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AN EMPIRICAL ANALYSIS OF VOLATILITY TRANSMISSION BETWEEN BIST AND INTERNATIONAL STOCK MARKETS

BIST VE ULUSLARARASI HİSSE SENEDİ PİYASALARI ARASINDAKİ VOLATİLİTE GEÇİŞİ ÜZERİNE BİR AMPİRİK UYGULAMA

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ABSTRACT

This paper empirically examines the transmission of volatility among Turkish equity market and five emerging markets and also five developed markets using bivariate vector auto regression-generalized autoregressive conditional heteroscedasticity [VAR(p)-GARCH(1,1)-BEKK] model. Using 4022 daily returns of benchmark stock market indices, from 1.7.1997 to 14.3.2013, volatility co-movement and spillover between the Turkish stock market and the markets of US, UK, Germany, France, Japan, South Korea, Brazil, Argentina, Russia and China is investigated. Results showed that BIST has a weak market interdependence with DAX30 but strong bidirectional volatility spillover with RTSI.

Keywords*:* Volatility spillover, VAR M-GARCH, BIST

ÖZ

Bu çalışmada Türkiye hisse senedi piyasası ile beş gelişmekte olan ülke ve beş gelişmiş ülke piyasaları arasındaki volatilite yayılma etkisi, iki değişkenli vektör otogregresyon-genelleştirilmiş otoregresif şartlı değişken varyans [VAR(p)-GARCH(1,1)-BEKK] modeli kullanılarak araştırılmıştır. Her bir ülkeye ait, 1.7.1997-14.3.2013 tarihleri arasındaki, hisse senedi gösterge endekslerinin 4022 günlük getiri serileri kullanılarak Türkiye hisse senedi piyasası ile ABD, İngiltere, Almanya, Fransa, Japonya, Güney Kore, Brezilya, Arjantin, Rusya ve Çin hisse senedi piyasaları arasındaki ortak volatilite hareketliliği ve yayılma etkisi incelenmiştir. Sonuç olarak, Borsa İstanbul ile DAX30 arasında düşük, fakat RTSI ile güçlü iki taraflı volatilite yayılma etkisi tespit edilmiştir.

***Anahtar Sözcükler*:** *Volatilite yayılması, VAR M-GARCH, BİST*

1. Introduction

Deregulation, globalization, and advances in information technology have dramatically changed the structure of domestic and world financial markets. There is sufficient evidence that information is now shared more intensively across the world's major equity markets, and that markets have become increasingly integrated (Baele, 2002:2).

Furthermore, development in the liberalization of capital movements and the securitization of stock markets enabled international financial markets to become increasingly interdependent and improved the possibilities for domestic stock markets to react quickly to new information from another equity market. All these made financial markets more correlated (Bozkurt and Akman, 2016) and connected than ever and understanding of the correlations and interactions among various financial markets is become a crucial issue for investors, financial institutions, and governments.

The understanding of such cross-market linkages and interactions can be useful for the pricing of securities, developing trading strategies, hedging strategies, and regulatory strategies within, and across, the markets (Brailsford, 1996; Theodossiou et al., 1997; Diebold and Yılmaz, 2008).

Volatility spillover, refers to the spread of market disturbances from one country to another, is a process observed through co-movements in stock prices, exchange rates, or capital flows. This means that shocks exist from global or local economy can transmitted across countries because of their financial linkages among market economies (Dornbusch and Claessens, 2000). In addition, volatilities in exchange rates of different currencies have a significant impact on the prices of commodities (Akman, 2016) which has a potential to affect economies.

After the success of the generalized auto-regressive conditional heteroscedasticity (GARCH) models in assessing the time-varying variances of financial data in the univariate case, many researchers have extended these models to multivariate dimension. Bollerslev, Engle, and Wooldridge (1988), Ng (1991), and Hansson and Hordahl (1998) has put understanding the co-movements of financial returns to main center of their studies. Multivariate GARCH models have also used to investigate volatility and correlation transmission and spillover effects in studies of contagion. These models allow for time-varying conditional variances as well as co-variances.

How news shocks from one international stock market influence, the volatility process of other markets has received a great attention from both academicians and practitioners over the last decades. Multivariate modeling framework leads to more relevant empirical models than working with separate univariate models. There has been a growth in interest in the modelling of time-varying multivariate stock return volatility. Often the current value of a variable depends not only on its past values, but also on past and/or current values of other variables (Schmidth, 2005). Price movements in one market can spread easily and instantly to another market.

The market shock, which arises in one market, affects not only the local market, but also other countries' equity markets that have economic linkages with that country which shock arises from. Existing empirical studies analyze primarily dynamic linkages between developed markets, with only some of them focusing on linkages between emerging markets, or between these and other foreign markets. This paper seeks to contribute to the literature on volatility spillover focusing on five major developed equity markets and five emerging markets.

2. Literature Review

Despite the fact that the volatility spillovers between different equity markets have been extensively examined, studies focused their attention on volatility within the developed financial markets (see, e.g., Eun and Shim (1989); Hamao et al. (1990); Lin et al. (1994); Lucey and Voronkova (2006); Susmel and Engle (1994); Karolyi (1995); Theodossiou and Lee (1993); Zhang et all, (2013)).

Hamao, Masulis and Ng (1990); King and Wadhwani (1990) and Schwert (1990) examined spillovers across major markets before and after the October 1987 stock market crash in the US. Research into cross-border links in emerging stock markets boosted by the growth and increasing openness of these markets, as well as the speed and virulence with which past financial crises in emerging market economies (EMEs) spread to other countries.

There are numerous studies exploring the relationships between the emerging markets of different regions, even though such work is still very scarce.

Kanas (1998) has used EGARCH model, which was developed by Nelson (1991) to seek volatility spillovers across the three largest European stock markets which belongs to London, Frankfurt and Paris during the period from 01/01/1984 to 07/12/1993. Reciprocal spillovers found to exist between London and Paris, between Paris and Frankfurt, and unidirectional spillovers from London to Paris.

Chou et al. (1999) have researched volatility spillover between the Taiwanese and US stock exchanges by using a bivariate BEKK model and proved that there is only a one-side linkage from developed US market to the emerging Taiwan market. In another study, Haroutounian and Price (2001) also find a volatility transmission from Poland to Hungary in a bivariate BEKK Model. Worthington and Higgs (2004) have examined volatility spillover among nine Asian developed and emerging markets. They have found the evidence of volatility transmission from the developed to emerging markets.

Kim and Rui (1999) have investigated the dynamic relationship among the US, Japan and UK daily stock market return and trading volume using MGARCH model. They found that there are significant return spillovers from New York and Tokyo to London, and from New York, London to Tokyo and from Tokyo to New York.

Ng (2000), by using bivariate GARCH model, has examined the magnitude and changing nature of volatility spillovers from Japan and US to six Pacific-Basin equity markets for the period between January 1975 and December 1996. She found that both regional and world factor are substantial for market volatility in the Pacific-Basin markets. However, for six countries, the world shock of the US is stronger than the regional one of Japan. Otherwise, Miyakoshi (2003) has observed the magnitude of return and volatility spillovers from Japan and the US to seven Asian equity markets for the period from 01.01.1998 to 30.04.2000. It is formed that a volatility spillover model deals with the US shock as an exogenous variable in a bivariate EGARCH for Japan and Asian markets. In contrast to Ng (2000), her study's results indicate that Asian markets volatility has been just influenced by the US significantly. In addition, volatility from the Asian to the Japanese market has negative effect.

In order to analyze the effect of further globalization and regional integration on the intensity by which global and regional market shocks are transmitted to local equity markets, Baele (2004) quantifies the magnitude and time-varying nature of volatility spillovers from the aggregate European (EU) and US market to 13 local European equity markets by estimating and comparing the results of four different bivariate models which are a constant correlation model, an asymmetric BEKK model, a regime-switching normal model and a regime-switching GARCH model. The crucial point of the paper is to account for time-varying integration introducing of regime-depend shock spillover intensities. The result of the study presents that there is one side contagion effect from US market to some local European local markets in times of high equity market volatility.

Cerge- El and Koblas (2008) studied to describe the time structure in which markets react to the information revealed in prices on other markets co-integration and Granger causality tests during the time period 2003-2005 in US, England, Germany, France, Poland, Czech Republic and Hungary stock markets. The U.S. market seemed to be an important source of information for the markets in London and Frankfurt. In all cases, the strongest reaction occurred within one hour, with the first reaction detected often after only five minutes. The results suggested that the markets react very quickly to the information revealed in the prices from other markets.

Fedorova and Saleem (2009) have examined the relationship between Eastern European and Russian stock markets, foreign exchange markets, and stock and foreign exchange markets estimating a bivariate VAR-GARCH-BEKK in the period from 1995 to 2008 covering Poland, Hungary, the Czech Republic and Russia. The results present that the evidence of direct linkage between the equity markets, both in regards of returns and volatility, as well as in currency markets and unidirectional volatility spillovers from currency to stock markets.

Xiao and Dhesi (2010) have examined volatility spillover effects and tested time-varying correlations across four major stock indices namely, CAC, DAX30, FTSE100 and S&P500 covering the period 5 January 2004 to 1 October 2009. They have used two types of multivariate generalized autoregressive conditional heteroscedasticity (MVGARCH) models, namely BEKK (Engle and Kroner, 1995) and DCC (Engle, 2002) in their research. The results of this study show that UK stock market is the main volatility transmitter within the European stock markets while US is one of the main exporter worldwide. The results also show that the time-varying conditional correlation exists between stock markets.

Arifin ve Normansyah (2011) have investigated volatility spillover effects of among five Asian countries through the bivariate VAR (1)-GARCH (1,1) model with BEKK over the period between 1st July 1997 and 26th April 2010 which has divided into three sub-20 samples that explains the period of Asian crisis, non-crisis, and subprime crisis. They found the evidence of the persistence of mean spillover effects for Malaysia and Singapore, during both crises. Besides, volatility spillover effects between the stock market and exchange rate within the economy has detected for three periods. The main results manifest that evidence of strong influence from exchange rate fluctuations to stock market volatility in ASEAN-5 countries.

In another study, the effects of volatility spillovers among five Asian stock markets have researched by Kang and Yoon (2011), using a VAR (1)-bivariate GARCH model for the sample covered from January 2, 2006 to January 31, 2011. To examine the effect of the global financial crisis of 2008, the sample period is divided the whole sample into two groups using the Chow known breakpoint test and the Hansen unknown breakpoint test. The results of the analyses show that there were unidirectional volatility spillovers from Korea, and Singapore to China in the pre-crisis period. This is the proof of the Chinese stock market was not closely related to other

Asian stock markets before the global financial crisis. In addition, in the post-crisis period, the strong volatility linkages monitored between the Chinese stock market and the other four Asian markets. It implies that after the crisis in Asia, Chinese stock market become integrated with the other emerging stock markets.

Taştan (2005) has analyzed dynamic interdependence, price and volatility transmissions and financial integration between Turkish stock market and equity markets of Germany, France, Britain and USA over the period 26.11.1990 - 20.08.2004. Enabling to measure the volatility spillover among these equity markets, he has used a vector auto regression-dynamic conditional correlations-multivariate generalized autoregressive conditional heteroscedasticity (VAR-DCC-MVGARCH) framework by taking into account the time-varying variance- covariance structure. The main results of the study are that ISE weakly integrated with major markets and the conditional covariance of ISE sometimes has negative values.

Korkmaz and Çevik (2009) have used GJR-GARCH model to examine volatility spillover from VIX Index, constructed using the implied volatilities of a wide range of S&P 500 index options, to 15 emerging markets. They have investigated that emerging stock markets have leverage effect in conditional variances that means bad news increase volatility further. The results of the analysis, covers the period from 01/2004-3/2009, also show that VIX index affects Argentina, Brazil, Mexico, Chili, Peru, Hungary, Poland, Turkey, Malaysia, Thailand and Indonesia stock markets through volatility spillover with leverage effect.

Taşdemir and Yalama (2010) have investigated volatility spillovers between Turkish and Brazilian stock markets with using a misspecification robust causality-in-variance test. Their observation covers the period from April 09, 1993 to April 10, 2009 and they found strong evidence supporting volatility spillovers from Istanbul Stock Exchange (ISE) to São Paulo Stock Exchange (BOVESPA). Their results also imply that financial crises may change the size and the direction of volatility spillovers between ISE and BOVESPA.

Evlimoğlu and Çondur (2012) have analyzed short-term relations among the ISE and Bovespa, Shanghai, Bombay, Moscow Times, Nikkei 225, DAX30 and S&P 500 indices through a correlation analysis and VAR model that covers the period from 5.1.2004 to 01.01.2010. An increase in inter-linkages between the ISE and other selected stock markets for post mortgage crisis period (1.8.2007-1.1.2010) was observed and they put forward that relationship with developed markets has soared sharply after the crisis. In addition, the results of the study presented that the correlation of US stock market and ISE has raised after the mortgage crisis.

3. Methodology

3.1. Data

The stock market indices used in this study comprise the Standard and Poor's 500 Index (S&P-500) of US, the Financial Times Stock Exchange Index (FTSE-100) of the UK, Deutscher Aktien Index (DAX-30) of Germany, Continuous Assisted Quotation Index (CAC-40) of France, the Sao Paulo Stock Exchange Index (BOVESPA) of Brazil, Buenos Aires Stock Exchange Merval Index (MERVAL) of Argentina, Korea Stock Exchange Kospi Index (KOSPI) of South Korea, Russian Trading System Cash Index (RTSI) of Russia, Borsa Istanbul Stock Exchange National 100 Index (XU100) for Turkey , The Nikkei Stock Average Index (Nikkei 225) of Japan and Shanghai Stock Exchange Composite Index (SHCOMP) of China.

Data are composed of eleven countries daily stock market closing prices from 1 July 1997 to 14 March 2013. The period includes the big events in recent years, bull market increase in Turkey (2004-2013), American mortgage crisis (2007.08-2008.10) and European sovereign debates crisis (2009.11- today). It's assumed that the returns are based on the local currency, so the effect of exchange rate changes is not considered. The data of dates which any series has a missing value due to no trading has removed from observation period. Thus, all the data collected on the same dates across the stock markets and there are 4022 observations. The series of daily returns computed as the difference between the logarithms of the closing prices in two consecutive trading days:

$$R_{it} = Ln\left(\frac{P_{it}}{P_{it-1}}\right)$$

where R_{it} and P_{it} denote the daily return in percentage and the closing price of index on day t, respectively.

3.2. Model

The Autogressive Conditional Heteroscedasticity (ARCH) process presented by Engle (1982) and the enhanced to generalized ARCH (GARCH) by Bollerslev (1986) are well known models for financial series' volatility.

However, these kinds of univariate estimation models ignore the possibility of having causality between volatilities in both directions and do not exploit the covariance between both series.

The spillover effect refers to the interaction between two series. When assessing spillover from one market to another or determining directions of spillover and temporal changes in the conditional correlation using MGARCH models are more superior to its univariate counterparts in the sense that you can test for all kinds of volatility relationships within the same model.

Problems associated with MGARCH can summarized as follows: first, curse of dimensionality is the common problem the existing models faced. Number of parameters in an MGARCH model often increases rapidly with of dimension of the model. Researchers seek ways to solve the problems by simplifying the models, but the simplified models cannot capture the relevant dynamics in the covariance structure; second, constraints and restrictions on the parameters to ensure the positive definiteness of covariance matrix and stationary are hard to derive and cause difficulties in numerical optimizations (Xu and Lin, 2008:1).

This paper investigates the relationship between BIST and foreign equity markets using the bivariate VAR-GARCH (1, 1) process, for which BEKK methodology adopted, proposed by Engle and Kroner (1995). Because, it does not require the estimation of many parameters as VECH model and the BEKK model guarantees that the covariance matrices in the system are positive by its constructions. Moreover, the BEKK kind of multivariate GARCH can used in association with a VAR specification, allowing a computation of VAR-coefficients that are efficient and consistent even if the residuals of the classical VAR do not present a Gaussian distribution and a constant variance (Zahnd and Schweiz, 2002: 85).

Let $\Im(t-1)$ be the sigma field generated by the past values of ε_t, and letting H_t be the conditional covariance matrix of the *k*-dimensional random vector ε_t. Letting H_t be measurable with respect to $\Im(t-1)$; then the a VAR (1)-GARCH (1, 1) model in a BEKK form can be written as;

The mean equation is;

$$y_t = k + \beta y_{t-1} + \varepsilon_t \tag{1}$$

for t=1,……,T with $\varepsilon_t I \Im_{t-1} \sim N(0, H_t)$

where:

$$H_t C + \sum_{i=1}^{q} A_i^{'} \varepsilon_{t-i} \varepsilon_{t-i}^{'} A_i + \sum_{i=1}^{p} G_i^{'} H_{t-i} G_i \tag{2}$$

Where; α and β are parameters and, C, A_i and G_i are kxk parameter matrices. The term $\varepsilon_t = (\varepsilon_{1,t}, \varepsilon_{2,t})'$ is the vector of residuals, which assumed to follow a bivariate conditional normal distribution with mean zero and conditional variance-covariance matrix. $\Im_{t-1}$ represents the information available at time t-1.

In the case with 2 dimensions, fort he mean equation:

$$y_t = \begin{matrix} y_{1t} \\ y_{2t} \end{matrix}, k = \begin{matrix} k_1 \\ k_2 \end{matrix}, \beta = \begin{matrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{matrix}, \varepsilon_t = \begin{matrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{matrix} \tag{3}$$

Where β is $2x2$ matrix of coefficients, ε_t is $2x1$ vector of estimated residuals in the mean equation (1) .

For the variance equation (2):

$$A_1 = \begin{matrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{matrix}, G_1 = \begin{matrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{matrix}, C = \begin{matrix} c_{11} & c_{12} \\ 0 & c_{22} \end{matrix} \tag{4}$$

We imply that in this BEKK model, a_{21} and a_{12} are different from each other, as are g_{21} and g_{12}. The variance system has 11 parameters for two equations. The parameters of the mean and the variance equation estimated by using maximum likelihood.

If we combine mean equation 1 and 2;

$$\begin{aligned} y_{1t} &= k_1 \beta_{11} y_{1t-1} + \beta_{12} y_{2t-1} + \varepsilon_{1t} \\ y_{2t} &= k_2 \beta_{21} y_{2t-1} + \beta_{22} y_{2t-1} + \varepsilon_{2t} \end{aligned} \tag{5}$$

where h_{it} is a conditional variance at time t of the stock return of country i and h_{ijt} denotes the conditional covariance between the stock returns of country i and country j (where i ≠ j) at time t.

Table 1 presents the descriptive statistics for the 10 series under investigation, for same sample periods up to March 2013.

Table 1. Descriptive Statistics of Historical Returns of Stock Exchange Indices

	SSE	S&P500	DAX30	FTSE100	CAC40	BOVESPA	MERVAL	KOSPI	RTSI	BIST	NIKKEI
Mean	0.00014	0.00014	0.00018	8.02E-0	6.81E-0	0.00036	0.00036	0.00024	0.00073	0.00094	-0.0001
Median	0.00000	0.00026	0.00043	0.00000	5.6E-05	0.00000	0.00000	0.00018	0.00047	9.39E-05	0.00000
Max.	0.09400	0.10957	0.10797	0.09384	0.10594	0.28832	0.16116	0.11284	0.91202	2.94951	0.13234
Min.	-0.0925	-0.0946	-0.0743	-0.0926	-0.0947	-0.1720	-0.1476	-0.1280	-0.8950	-2.91524	-0.1211
Std. Dev.	0.01586	0.01311	0.01608	0.01266	0.01540	0.02168	0.02169	0.01952	0.03470	0.07018	0.01541
Skew.	-0.1117	-0.1805	-0.0356	-0.1497	0.00230	0.36957	-0.2509	-0.1969	-0.1150	0.59670	-0.3060
Kurt.	7.49077	10.3263	6.65598	8.53156	7.34140	16.5214	8.74348	7.39247	235.752	1516.58	9.16863
JB	3388.02	9016.90	2240.81	5142.78	3158.58	30730.6	5570.40	3259.32	907863.	3.84E+08	6439.67
Prob.	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
Sum	0.59654	0.56213	0.74259	0.32274	0.27389	1.48286	1.45295	0.97124	2.95752	3.79098	-0.4883
Sum Sq.Dev.	1.01236	0.69105	1.03973	0.64504	0.95450	1.89084	1.89173	1.53299	4.84425	19.8063	0.95530
Obs.	4022	4022	4022	4022	4022	4022	4022	4022	4022	4022	4022

Table 1 presents summary of statistics for S&P 500, DAX30, FTSE 100, CAC 40, BOVESPA, MERVAL, KOSPI, RTSI, BIST 100, NIKKEI 225 and SSE Share Price Index. The daily mean returns are positive except NIKKEI 225. The standard deviation of BIST 100, RTSI, MERVAL and BOVESPA are higher among eleven stock indices. Negative skewness of S&P 500, DAX30, FTSE 100, SSE, MERVAL, KOSPI, RTSI, and NIKKEI 225 indicate that the distributions of returns for eight markets negatively skewed. Skewness is positive for CAC 40, BOVESPA and BIST. This means that extreme negative and positive returns are likely to realize for these stock markets. The Jarque Bera statistic strongly rejects normality of all series at 1% level of significance. At the same time, significant and big size kurtosis coefficients are indicating that outliers may occur with a probability, higher than the normal distribution.

Table 2. Unconditional Cross-Correlations of Indices

	BIST	**BOVESPA**	**CAC40**	**DAX30**	**FTSE100**	**KOSPI**	**MERVAL**	**NIKKEI**	**S&P500**	**RTSI**	**SSE**
BIST	1.000	0.1032	0.1395	0.1388	0.1346	0.1159	0.0701	0.0808	0.0783	0.0917	0.0174
BOVESP	0.1032	1.0000	0.4182	0.4205	0.4230	0.1957	0.5505	0.1549	0.5781	0.1833	0.0717
CAC40	0.1395	0.4182	1.0000	0.8649	0.8660	0.2536	0.3665	0.2940	0.5439	0.3213	0.0768
DAX	0.1388	0.4205	0.8649	1.0000	0.7962	0.2530	0.3534	0.2647	0.5822	0.3115	0.0703
FTSE100	0.1346	0.4230	0.8660	0.7962	1.0000	0.2761	0.3809	0.3033	0.5226	0.3363	0.0794
KOSPI	0.1159	0.1957	0.2536	0.2530	0.2761	1.0000	0.1536	0.4570	0.1421	0.2072	0.1353
MERVAL	0.0701	0.5505	0.3665	0.3534	0.3809	0.1536	1.0000	0.1383	0.4538	0.1971	0.0385
NIKKEI	0.0808	0.1549	0.2940	0.2647	0.3033	0.4570	0.1383	1.0000	0.1195	0.2183	0.1773
S&P500	0.0783	0.5781	0.5439	0.5822	0.5226	0.1421	0.4538	0.1195	1.0000	0.1723	0.0238
RTSI	0.0917	0.1833	0.3213	0.3115	0.3363	0.2072	0.1971	0.2183	0.1723	1.0000	0.0672
SSE	0.0174	0.07172	0.07689	0.0703	0.0794	0.1353	0.0385	0.1773	0.0238	0.0672	1.0000

Table 2 provides the unconditional cross-correlations between the examined equity markets. The table shows the pattern of linear dependence among the markets. As it seen in the table, all of these equity markets exhibit a positive correlation with BIST over the period but their correlations are not very strong. Table 2 indicates that the correlation of BIST with old stock markets is at higher degree according to its counterparts (the emerging economies).

Table 3. Stationary Tests of Variables

Variable	Unit Root Test	ADF Test Statistics		PP Test Statistics	
		Critical Value	Prob.	Critical Value	Prob.
BIST	Intercept	-21.21691	0.0000	-86.72776	0.0001
	Trend&Intercept	-21.23268	0.0000	-87.77689	0.0001
	None	-21.12645	0.0000	-82.01191	0.0001
BOVES	Intercept	-62.29047	0.0001	-62.38200	0.0001
	Trend&Intercept	-62.28298	0.0000	-62.37404	0.0000
	None	-62.28099	0.0001	-62.36431	0.0001
CAC40	Intercept	-31.01882	0.0000	-65.51680	0.0001
	Trend&Intercept	-31.02773	0.0000	-65.53428	0.0000
	None	-31.02052	0.0000	-65.52184	0.0001
DAX30	Intercept	-64.05725	0.0001	-64.16670	0.0001
	Trend&Intercept	-64.04964	0.0000	-64.15886	0.0000
	None	-64.04964	0.0000	-64.16564	0.0001
FTSE100	Intercept	-30.90164	0.0000	-65.82996	0.0001
	Trend&Intercept	-30.89867	0.0000	-65.82193	0.0000
	None	-30.90121	0.0000	-65.83365	0.0001
KOSPİ	Intercept	-60.81875	0.0001	-60.77598	0.0001
	Trend&Intercept	-60.81568	0.0000	-60.77274	0.0000
	None	-60.81786	0.0001	-60.77526	0.0001
MERVAL	Intercept	-59.45743	0.0001	-59.50653	0.0001
	Trend&Intercept	-59.46776	0.0000	-59.51211	0.0000
	None	-59.44947	0.0001	-59.50263	0.0001
NIKKEI	Intercept	-47.63890	0.0001	-65.37080	0.0001
	Trend&Intercept	-47.64836	0.0000	-65.37721	0.0000
	None	-47.64011	0.0001	-65.37153	0.0001
RTSI	Intercept	-29.84009	0.0000	-58.69006	0.0001
	Trend&Intercept	-29.84153	0.0000	-58.69627	0.0000
	None	-29.79505	0.0000	-58.59577	0.0001
S&P500	Intercept	-48.96430	0.0001	-69.23759	0.0001
	Trend&Intercept	-48.95822	0.0000	-69.22822	0.0000
	None	-48.96168	0.0001	-69.22061	0.0001
SSE	Intercept	-63.34902	0.0001	-63.35168	0.0001
	Trend&Intercept	-63.34474	0.0000	-63.345	0.0000
	None	-63.35057	0.0001	-63.35322	0.0001

The first step of the time series analysis is to test if the time series is stationary or it contains a unit root, which is usually the case for financial time series. Both Augmented Dickey Fuller (1979,

1981) ADF and Philips Peron (1990) PP tests (in three form) are used to check the stationary property of the stock indices series. The results shown in Table 3 indicate that the null hypothesis of unit root rejected at the 1% significance level for all the variables at their return level. Hence, it is clear that all of the return series are stationary and integrated at first order, I (1).

Table 4. Bai-Perron Multiple Breakpoint Tests

Sample: 1 4022		Included observations: 4022			Break test options: Trimming 0.15, Max. breaks 5, Sig. level 0.05						
Sequential F-statistic determined breaks:				0		Sequential F-statistic determined breaks:				0	
Significant F-statistic largest breaks:				0		Significant F-statistic largest breaks:				0	
UDmax determined breaks:				0		UDmax determined breaks:				0	
WDmax determined breaks:				0		WDmax determined breaks:				0	
		Scaled	Weighted	Critical				Scaled	Weighted	Critical	
Breaks	F-statistic	F-statistic	F-statistic	Value		Breaks	F-statistic	F-statistic	F-statistic	Value	
1	5.8525	5.8525	5.8525	8.58		1	1.1718	1.1718	1.1718	8.58	
2	4.5239	4.5239	5.3761	7.22		2	1.6868	1.6868	2.0045	7.22	
3	4.0163	4.0163	5.7819	5.96		3	2.3260	2.3260	3.3484	5.96	
4	4.4529	4.4529	7.6565	4.99		4	3.0316	3.0316	5.2126	4.99	
5	2.6033	2.6033	5.7126	3.91		5	1.5573	1.5573	3.4173	3.91	
UDMax statistic		5.852537	UDMax critical value**		8.88	UDMax statistic		3.031560	UDMax critical value**		8.88
WDMax statistic		7.656539	WDMax critical value**		9.91	WDMax statistic		5.212583	WDMax critical value**		9.91
* Significant at the 0.05 level.						* Significant at the 0.05 level.					
** Bai-Perron (Econometric Journal, 2003) critical values.						** Bai-Perron (Econometric Journal, 2003) critical values.					

Structural break analysis employed to test for possibly changing in the nature of stock market co-movements. There are many statistical test related to present the problem of structural change. Among these works Bai and Perron (2003a) who illustrate the usefulness of the tests to determine the number of breaks, overcome the problem of multiple break points.

Bai Perron (2003b) the multiple breakpoint test indicates that there are 5 breaks. This assumes that the variable trimming is equal to 0.15, signifying that the average distance between two break dates is at least 0.15*T "time steps", where T represents the sample on which we are testing for the existence of a break.

The "UDmax" and "WDmax" results show the number of breakpoints as determined by application of the unweighted and weighted maximized statistics. The null hypothesis of stability accepted for all the studied markets since the Bai Perron's test detects no-breakpoints for the eleven equity markets.

Table 5. ARCH LM Test Statistics

ARCH LM Test				ARCH LM Test			
Variable	**Lag**	**Obs*R-squared**	**Prob. Chi-Square**	**Variable**	**Lag**	**Obs*R-squared**	**Prob. Chi-Square**
BIST	1	0.001000	0.9748	MERVAL	1	183.890400	0.0000
	5	0.006531	1.0000		5	347.075100	0.0000
	10	1001.193000	0.0000		10	424.855800	0.0000
BOVESPA	1	160.763600	0.0000	NIKKEI	1	113.855600	0.0000
	5	337.538100	0.0000		5	1002.129000	0.0000
	10	383.153000	0.0000		10	1086.589000	0.0000
CAC40	1	132.442100	0.0000	RTSI	1	0.141616	0.7067
	5	597.091400	0.0000		5	1275.622000	0.0000
	10	660.094200	0.0000		10	1543.870000	0.0000
DAX30	1	109.779000	0.0000	S&P500	1	163.337800	0.0000
	5	590.299100	0.0000		5	766.990700	0.0000
	10	679.738000	0.0000		10	923.971000	0.0000
FTSE100	1	186.721800	0.0000	SSE	1	96.258820	0.0000
	5	832.487900	0.0000		5	225.6995	0.0000
	10	881.572900	0.0000		10	285.4215	0.0000
KOSPI	1	116.613400	0.0000				
	5	435.207600	0.0000				
	10	487.575800	0.0000				

The LM test statistic shows that there is evidence for ARCH effect and time varying volatility.

Since we use GARCH process to model, the variance in the index returns. Table 5 about Engle's ARCH-LM statistics, clearly shows the presence of ARCH effects in returns up to 10 lags. The null hypothesis of no ARCH effects rejected for each return series at 5% level of significance.

Schwarz and Hannan Quin information values used for the models and preferable lag X model applied for each M-GARCH Model. If two criteria show contradictable results, SBIC is more reliable. Thus, the optimal lag length for the entire group is based on SBIC. For all the group except BIST-RTSI and BIST-SP 500 SIC suggests VAR models with no lags, but SBIC selects only one lag for BIST-SP 500 and two lags for BIST-RTSI.

Table 6. Lag Length Criteria Selection

Variable	Lag	SC	HQ	Variable	Lag	SC	HQ
BIST-BOVESPA	0	-7.304801*	-7.306826*	BIST-MERVAL	0	-7.298302*	-7.300326
	1	-7.300414	-7.306488		1	-7.295134	-7.301207*
	2	-7.293395	-7.303518		2	-7.286974	-7.297096
	3	-7.287721	-7.301893		3	-7.278776	-7.292948
	4	-7.279919	-7.298139		4	-7.270950	-7.28917
	5	-7.273062	-7.295332		5	-7.263369	-7.285638
Variable	Lag	SC	HQ	Variable	Lag	SC	HQ
BIST-CAC40	0	-7.997289*	-7.999314*	BIST-NIKKEI	0	-7.983369*	-7.985393*
	1	-7.991996	-7.99807		1	-7.977411	-7.983484
	2	-7.98691	-7.997032		2	-7.971532	-7.981655
	3	-7.983458	-7.99763		3	-7.96475	-7.978922
	4	-7.977001	-7.995222		4	-7.95666	-7.97488
	5	-7.973312	-7.995581		5	-7.948778	-7.971047
Variable	Lag	SC	HQ	Variable	Lag	SC	HQ
BIST-DAX30	0	-7.911879*	-7.913904	BIST-RTSI	0	-6.363447	-6.365472
	1	-7.908762	-7.914835*		1	-6.36162	-6.367694
	2	-7.902708	-7.912830		2	-6.380661*	-6.390784*
	3	-7.897000	-7.911171		3	-6.373803	-6.387975
	4	-7.890780	-7.909001		4	-6.369405	-6.387625
	5	-7.885940	-7.908209		5	-6.363019	-6.385288
Variable	Lag	SC	HQ	Variable	Lag	SC	HQ
BIST-FTSE100	0	-8.388127*	-8.390152	BIST-S&P500	0	-8.307142	-8.309167
	1	-8.382619	-8.388693		1	-8.313284*	-8.319357*
	2	-8.379101	-8.389224		2	-8.307949	-8.318072
	3	-8.381371	-8.395542		3	-8.30016	-8.314332
	4	-8.377460	-8.395680*		4	-8.292114	-8.310334
	5	-8.373093	-8.395362		5	-8.28673	-8.309
Variable	Lag	SC	HQ	Variable	Lag	SC	HQ
BIST-KOSPI	0	-7.517627*	-7.519652*	BIST-SSE	0	-7.925495*	-7.927519*
	1	-7.512188	-7.518261		1	-7.918421	-7.924494
	2	-7.504517	-7.514640		2	-7.910885	-7.921007
	3	-7.496573	-7.510744		3	-7.904556	-7.918728
	4	-7.489426	-7.507646		4	-7.898314	-7.916535
	5	-7.482483	-7.504752		5	-7.890679	-7.912949

Table 7 represents equations of conditional co-variances of selected equity markets with Turkish equity market. Each column corresponds to the equation of conditional covariance of the specified series with BIST. The volatility spillover effect is captured by a_{12} and a_{21}, where a_{21} measures the effect on volatility of the Turkish equity market caused by shocks in the foreign equity market, and a_{12} captures the effect on volatility of the foreign equity market resulting from shocks in the BIST.

As the diagonal parameters a_{11} and a_{22} are statistically significant, the returns of all series depend on their first lags and g_{11}, g_{22} are all statistically significant, indicating a strong GARCH (1,1) process driving the conditional variances of the all indices. In other words, own past shocks and volatility effect the conditional variance of all equity indices.

Hypotheses tested are given as below:

H_0 1: No volatility spillover from regional markets: $a_{12} = g_{12} = 0$.

H_0 2: No volatility spillover from global markets: $a_{21} = g_{21} = 0$.

H_0 3: No volatility spillover from regional and global markets: $a_{12} = g_{12} = a_{21} = a_{21} = 0$.

Table 7. GARCH BEKK Estimations

	BIST-BOVESPA			BIST-CAC40		
	coef	**t-stat**	**prob.**	**coef**	**t-stat**	**prob.**
µ1	0.0000	0.0760	0.9394	-0.0007	-2.1816	0.0291
µ2	0.0025	10.3961	0.0000	0.0011	6.1031	0.0000
c11	0.0000	0.0148	0.9882	0.0069	15.2501	0.0000
c12	0.0000	0.0151	0.9879	0.0010	7.1047	0.0000
c22	0.0000	0.0010	0.9992	0.0000	0.0001	0.9999
a11	0.0835	7.8935	0.0000	1.2849	37.6955	0.0000
a12	-0.1247	-14.2887	0.0000	-0.0756	-9.5998	0.0000
a21	0.5652	18.0997	0.0000	-2.1860	-45.1422	0.0000
a22	0.4875	37.3099	0.0000	-0.1288	-9.2599	0.0000
g11	0.9731	248.1976	0.0000	0.5902	93.1725	0.0000
g12	0.0742	46.4019	0.0000	0.0246	9.7041	0.0000
g21	-0.5486	-48.1264	0.0000	0.0826	4.5113	0.0000
g22	0.8703	207.4669	0.0000	0.9594	322.8782	0.0000
a12+g12	0.9539			1.9993		
a22+g22	0.9951			0.9371		
a1*a2+g1*g2	0.8876			0.4007		

	BIST-DAX30			BIST-FTSE100		
	coef	**t-stat**	**prob.**	**coef**	**t-stat**	**prob.**
µ1	0.0015	3.6053	0.0003	0.0009	2.4658	0.0137
µ2	0.0007	3.9821	0.0001	0.0005	3.5345	0.0004
c11	0.0073	8.2100	0.0000	0.0065	16.5318	0.0000
c12	0.0131	36.0243	0.0000	0.0005	4.5124	0.0000
c22	0.0000	0.0000	1.0000	0.0000	0.0000	1.0000
a11	0.1569	5.1994	0.0000	0.8670	31.5450	0.0000
a12	-0.1049	-4.4171	0.0000	-0.0881	-13.7034	0.0000

a21	1.0440	17.0668	0.0000	-2.2185	-53.0996	0.0000
a22	-0.5591	-19.1475	0.0000	-0.0369	-2.8411	0.0045
g11	0.8485	90.5942	0.0000	0.6704	80.1403	0.0000
g12	0.0865	8.9135	0.0000	0.0353	13.9091	0.0000
g21	-0.6989	-9.4722	0.0000	0.0636	3.6821	0.0002
g22	0.1028	1.9017	0.0572	0.9542	285.0801	0.0000
a12+g12	0.7446			1.2012		
a22+g22	0.3231			0.9119		
a1*a2+g1*g2	-0.0005			0.6077		

	BIST-KOSPI			**BIST-MERVAL**		
	coef	**t-stat**	**prob.**	**coef**	**t-stat**	**prob.**
µ1	-0.0009	-3.0806	0.0021	0.0008	2.4305	0.0151
µ2	0.0011	5.4324	0.0000	0.0006	1.8669	0.0619
c11	0.0064	14.8649	0.0000	0.0014	1.4473	0.1478
c12	0.0008	6.1564	0.0000	0.0040	13.3706	0.0000
c22	0.0000	-0.0003	0.9998	0.0000	0.0002	0.9998
a11	1.3352	50.8520	0.0000	-1.1328	-43.7750	0.0000
a12	-0.0719	-8.2318	0.0000	-0.1649	-10.9257	0.0000
a21	-1.5998	-46.3400	0.0000	0.8810	32.0414	0.0000
a22	-0.1512	-14.5477	0.0000	-0.1160	-10.9450	0.0000
g11	0.5990	92.0359	0.0000	0.7799	139.4096	0.0000
g12	0.0230	8.7204	0.0000	-0.0381	-10.9438	0.0000
g21	0.0246	1.7883	0.0737	0.0778	5.7578	0.0000
g22	0.9694	400.6854	0.0000	0.9598	190.7723	0.0000
a12+g12	2.1415			1.8915		
a22+g22	0.9625			0.9346		
a1*a2+g1*g2	0.3787			0.8799		

	BIST-NIKKEI			**BIST-RTSI**		
	coef	**t-stat**	**prob.**	**coef**	**t-stat**	**prob.**
µ1	-0.0035	-12.0080	0.0000	-0.0033	-10.1661	0.0000
µ2	0.0005	2.5198	0.0117	0.0003	0.8580	0.3909
c11	0.0103	16.1705	0.0000	0.0101	19.3599	0.0000
c12	0.0086	36.7010	0.0000	0.0026	2.7333	0.0063
c22	0.0000	0.0001	0.9999	-0.0096	-19.9386	0.0000
a11	1.8347	55.6263	0.0000	-2.0066	-41.4312	0.0000
a12	0.0056	0.4416	0.6588	-0.0911	-5.9049	0.0000
a21	-1.9910	-35.6033	0.0000	0.4681	13.4365	0.0000

Table 7 GARCH BEKK Estimations (contd.)

a22	-0.1294	-6.9764	0.0000	-1.0420	-39.3979	0.0000
g11	0.3180	26.0309	0.0000	0.5912	36.0598	0.0000
g12	0.1440	29.8813	0.0000	-0.0074	-4.4546	0.0000
g21	-0.9005	-36.2856	0.0000	0.1137	6.7033	0.0000
g22	0.5988	64.9340	0.0000	0.6954	56.3023	0.0000
a12+g12	3.4671			4.3760		
a22+g22	0.3753			1.5694		
a1*a2+g1*g2	-0.0469			2.5021		

	BIST-S&P500			**BIST-SSE**		
	coef	**t-stat**	**prob.**	**coef**	**t-stat**	**prob.**
µ1	0.0003	0.5653	0.5718	-0.0050	-17.1690	0.0000
µ2	0.0009	7.1488	0.0000	0.0002	1.0127	0.3112
c11	-0.0013	-1.8583	0.0631	0.0092	16.9420	0.0000
c12	-0.0005	-2.0015	0.0453	0.0005	0.8909	0.3730
c22	0.0000	0.0001	1.0000	-0.0016	-6.4954	0.0000
a11	0.0578	7.6473	0.0000	1.9610	63.2222	0.0000
a12	-0.0660	-13.3423	0.0000	-0.0124	-1.4801	0.1389
a21	0.6716	13.6577	0.0000	-0.3172	-6.0054	0.0000
a22	0.4566	34.0880	0.0000	0.2252	18.6514	0.0000
g11	0.9864	264.8683	0.0000	0.5581	68.6355	0.0000
g12	0.0530	49.5685	0.0000	0.0027	1.4347	0.1514
g21	-0.8234	-46.7202	0.0000	0.0741	2.7817	0.0054
g22	0.8697	179.5109	0.0000	0.9696	326.9040	0.0000
a12+g12	0.9763			4.1571		
a22+g22	0.9649			0.9909		
a1*a2+g1*g2	0.8842			0.9827		

The observation period of our study covers 16 years and because of this, it is just analyzing the long run transmissions between BIST and chosen equity markets.

Evidence of integration is found, in terms of returns and volatility linkages, among the different equity markets. There are bi-directional return spillovers (shock transmissions) from the BIST index to the indices of BOVESPA, CAC 40, DAX30, FTSE100, KOSPI, MERVAL, RTSI and S&P 500. Any uni-directional linkage is not found -regarding transmission of shocks from BIST to NIKKEI and SSE- due to statistically insignificant off-diagonal parameter a_{12}. Interestingly the direction is from Nikkei and SSE to BIST, as only the off-diagonal parameter a_{21} is statistically significant at the 5% level of significance, meaning that Tokyo and Shanghai Stock Exchanges' shocks affect the mean returns on the Turkish Equity market. This may be associated with different opening and closing time due to time zone difference. As shown in Table 7 the estimated diagonal parameters a_{11} and a_{22} are statistically significant implying presence of ARCH effect in the stock markets. Also, statistically significant parameters g_{11} and g_{22} are all indicating a strong GARCH process driving the conditional variances of all the indices. This means, the own past shocks and past volatility of all markets, except German Stock Exchange (because, g_{22} parameter of DAX30's volatility model is insignificant at 5 % level of significance) are significant and affect the conditional variance of two . The significant and smaller parameters a_{12} according to a_{21}, show that there is a weak past shock spillover from BIST to the other equity market than past shock effect from international equity markets to BIST.

The statistically significant off-diagonal elements of matrix G, which capture the cross-market volatility spillovers, present bi-directional volatility transmission from one market to another. Besides, the GRACH parameters of the own volatility in all markets are also significantly close to one shows symmetric cross-volatility persistence exists between equity markets. The sum of the ARCH and GARCH effects is less than one in all exchanges except RTSI, implying a mean-reverting conditional volatility process shows shock transmission.

4. Conclusion

In this paper, the volatility transmission across BIST (Turkey) and some important international (emerging and developed) stock markets is examined by using [VAR(p)-GARCH(1,1)-BEKK] model.

There is strong evidence of bi-directional contemporaneous volatility spillover between BIST and most of the foreign exchange markets. Turkish stock market discovered relatively well linked to the international stock markets selected in the study. This may be due to the increased economic and financial links and the fast moving attempts of deregulation and integration initiated by the Turkey after 2001.

There are bidirectional volatility linkages between BIST and US, UK, Germany, France, Japan, South Korea, Brazil, Argentina and Russia stock markets. The overall persistence of stock market volatility is highest for KOSPI (South Korea) (0.96935) and lowest for DAX30 (Germany) (0.10284). There is significant influence of developed markets on Turkish equity market. It is found that BIST has a weak market interdependence with DAX30 but strong bidirectional volatility spillover with RTSI (Russia).

The empirical results of this study show significant conditional correlation and volatility transmission across BIST and selected equity markets. As a conclusion, Turkish equity market is integrated with both emerging and developed markets and responds to news currently existing in the other markets. Results we obtained support the results of previous studies. Results of this study are crucial for financial market participants and practitioners for risk management and building an optimal portfolio. This paper could be extended by dividing sample periods into sub-samples. The comparisons of different sub-sample periods could probably supply more interesting findings.

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