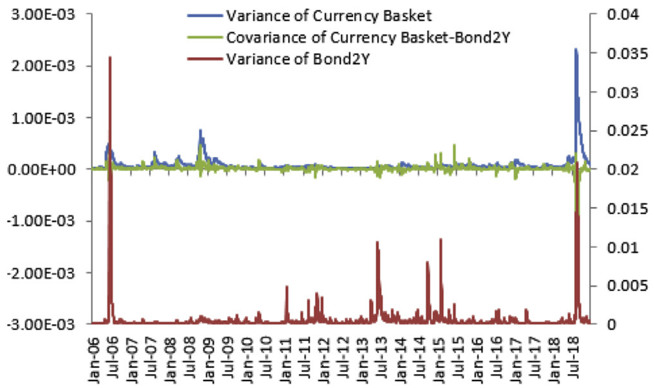

Fig. 3. Currency basket – Bond2Y.

Among the stock submarkets, note that the banking index is the most volatile in the sectoral distinct. The return series are highly leptokurtic, especially the foreign exchange market indicators. The stock market series are negatively skewed and the others positively. According to the Jarque-Bera test, the null hypothesis of normality for the distribution of all series is rejected at the significance level of 1%.

In general, time series data is dominated by stochastic trends and has a unit root. If the data in the analysis has a unit root, then the credibility of the results is doubtful. Here, the study used the Augmented Dickey Fuller (ADF) test developed by Dickey and Fuller (1979) and the PP test developed by Phillips and Perron (1988) to test the hypothesis, which showed that the return series are stationary.

As mentioned above, the return series was used for all variables (with the formula of $log(P_t / P_{t-1})$). Table 2 indicates that for the return series, the hypothesis of there being a unit root is rejected at the 1% level of significance. The graphs of the return series are presented in Appendix A, with Figs. 4, 5, and 6.

5. Estimation results

This section investigates spillover effects in two cases: spillover in mean and spillover in variance. By this distinction, it directs attention to exogenous and endogenous volatilities. The spillover in mean is predictable volatility, while the spillover in variance is unpredictable, which is why the spillover in variance is mostly called uncertainty in the literature.

This research had a total of 12 variables and examined all combinations thereof. To search for the effects of global markets, it integrated the VIX index as an exogenous explanatory variable in all of the domestic asset pairs' mean equations. In this way, it was able to separate the effect of global factors that might drive the observed changes in the asset prices. Then the errors may give a clearer picture of the spillover effects between the domestic asset classes.[2] Before presenting all results, it examines two main market variables plus VIX index in the equations as an example: basket rate ($e_{B/£}$) and BIST100 index (s_{100}). The reader can follow the same procedure with the other combinations.

To search for volatility in a spillover, one needs to search for the ARCH effect in the residuals. Therefore, it first determined the vector autoregressive (VAR) presentation of the variables. For the model, the Schwartz criterion revealed that the best lag length is equal to one. Hence, one can write the mean equations as follows in VAR(1) form:

$$e_{B/£,t} = c_{10} + \gamma_{11} e_{B/£,t-1} + \gamma_{12} s_{100,t-1} + \gamma_{13} g_{vix,t-1} + \varepsilon_{e,t} \quad (11)$$

$$s_{100,t} = c_{20} + \gamma_{21} e_{B/£,t-1} + \gamma_{22} s_{100,t-1} + \gamma_{23} g_{vix,t-1} + \varepsilon_{s,t} \quad (12)$$

Table 3 shows the coefficients of the VAR model and the ARCH tests for the basket and BIST100 returns, as calculated by Equations (11) and (12). According to Table 3, the null hypothesis of no ARCH effect in residuals was rejected for both equations. This suggested that the selected specification might be estimated using the BEKK-GARCH method. Appendix B presents the ARCH effect test results for the other remaining variable couples. When it was checked, all variable couples in the VAR models suggested that proceeding with the BEKK-GARCH method was appropriate.

The BEKK-GARCH presentation of the variables under investigation is as follows:

$$e_{B/£,t} = \alpha_{10} + \beta_{11} e_{B/£,t-1} + \beta_{12} s_{100,t-1} + \beta_{13} g_{vix,t-1} + u_{e,t} \quad (13)$$

$$s_{100,t} = \alpha_{20} + \beta_{21} e_{B/£,t-1} + \beta_{22} s_{100,t-1} + \beta_{23} g_{vix,t-1} + u_{s,t} \quad (14)$$

$$R_t = \alpha + \beta R_{t-1} + \beta' G_{t-1} + U_t \quad (15)$$

$$U_t | \Omega_{t-1} \sim N(0, H_t) \quad (16)$$

$$\mathrm{H}_t = CC' + AE_{t-1}E'_{t-1}A' + B\mathrm{H}_{t-1}B' \quad (17)$$

$$h_{12,t} = c_{11}c_{21} + a_{11}a_{22}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + b_{11}b_{22}h_{12,t-1} \quad (18)$$

Table 4 shows the conditional mean return part of the BEKK-GARCH presentation of the model in Equations (13) and (14). The β_{12} coefficient captures the mean spillover from BIST100 to basket rate, while the β_{21} coefficient gives the mean spillover from basket rate to BIST100 index. The values showed that both coefficients are significant at the 1% level and that a 1% increase in the BIST100 index may cause basket rate to reduce by 0.03%, while a 1% increase in basket rate decreases the BIST100 rate by 0.09%. The coefficients of β_{13} and β_{23} indicated the mean spillover from global market to basket rate and BIST100 index, respectively. As can be seen from Table 4, there was no spillover from global markets to the basket rate while an increase in VIX index decreased the BIST Index return by 0.03%. These findings implied that there was a negative and strong relationship as expected between stock market and foreign exchange market returns and the VIX index was effective on stock market returns but not on the foreign exchange market.

The estimated coefficients of the conditional mean returns for the remaining couples are presented in Appendix C1 and C2. The lower triangular matrix in Appendix C1 displays the models' β_{12} and β_{13} coefficients, and the upper triangular matrix in Appendix C1 indicates their β_{21} and β_{23} coefficients, as stated in Equations (13) and (14), as an example of the basket currency and BIST100 variables. According to these values, the dollar returns were negatively influenced by the BIST100, BIST30, banking and service stock returns, but euro returns or basket returns were not affected by any returns of stock or bond markets. On the other hand, all stock returns were negatively affected by dollar returns and basket returns, except for the industry sector that did not respond to basket rate return; but Vardar et al. (2008) found that only the service sector respond to dollar return. Bond returns also positively respond to all exchange market returns including euro returns.

Similar to the findings of Rajo-Rubio, Berke and McMillian (2017), the lagged return values of global market (VIX index) led to a negative impact on all stock market returns. As can be seen from

[2] The authors thank the editor and the anonymous referees for their comments and suggestions.

the table in Appendix C, 2-year and 5-year bond yields were under the influence of all other domestic and global market returns with one-day lag. This result was similar to that in Çiçek (2008), whose study indicated that the bond market (2-year bond yield) was under the influence of both stock (BIST100) and exchange rate (USD/TRY) markets. According to the findings, while exchange rate returns positively affected the bond market (when the exchange rate increases, meaning the Turkish lira depreciates, the bond returns increase), there was no mean spillover from bond market returns to the exchange rate returns. Moreover, only industry return was under the influence of the 2-year bond return.

On the other hand, the β_{11} and β_{22} coefficients in Table 4 are the coefficients of own past return transmissions from the exchange rate and stock markets, respectively. Note that the coefficient of the stock market was insignificant, while the coefficient of the own mean return spillover effect of the exchange rate was significant at the 10% level and relatively higher than the return spillover effect between the two markets. Therefore, one may say that the exchange rate returns were under the influence of the stock market returns less than of own past returns.[3]

Having the conditional mean equations, the study estimated the bivariate diagonal BEKK-GARCH(1,1) model using the basket rate, BIST100 variables and VIX index variables. In Equation (7), $a_{11}*a_{22}$ multiplication captures the spillover effect in volatility and $b_{11}*b_{22}$ informs about the persistence of the GARCH effect. The first need was to get the coefficients of the H matrix in Equation (5), presented in Table 5.

According to Table 5, for the interdependency relationship of the basket exchange rate and stock markets, all the coefficients were statistically significant at the 1% level. The coefficient of $\varepsilon_{1,t-1}\varepsilon_{2,t-1}$ was computed by multiplying a_{11} and a_{22} and was equal to 0.0595. If this coefficient is statistically different from zero, there is a spillover effect in volatility.

The Wald test was applied, where the null hypothesis was that there was no spillover effect in volatility. Since the null hypothesis was rejected, as shown in Table 6, it suggested a spillover effect in the foreign exchange basket and the BIST100 index. It also presented stability conditions (Eq. (6)) for the conditional covariance equation in Table 6, which provided conditional covariance matrices guaranteed to be stationary.

When checking the other volatility spillover coefficients among remaining variables in the covariance equations, all coefficients were statistically significant (see the table in Appendix E for Chi-Square statistics of Wald Tests for h_{12} equations), which means there was volatility spillover between each market couple. Furthermore, conditional covariance matrices were guaranteed to be stationary by providing the condition that $a_{11}*a_{22}+b_{11}*b_{22}<1$.[4] When examining the details of volatility spillover between the stock and currency markets, Appendix E showed that the spillover effects among all sector stocks and exchange rates were positive, which supported the findings of Vardar et al. (2008). The highest volatility spillover was calculated between 2-year bond yield and industry stocks (0.1264). In general, the 2-year bond yield had a high volatility spillover with all variables. The results also indicated that the bond market was much affected by global financial volatility.

The last focus was on the coefficient of the lag term of conditional covariance ($h_{12,t-1}$), which gave information about the persistence of the GARCH term. By multiplying the b_{11} and b_{22} coefficients in Table 5, it yielded a coefficient of 0.9236. The Wald test results for persistence in conditional covariance are presented in Table 6. The coefficient was so persistent that it took Figs. 4, 5 and 6a value close to 1. Since the volatility spillover between basket currency and the stock market seems highly persistent, with a value of 0.9236, we may say there is strong persistence in conditional covariance.

Figures, 1, 2 and 3 show the conditional covariances estimated by the diagonal BEKK for three main domestic markets. As proxies of these markets, the study used a currency basket for foreign exchange, the BIST100 index for the stock market and the two-year Treasury bond yield for the bond market.

It is useful to explain why the timeline graphs of the same variables in Figs. 1–3are not exactly the same. For example, BIST100 (red line) in Fig. 1 is not exactly the same as BIST100 (blue line) in Fig. 2. This is because the two BIST100 variance series were derived from different BEKK-GARCH models. However, it is important to realise that they are similar and follow nearly the same path.

6. Conclusions

This article examines return and volatility transmissions among domestic financial markets and from global financial markets to local ones. It focuses on the case of the Turkish financial markets, as the Turkish economy is well integrated into the global financial markets and has experienced turmoil in its financial markets, especially after 2013, following the announcement of the Fed's tapering program. The main contribution of this study is to capture both the mean and variance spillover between the main markets (domestic stock, currency, and bond markets, and global financial markets) and the subgroup variables under investigation. It employed the diagonal BEKK-GARCH method, which solved the problem of positive definiteness in the covariance process.

The results for the conditional mean and variance equations were both statistically and economically important. The conditional mean equations suggested that all sector stock returns were negatively influenced by dollar and basket returns, but not by euro returns except for service and food returns. The conditional covariance equations revealed that the spillover between all the exchange rates and the industry sector were the highest, while that between all the exchange rates and the banking sector were the lowest. These findings indicated that there was a trade-off for economic agents between currency and stock returns, but they suggested that exchange rate fluctuations may affect industries more than banks, since the production costs depend on the value of the dollar and banks are likely to have some measures.

At the same time, the study captured strong and statistically significant spillover between bond returns and stock markets returns. These findings revealed that the arbitrage preferences of economic agents work well for these two markets and that the economic agents are willing to sell one when the other returns rise. For the effects of the global markets, an increase in the volatility index of the global financial markets decreased the returns of all stocks and increased the returns of all bonds, as expected. Additionally, dollar returns were negatively and significantly affected by the global markets. These findings implied that the Turkish stock and bond markets plus dollar returns were intensely integrated into the global markets. Therefore, politicians and policymakers, as well as economic agents and investors, should closely monitor developments in the global financial markets.

Appendix A. Time line graphs of return series

[3] Other than those included in the text as examples for exchange rate and stock market, all estimated β_{11} and β_{22} values are presented in Appendix D.

[4] For the stationarity of conditional covariance matrices of the other remained variable couples, see Appendix F.

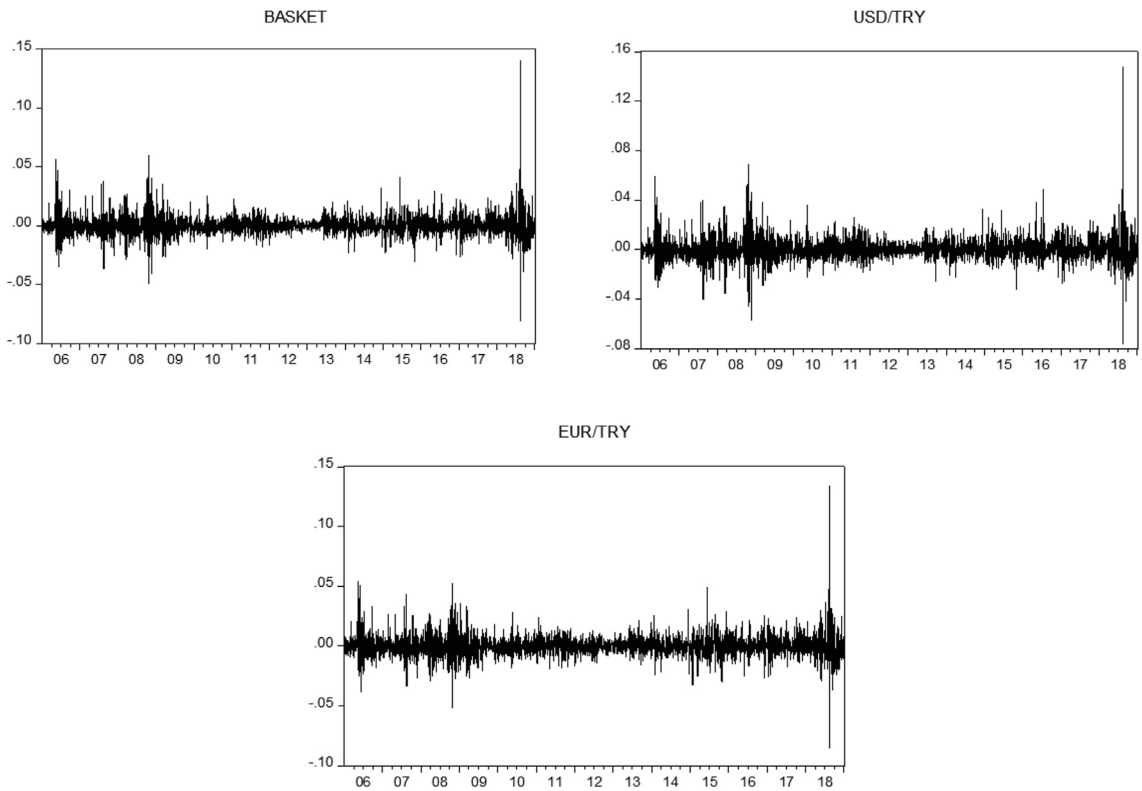

Fig. 4. Foreign Exchange Market Return Series.

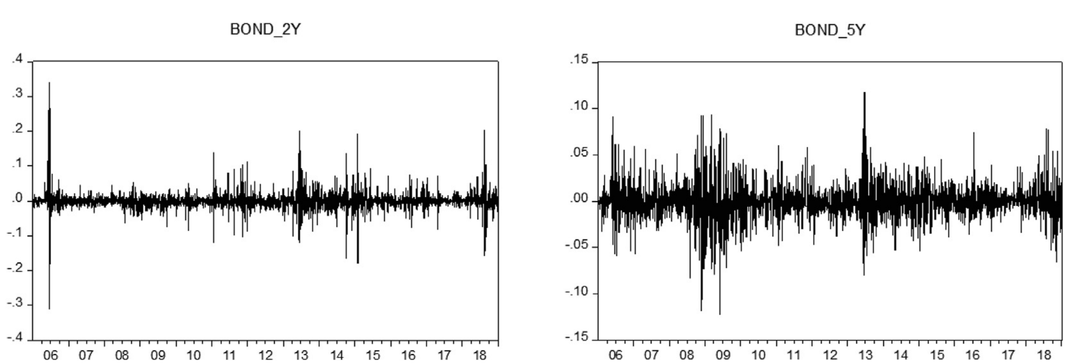

Fig. 5. Bond Market Return Series.

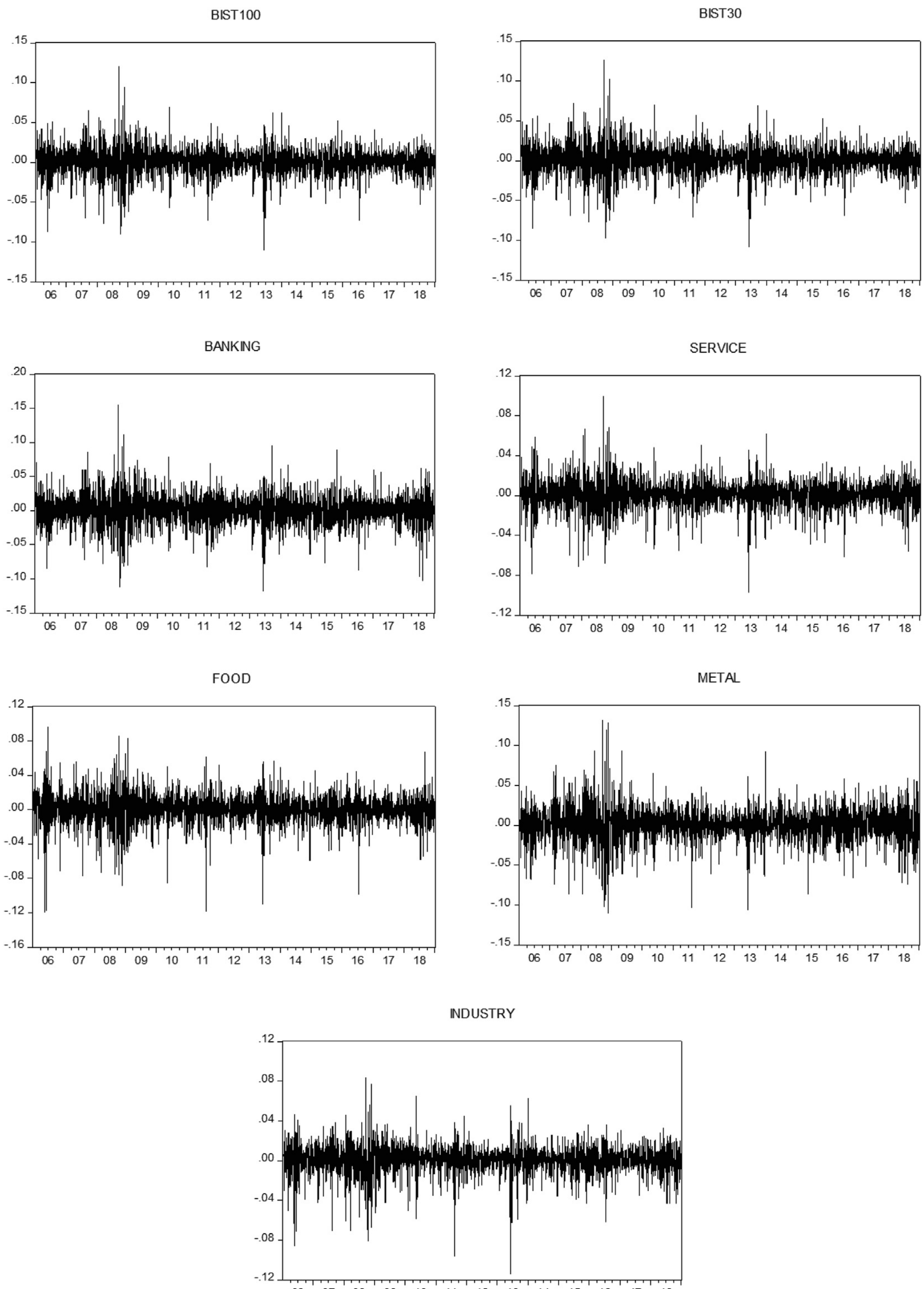

Fig. 6. Stock Market Return Series.

Appendix B. ARCH Tests Results for VAR Estimates

		Dependent Variables											
		$e_{B/£}$	$e_{\$/£}$	$e_{€/£}$	s_{100}	s_{30}	s_{bnk}	s_{srv}	s_{food}	s_{met}	s_{ind}	b_{2y}	b_{5y}
Independent Variables	$e_{B/£}$	–	405.4368*	405.3116*	378.8072*	380.9677*	387.4901*	377.3670*	397.0190*	394.0242*	373.1000*	398.1756*	401.0601*
	$e_{\$/£}$	316.9930*	–	317.0816*	318.8030*	319.5490*	321.8272*	316.4100*	325.5025*	327.3549*	315.0269*	327.1189*	328.0647*
	$e_{€/£}$	467.5981*	467.9803*	–	475.6409*	478.5419*	488.0377*	473.3155*	495.4392*	490.0666*	466.8584*	492.7567*	502.4128*
	s_{100}	39.6672*	37.1475*	42.4315*	–	39.6510*	44.7634*	43.1106*	41.9824*	45.1560*	42.5701*	46.3662*	44.0548*
	s_{30}	39.9015*	37.7074*	42.3581*	38.9796*	–	44.4218*	41.8682*	41.5462*	44.4950*	41.0654*	45.6652*	43.6830*
	s_{bnk}	24.7491*	22.0953*	28.1787*	30.6320*	30.9955*	–	30.3078*	28.9027*	31.1728*	29.4857*	32.5840*	30.6370*
	s_{srv}	76.9535*	74.6303*	79.9222*	83.3061*	83.9769*	84.8054*	–	81.0426*	83.2460*	81.1509*	83.7397*	82.6749*
	s_{food}	197.8818*	192.8393*	199.8855*	205.7714*	204.3635*	201.8307*	202.3184*	–	207.3182*	213.1944*	204.3688*	199.8311*
	s_{met}	101.9352*	101.7101*	101.4253*	96.9189*	98.5195*	98.2992*	96.4286*	98.6226*	–	94.2900*	101.9848*	101.0671*
	s_{ind}	110.4454*	105.2440*	113.1235*	113.6758*	112.8793*	114.5893*	112.9439*	110.6126*	110.9452*	–	116.7983*	111.5547*
	b_{2y}	647.6853*	649.4290*	668.0632*	736.6175*	728.3046*	713.4160*	699.7517*	740.1701*	736.7475*	765.3537*	–	647.0004*
	b_{5y}	387.0704*	368.8779*	387.8370*	383.8466*	381.7313*	378.9307*	379.8081*	393.5106*	393.4043*	393.5068*	399.8807*	–

(1) ARCH tests depend on the OLS estimates of Equations (11) and (12). (2) Upper triangle area displays ARCH test results of Eq. (11) while lower triangle area shows ARCH test results of Eq. (12). (3) * indicates rejection of the null hypothesis (there is no ARCH effect) at the 1% significance level.

Appendix C. β_{12}, β_{13}, β_{21} and β_{23} Coefficients of Conditional Mean Equations (13) and (14). (Mean Spillover and Global Market Effects)

		Dependent Variables											
		$e_{B/£,t}$	$e_{\$/£,t}$	$e_{€/£,t}$	$s_{100,t}$	$s_{30,t}$	$s_{bnk,t}$	$s_{srv,t}$	$s_{food,t}$	$s_{met,t}$	$s_{ind,t}$	$b_{2y,t}$	$b_{5y,t}$
Independent Variables	$e_{B/£,t-1}$	–	0.0402	**0.1168***	**−0.0890***	**−0.0849***	**−0.1682***	**−0.0737***	**−0.1121***	**−0.0838****	−0.0275	**0.5339***	**0.3921***
	$g_{vix,t-1}$	–	−0.0026	**−0.0006***	**−0.0256***	**−0.0258***	**−0.0275***	**−0.0201***	**−0.0250***	**−0.0226***	**−0.0247***	**0.0095***	**0.0072***
	$e_{\$/£,t-1}$	0.0282	–	**0.0496***	**−0.1363***	**−0.1375***	**−0.2417***	**−0.0880***	**−0.1175***	**−0.1543***	**−0.0740***	**0.5067***	**0.3658***
	$g_{vix,t-1}$	−0.0015	–	−0.0006	**−0.0235***	**−0.0236***	**−0.0242***	**−0.0190***	**−0.0239***	**−0.0302***	**−0.0226***	**0.0071***	**0.0059****
	$e_{€/£,t-1}$	−0.0389	0.0215	–	−0.0193	−0.0126	−0.0490	**−0.0466****	**−0.0734***	−0.0121	0.0181	**0.3813***	**0.2697***
	$g_{vix,t-1}$	−0.0015	−0.0027	–	**−0.0263***	**−0.0264***	**−0.0289***	**−0.0298***	**−0.0259***	**−0.0233***	**−0.0251***	**0.0171***	**0.0119***
	$s_{100,t-1}$	−0.0092	**−0.0204****	−0.0028	–	**−0.3729****	0.0016	**−0.0591***	**0.0344****	**−0.0672***	−0.0332	**−0.1789***	**−0.0997***
	$g_{vix,t-1}$	−0.0008	**−0.0038****	0.0008	–	**−0.0257***	**−0.0233***	**−0.0221***	**−0.0269***	**−0.0259***	**−0.0245***	**0.0185***	**0.0131***
	$s_{30,t-1}$	−0.0088	**−0.0187****	−0.0030	**0.2486*****	–	0.0533	**−0.0487****	**0.0313****	**−0.0558***	−0.0224	**−0.1655***	**−0.0949***
	$g_{vix,t-1}$	−0.0008	**−0.0038****	0.0007	**−0.0253***	–	**−0.0229***	**−0.0220***	**−0.0270***	**−0.0260***	**−0.0244***	**0.0185***	**0.0131***
	$s_{bnk,t-1}$	−0.0047	**−0.0102*****	−0.0029	−0.0445	−0.0603	–	**−0.0364***	0.0197	**−0.0477***	**−0.0277****	**−0.1366***	**−0.0722***
	$g_{vix,t-1}$	−0.0007	**−0.0037****	0.0009	**−0.0239***	**−0.0238***	–	**−0.0226***	**−0.0281***	**−0.0276***	**−0.0253***	**0.0186***	**0.0139***
	$s_{srv,t-1}$	−0.0064	**−0.0245***	0.0372*	0.0130	0.0043	−0.0227	–	0.0031	**−0.0432*****	−0.0091	**−0.1471***	**−0.0767***
	$g_{vix,t-1}$	−0.0010	**−0.0044***	0.0007	**−0.0253***	**−0.0252***	**−0.0263***	–	**−0.0266***	**−0.0238***	**−0.0240***	**0.0217***	**0.0139***
	$s_{food,t-1}$	−0.0051	−0.0045	−0.0052	−0.0260	−0.0295	**−0.0493****	**−0.0235*****	–	**−0.0479***	**−0.0333****	**−0.0830***	**−0.0454***
	$g_{vix,t-1}$	−0.0004	**−0.0039****	0.0016	**−0.0267***	**−0.0268***	**−0.0295***	**−0.0216***	–	**−0.0261***	**−0.0252***	**0.0262***	**0.0161***
	$s_{met,t-1}$	−0.0052	0.0056	−0.0010	0.0133	0.0084	−0.0129	−0.0013	**0.0298****	–	**0.0176**	**−0.0732***	**−0.0385***
	$g_{vix,t-1}$	−0.0002	**−0.0060***	0.0017	**−0.0241***	**−0.0240***	**−0.0268***	**−0.0195***	**−0.0256***	–	**−0.0241***	**0.0234***	**0.0150***
	$s_{ind,t-1}$	0.0039	−0.0076	0.0103	−0.0020	−0.0230	−0.0533	**−0.0400*****	**0.0615****	**−0.1155***	–	**−0.1635***	**−0.0781***
	$g_{vix,t-1}$	−0.0001	**−0.0032*****	0.0016	**−0.0238***	**−0.0238***	**−0.0257***	**−0.0200***	**−0.0253***	**−0.0246***	–	**0.0213***	**0.0143***
	$b_{2y,t-1}$	−0.0046	−0.0050	−0.0025	−0.0140	−0.0145	−0.0133	−0.0065	−0.0083	−0.0165	**−0.0139*****	–	**0.0090***
	$g_{vix,t-1}$	−0.0001	**−0.0039****	0.0020	**−0.0264***	**−0.0267***	**−0.0306***	**−0.0210***	**−0.0287***	**−0.0252***	**−0.0247***	–	**0.0164***
	$b_{5y,t-1}$	0.0012	0.0047	−0.0004	−0.0090	−0.0089	−0.0226	0.0054	−0.0210	0.0206	0.0078	**0.2922***	**-**
	$g_{vix,t-1}$	−0.0004	**−0.0041***	0.0013	**−0.0252***	**−0.0254***	**−0.0280***	**−0.0210***	**−0.0269***	**−0.0259***	**−0.0237***	**0.0194***	**-**

(1) Lower triangular area displays β_{12} and β_{13} coefficients while upper triangular area shows β_{21} and β_{23} coefficients. The mean spillover is on the upper side in each row while the global market effect is on the lower side. (2) *, **, and *** indicate 1%, 5%, and 10% significance levels, respectively. (3) Standard errors are not given in the table due to space restrictions but can be provided upon request.

Appendix D. β_{11} and β_{22} Coefficients of Conditional Mean Equations (13) and (14) (Mean Spillover and Global Market Effects)

		Dependent Variables											
		$e_{B/£}$	$e_{\$/£}$	$e_{€/£}$	s_{100}	s_{30}	s_{bnk}	s_{srv}	s_{food}	s_{met}	s_{ind}	b_{2y}	b_{5y}
Independent Variables	$e_{B/£}$	–	−0.0433	−0.1085*	−0.0395**	−0.0408**	−0.0643*	−0.0103	−0.0288***	0.0122	0.0088	−0.1517*	−0.1154*
	$e_{\$/£}$	−0.0262	–	**−0.0432****	**−0.0553***	**−0.0569***	**−0.0809***	−0.0153	**−0.0299*****	−0.0001	−0.0062	**−0.1541***	**−0.1156***
	$e_{€/£}$	0.0419	−0.0254	–	−0.0201	−0.0214	**−0.0408***	−0.0001	−0.0236	0.0227	0.0171	**−0.1384***	**−0.0872***
	s_{100}	**−0.0333***	**−0.0346***	**−0.0350***	–	**0.3335****	−0.0176	**0.0610****	−0.0308	**0.0564***	0.0517	**−0.1437***	**−0.0727***
	s_{30}	**−0.0320*****	**−0.0337*****	**−0.0336*****	**−0.2761*****	–	−0.0503	**0.0540****	−0.0294	**0.0525***	0.0420	**−0.1435***	**−0.0731***
	s_{bnk}	−0.0191	−0.0181	−0.0275	0.0541	0.0729	–	**0.0461****	−0.0298	**0.0452****	**0.0494****	**−0.1425***	**−0.0678***
	s_{srv}	−0.0154	−0.0232	−0.0213	−0.0285	−0.0257	−0.0187	–	−0.0117	**0.0356*****	0.0196	**−0.1260***	**−0.0500***
	s_{food}	−0.0080	−0.0068	−0.0240	−0.0078	−0.0105	0.0066	0.0142	–	0.0262	**0.0367*****	**−0.1231***	**−0.0532***
	s_{met}	−0.0158	−0.0210	−0.0257	−0.0265	−0.0247	−0.0239	0.0080	**−0.0320*****	–	−0.0129	**−0.1168***	**−0.0442****
	s_{ind}	−0.0274	**−0.0309*****	**−0.0316*****	−0.0165	−0.0056	−0.0139	**0.0370*****	**−0.0455****	**0.0707***	–	**−0.1282***	**−0.0553***
	b_{2y}	−0.0077	−0.0043	**−0.0274*****	−0.0174	−0.0208	**−0.0357****	−0.0001	−0.0173	0.0051	0.0148	–	−0.0144
	b_{5y}	−0.0099	−0.0139	−0.0262	−0.0193	−0.0218	**−0.0414****	0.0041	−0.0165	0.0164	0.0219	**−0.2248***	–

(1) Lower triangular area displays β_{11} coefficient while upper triangular are shows β_{22} coefficients. (2) *, **, and *** indicate 1%, 5%, and 10% significance levels, respectively. (3) Standard errors can be provided upon request.

Appendix E. Coefficients for Conditional Covariance Equations (Volatility Spillover and Volatility Persistence Effects)

		a_{11}*a_{22} Coefficients in Covariance Eq. (18) (Volatility Spillover Effect)											
		$e_{B/£}$	$e_{\$/£}$	$e_{€/£}$	s_{100}	s_{30}	s_{bnk}	s_{srv}	s_{food}	s_{met}	s_{ind}	b_{2y}	b_{5y}
b_{11}*b_{22} Coefficients in Covariance Eq. (18) (Volatility Persistence Effect)	$e_{B/£}$	–	0.0572*	0.0586*	0.0595*	0.0557*	0.0507*	0.0600*	0.0790*	0.0739*	0.0808*	0.1147*	0.0777*
		–	144.85	146.75	123.86	122.47	102.93	119.97	139.26	133.54	134.97	163.02	159.90
	$e_{\$/£}$	**0.9352***	–	**0.0579***	**0.0550***	**0.0523***	**0.0483***	**0.0572***	**0.0768***	**0.0702***	**0.0754***	**0.1162***	**0.0773***
		36393.43	–	145.47	116.57	115.46	96.73	117.22	135.74	126.01	126.47	155.57	160.65
	$e_{€/£}$	**0.9341***	**0.9345***	–	**0.0602***	**0.0557***	**0.0510***	**0.0608***	**0.0787***	**0.0743***	**0.0793***	**0.1052***	**0.0737***
		35771.73	35861.59	–	123.99	121.56	103.32	117.90	130.16	130.71	132.00	146.32	145.91
	s_{100}	**0.9236***	**0.9253***	**0.9200***	–	**0.0706***	**0.0628***	**0.0493***	**0.0604***	**0.0602***	**0.0612***	**0.1000***	**0.0579***
		22819.87	21237.57	19159.34	–	122.19	111.81	101.16	113.08	112.54	106.05	128.03	120.80
	s_{30}	**0.9290***	**0.9294***	**0.9263***	**0.9037***	–	**0.0509***	**0.0470***	**0.0572***	**0.0555***	**0.0575***	**0.0944***	**0.0546***
		27089.34	24204.37	22622.83	15198.51	–	112.59	103.40	113.79	110.00	109.09	125.60	119.22
	s_{bnk}	**0.9321***	**0.9315***	**0.9295***	**0.9103***	**0.9351***	–	**0.0508***	**0.0867***	**0.0647***	**0.0746***	**0.0891***	**0.0498***
		25563.31	22312.19	21761.86	13249.35	25279.25	–	91.29	116.52	104.10	100.61	106.99	100.64
	s_{srv}	**0.9215***	**0.9226***	**0.9172***	**0.9308***	**0.9350***	**0.9193***	–	**0.0603***	**0.0563***	**0.0552***	**0.1013***	**0.0631***
		20879.99	19643.41	16838.76	19851.18	23616.47	12641.06	–	107.64	101.04	99.32	132.25	123.06
	s_{food}	**0.8956***	**0.8931***	**0.8856***	**0.9103***	**0.9158***	**0.8726***	**0.9071***	–	**0.0783***	**0.0740***	**0.1227***	**0.0832***
		11228.28	10335.40	8627.14	14013.10	16113.95	7970.07	11776.44	–	108.29	113.33	122.77	124.49
	s_{met}	**0.9031***	**0.9046***	**0.8969***	**0.9177***	**0.9245***	**0.9036***	**0.9220***	**0.8800***	–	**0.0792***	**0.1128***	**0.0792***
		12863.52	12719.57	10724.36	15844.15	18780.42	10868.63	15694.24	7105.67	–	103.00	130.85	121.47
	s_{ind}	**0.8906***	**0.8943***	**0.8879***	**0.9051***	**0.9148***	**0.8708***	**0.9180***	**0.8934***	**0.8765***	–	**0.1264***	**0.0803***
		9932.22	9765.88	9274.90	12027.24	16118.50	6110.00	13136.24	9348.42	5949.06	–	134.91	128.66
	b_{2y}	**0.8490***	**0.8310***	**0.8546***	**0.8441***	**0.8462***	**0.8431***	**0.8373***	**0.8161***	**0.8313***	**0.8258***	–	**0.1176***
		9634.21	7229.72	9925.35	7997.04	8264.50	7514.87	7280.55	5744.95	6950.11	6102.12	–	120.24
	b_{5y}	**0.9165***	**0.9159***	**0.9149***	**0.9306***	**0.9346***	**0.9382***	**0.9206***	**0.8813***	**0.9030***	**0.9033***	**0.8706***	-
		27300.63	26510.28	22621.35	30164.24	34687.98	33990.78	23966.53	7661.24	15227.39	14063.50	14250.82	-

(1) Upper triangular area displays volatility spillover coefficients while lower triangular area shows the persistence of volatility. (2) * indicates 1% significance level. (3) Standard error can be provided upon request. (4) Second values in each row are the Chi-Squares of Wald Tests.

Appendix F. Stability Conditions of $h_{12,t}$ in Eq. 18

	$e_{B/£}$	$e_{\$/£}$	$e_{€/£}$	s_{100}	s_{30}	s_{bnk}	s_{srv}	s_{food}	s_{met}	s_{ind}	b_{2y}	b_{5y}
$e_{B/£}$	–	0.9924	0.9928	0.9831	0.9847	0.9828	0.9815	0.9746	0.9770	0.9714	0.9637	0.9942
$e_{\$/£}$	–	–	0.9924	0.9803	0.9817	0.9797	0.9798	0.9699	0.9748	0.9697	0.9472	0.9932
$e_{€/£}$	–	–	–	0.9802	0.9820	0.9805	0.9780	0.9643	0.9713	0.9673	0.9598	0.9886
s_{100}	–	–	–	–	0.9742	0.9731	0.9800	0.9706	0.9778	0.9664	0.9441	0.9885
s_{30}	–	–	–	–	–	0.9860	0.9820	0.9730	0.9800	0.9723	0.9406	0.9892
s_{bnk}	–	–	–	–	–	–	0.9700	0.9593	0.9683	0.9455	0.9322	0.9880
s_{srv}	–	–	–	–	–	–	–	0.9674	0.9782	0.9732	0.9386	0.9836
s_{food}	–	–	–	–	–	–	–	–	0.9583	0.9674	0.9389	0.9646
s_{met}	–	–	–	–	–	–	–	–	–	0.9557	0.9441	0.9823
s_{ind}	–	–	–	–	–	–	–	–	–	–	0.9523	0.9836
b_{2y}	–	–	–	–	–	–	–	–	–	–	–	0.9882
b_{5y}	–	–	–	–	–	–	–	–	–	–	–	–

All conditional covariance matrices are stationary since $a_{11}*a_{22}+b_{11}*b_{22}<1$ condition is hold.

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