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EXAMINATION OF VOLATILITY STRUCTURE BETWEEN TURKISH STOCK MARKET AND COMMODITY MARKETS: A PERSPECTIVE FOR THE PERIOD OF 2015-2019

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ABSTRACT

Commodity markets, both in the past and in modern times, have had an extraordinary economic impact on individuals and societies. Although it is not known exactly when and where commodity markets started, it is thought that it started about 6000 years ago with rice trade in China. Commodities, as raw material providers used in production, have an intensive usage area. This study aims to examine the global commodity prices such as gold ounce price, silver ounce price, copper price, Brent crude oil price, and natural gas prices, and the volatility structure in the Borsa Istanbul 100 index, representing the Turkey Stock Market. For this purpose, daily closing prices for the period of 2015 January-2019 December were examined in the study. To investigate the time evolution of correlations between the commodities and stock market, the dynamic conditional correlation (DCC) GARCH model is used. The results show that the volatility between the BIST 100 index and commodity prices has constant effects and a comprehensive volatility clustering arises.

Keywords: *Commodity Prices, Turkish Stock Market, Volatility*

Jel Codes: *G11, G15, C22*

TÜRK BORSASI İLE EMTİA PİYASALARI ARASINDAKİ OYNAKLIK YAPISININ İNCELENMESİ: 2015-2019 PERİYODU İÇİN BİR PERSPEKTİF

ÖZ

Emtia piyasaları gerek geçmişte ve gerekse modern zamanlarda, bireyler ve toplumlar üzerinde olağanüstü bir ekonomik etkiye sahip olmuştur. Emtia piyasalarının tam olarak ne zaman ve nerede başladığı kesin olarak bilinemese de yaklaşık 6000 yıl önce Çin'de pirinç ticareti yapılmasıyla başladığı sanılmaktadır. Emtialar, üretimde kullanılan hammadde sağlayıcıları olarak yoğun kullanım alanına sahiptir. Bu çalışmanın amacı, küresel emtia fiyatları olarak altın ons fiyatı, gümüş ons fiyatı, bakır fiyatı, Brent tipi ham petrol varil fiyatı ile doğal gaz fiyatları ile Türk Borsasını temsilen Borsa İstanbul 100 endeksi bağlamında oynaklık yapısının incelenmesidir. Bu amaçla çalışmada 2015 Ocak-2019 Aralık periyodu için günlük kapanış değerleri ele alınmıştır. Emtialar ve menkul kıymet borsası arasındaki korelasyonu araştırmak için dinamik koşullu korelasyon (DCC) GARCH yöntemi kullanılmıştır. Bulgular, BIST 100 endeksi ile emtia fiyatları arasındaki oynaklığın sürekli etkilere sahip olduğunun ve kapsamlı bir volatilite kümelenmelerinin oluştuğu sonucunu vermektedir.

Anahtar Kelimeler: *Emtia Fiyatları, Türk Borsası, Oynaklık*

Jel Kodları: *G11, G15, C22*

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1. INTRODUCTION

Commodity, came into use in English from the French "*commodité*", can be defined as homogeneous products, which are used in the sense of object or service providing convenience and benefit, and which have a certain demand, can be supplied in the markets without product differentiation, each having the same feature and function. Account owners have been trading in commodity markets for hundreds of years. Commodities represent a wide range of products. Commodities, which composes of many main groups such as precious metals, industrial metals, food and agricultural products, forestry products, energy products and chemicals, are traded at the product-oriented commodity markets, as well as in private markets on the financial or derivative markets. Commodities play an important role in the world economy with their physical properties, necessity for production and their place in the financial system. Commodities, an indispensable element of commercial and daily life, have been traded as an important economic asset since the beginning of human history. Commodity prices have started to show significant volatility due to increasing consumption, depleted resources, the phenomenon of globalization and technological developments and especially after the oil crisis in 1973. Developments and changes in the world economy caused the prices of commodities used as a means of production, investment and consumption to fluctuate in terms of width, size and duration, and this fluctuation, on the other hand, caused changes in the general economic balance by having impacts on other markets. The significance of this study lies in the fact that it is one of the most comprehensive and recent date studies which have investigated the relationsip betweeen Turkish stock market and commodity prices by using DCC GARCH model. Furthermore, this study attempts to fill the gap in empirical studies and associated theory which remains unexplored and not broadly discussed in the literature. In the first chapter, the studies examining the effects of commodity prices on stock prices will be summarized in the literature review section. The next stage will explain the data set and method used in the study. The last chapter will present and interpret the results obtained.

2. LITERATURE REVIEW

Al-Mudhaf and Goodwin (1993, 181) examined the relationship between the returns of 29 oil companies traded in NYSE and oil prices for 1973 and determined that the returns increased after oil crisis. Sadorsky (1999,449) researched the effect of oil prices and instability in oil prices on stock returns for the period of January 1947 - April 1996 in the United States. Based on the findings of Sadorsky, it was stated that changes in oil prices played an important role in explaining the change in stock returns and that there was a significant and positive relationship between them. Papapetrou (2001,511) examined whether oil prices had an effect on the formation of stock prices in Greece for the period 1989-1999. Findings show that oil prices have an impact on the formation of stock price movements and that increases in oil prices have reduced stock returns. In their study using monthly data for the period of July 1959 and March 2004, Gorton and Rouwenhorst (2004,47) observed a negative relationship between stock exchanges and commodity prices. El-Sharif et al. (2005, 819) examined the relationship between crude oil prices and the stock returns of businesses in the oil and gas sector in England. In their study using multiple factor analysis for the period of January 1989-June 2001, the authors found that crude oil prices, capital markets and exchange rate changes were effective in stock returns. Reitz and Westerhoff (2007, 231) examined the relationship between commodity prices and stock markets. Using monthly data for various commodities such as cotton, sugar or zinc, STAR-GARCH model indicates that stock markets positively depend on commodity prices. In their study examining the factors that affect the formation of stock returns 109 gas and oil companies traded on the Canadian Stock Exchange for the period 1995-2002, Boyer and Filion (2007,428) determined that the increases in oil and natural gas prices contributed positively to stock returns. In their study discussing monthly data for the period of 1973-2006, Kilian and Park’ın (2009,1267) investigated the relationship between oil prices and the stock market, used the VAR method in these studies, and as a result of the analysis of the data, they found that there was a negative relationship between the oil prices and the stock market. Johnson and Soenen (2009,69) tested the effects of world commodity prices on stock returns on South American exchanges. They found a consistent and significant relationship with various commodity price indices on the Argentina, Brazil and Peru exchanges. They concluded that the stock returns of the Argentina and Peru stock exchanges reacted in particular to the changes in industrial and precious metal prices on the same day.

In their study testing the relationship between gold prices, oil prices and stock prices in Pakistan for the period 2002 and 2010, Irshad et al. (2010, 6) found that there was no long-term relationship between these assets. In their study examining the long-term relationship between four stocks operating in the energy sector and the electricity index for the period of July 2000-August 2009 In Turkey, Guler et al. (2010) determined that the variables act together in the long-term. Jacobsen et al. (2010) investigated the relationship between price movements of industrial metals such as copper and aluminum with stock returns and macroeconomic variables. They concluded that while the increase in industrial metal prices was positively met in the stock market during stagnation periods, the economy was met negatively during the expansion periods. They reached the conclusion that, during the economic expansion period, on a monthly basis, while one-unit standard deviation increase in industrial metal returns creates an expectation of a 1.5% drop in stock market returns, this creates an expectation of an increase of around 0.5% during the recession periods. In addition, they concluded that a one-month increase in metal prices increased industrial production, capacity utilization rate and producer price index (PPI), and decreased unemployment rate in the following month. In their study investigating whether gas and oil companies operating in the Czech Republic, Hungary, Poland, Romania and Slovenia are affected by oil prices for the period 1998-2008, Mohanty et al. (2010) discussed 8 companies. As a result of the study, it was emphasized that there was no relationship between oil prices and stock prices. Choi and Hammoudeh (2010, 4388), investigated the volatility behavior commodity and stock markets in a regime switching environment. The dynamic conditional correlations indicate increasing correlations among all the commodities since the 2003 Iraq war but decreasing correlations with the S & P 500 index. The commodities also show different volatility persistence responses to financial and geopolitical crises, while the S & P 500 index responds to both financial and geopolitical crises.

In their study, Hacıhasanoğlu and Soytaş (2011, 53), they took oil as a representative of commodity prices, since it has the largest trade volume. The S & P 500 index is used to represent global stock markets. The impact of oil price volatility on stock prices is also examined. The Toda and Yamamoto procedure is applied to three different time periods in which oil prices were following different trends. The authors find evidence in favor of the hypothesis that the existence, nature and the magnitude of the relationship between oil and stock prices are subject to structural changes that depend on various factors. In the study examining the relationship between stock index returns and commodity returns in the USA, Zapata et al. (2012, 355) determined that there was a negative correlation between stock and commodity prices. Nangolo and Musingwini (2012,459) investigated the relationship between gold, silver and copper mines and stocks traded on the Johannesburg Stock Exchange with correlation analysis. They tried to determine which of the spot, future and long-term prices of gold, silver and copper mines had the greatest impact in the stock valuation process. They found that there was a correlation between commodity prices in the mining sector stock prices in the period of 2004-2010, this correlation was stronger in commodity spot and futures prices compared to long-term prices. In their study testing the relationship between oil prices and securities markets as of the period between 1996 and 2007 in Bahrain, Kuwait, Oman and Saudi Arabia, Arouri and Rault (2012,242) used the seemingly unrelated regression model and found that the increase in oil prices for countries outside Saudi Arabia had a positive effect on stock prices. In their study investigating whether the effect on the July 2011-June 2012 period, the change in the price of gold in the gold industry for companies operating in Turkey in stock returns, Sadeghzadeh and Eren (2012) could not identify any relationship between gold price and company returns in the long term. In their study investigating the connection between Chinese stock exchanges and international food commodity prices, when analyzed the daily returns of Shanghai and Shenzhen stock exchanges and international food commodity prices for the period 2000-2010; Kang et al (2013,147) determined the existence of a two-way relationship between wheat, corn, soybean and soybean oil and the stock markets, and a one-way relationship between rice and stock exchanges. However, stock market price indices respond negatively to the increase in food commodity future prices, while food commodity future prices respond positively to the increase in Chinese stock markets. In their study, Mensi et al. (2013, 15) employs a VAR-GARCH model to investigate the return links and volatility transmission between the S & P 500 and commodity price indices for energy, food, gold and beverages over turbulent period from 2000 to 2011. They find there is a significant transmission among the S & P 500 and commodity markets and the past shocks and volatility of the S & P 500 influenced the oil and gold markets.

In the study conducted by Yildirim et al. (2014, 130) and aimed to test the effects of volatility experienced in global commodity prices on companies' stock returns, the analysis of the stock prices of the main metal industry companies traded in BIST with international iron and steel price changes in the period of 1999:01-2012:06 has been carried out with co-integration, error-correction models and causality tests. The construction iron and wire rod prices and Kardemir (D) and Izdemir (B) return indices for stocks were used in the study. As a result of the study, it has been determined that there is a long-term co-integration relationship between iron and steel prices and stock returns, but there is no causal relationship between them. In their study examining the relationship between oil prices and stock market for the Tunisian market, Hamma et al. (2014, 109) determined a one-way positive relationship from oil price to stock price.

Barunik et al. (2016, 186), employ a wavelet approach and conduct a time-frequency analysis of dynamic correlations between pairs of key traded assets (gold, oil and stocks) covering the period from 1987 to 2012. The analysis is performed on both intraday and daily data. It is shown that heterogeneity in correlations across a number of investment horizons between pairs of assets is a dominant feature during times of economic downturn and financial turbulence for all three pairs of the assets under research. Heterogeneity prevails in correlations between gold and stocks. After the 2008 crisis, correlations among all the three assets increase and become homogeneous. Mohammad Nor and Masih (2016) investigated the dynamic relationship between spot and future palm oil prices and stock market prices of a major palm oil producer. The results showed that stock market prices lead spot and futures palm oil prices rather than vice versa for the Malaysian markets. In the study of Eyuboglu and Eyuboglu (2016, 139-140), for the period of 2003:5-2014:12, it was aimed to test, by using monthly data, how and to what extent metal prices (gold, silver, and copper) are effective on stock prices of 6 companies in Borsa Istanbul, operating in the mining industry. In the study, dollar-based prices related to the variables were used. Whether there is a long-term relationship between metal prices and company stock prices, on the other hand, was tested by Johansen co-integration method. Findings show that there was no long-term relationship between stock prices and metal prices. The short-term relationship was estimated by standard Least –Square Method, copper prices were found to affect stock prices negatively, while gold prices had a positive effect on stock prices. As a result, the findings revealed that investors should consider other variables in addition to metal prices when making investments in these companies. Gyasi (2016, 10) examined the linkage between the Ghana stock exchange market and the commodity price changes-cocoa, crude oil and gold prices, the major exports of Ghana. The study especially aims at the linkage between the Ghana stock market and crude oil prices with the reason that Ghana started exporting oil in commercial quantities in the late 2010. Gyasi estimated a bivariate GARCH-BEKK model proposed by Engle and Kroner using daily returns from MSCI and world commodity prices. The author found evidence of a strong bi-directional linkage between the Ghana equity market, gold and crude oil prices both in regards of returns and volatility. De Nicola et al. (2016, 28) aimed to test commodity prices on stock returns. Using monthly data between 1970 and 2013 to provide a comprehensive analysis of the extent of co-movement among the nominal price returns of 11 major energy, agricultural, and food commodities, they found that the price returns of energy and agricultural commodities are highly correlated; the overall level of co-movement among commodities increased in recent years, especially between energy and agricultural commodities, and in particular in the cases of maize and soybean oil, which are important inputs in the production of biofuels; and the stock market volatility is positively associated with the co-movement of price returns across markets, especially after 2007. Baldi et al. (2016, 277), analyze Volatility Impulse Response Function from stock markets to agricultural commodity markets over a symmetric window before and after two of the most important bubble bursts since the new millennium, the 2000 dot.com bubble and the 2008 financial crises. Results highlight that volatility spillover increased significantly after the 2008 financial crises, signalling a rising interconnection between financial and agricultural commodity markets. Raza et al. (2016, 290), examine the asymmetric impact of gold prices, oil prices and their associated volatilities on stock markets of emerging economies. Monthly data are used for the period January 2008 till June 2015. The nonlinear ARDL approach is applied in order to find short-run and long-run asymmetries. The empirical results indicate that gold prices have a positive impact on stock market prices of large emerging BRICS economies and a negative impact on the stock markets of Mexico, Malaysia, Thailand, Chile and Indonesia. Oil prices have a negative impact on stock markets of all emerging economies. Gold and oil volatilities have a negative impact on stock markets of all emerging economies in both the short- and the long-run.

Junttila et al. (2017, 255), based on daily data from 1989-2016 find that the correlations between some relevant commodity market futures and equity returns in the aggregate U.S. market, and specifically in the energy sector stocks have changed strongly during the stock market crisis periods. The correlation between crude oil futures and aggregate U.S. equities increases in crisis periods, whereas in case of gold futures the correlation becomes negative, which supports the safe haven hypothesis of gold. For energy sector equities, the dynamics of hedge ratio does not support using either crude oil or gold futures for cross hedging during stock market crises. Ibrahim et al. (2018, 146), investigated the Islamic Stock Market and commodity prices in Malaysia using monthly data between November 2008 to October 2017. Several methods are employed to answer the issue of the study which are unit root tests and Johansen's cointegration test, followed by long-run structural modelling (LRSM) and vector error-correction modelling (VECM), variance decompositions (VDCs), impulse response functions (IRFs) and persistence profile (PP). The results showed that spot Kijang Gold lags all investment avenues in Malaysia. It indicated that the performance of the Kijang Gold is dependent on FTSE Bursa Malaysia Emas Shariah Index, macroeconomic variables and strategic commodities. The aim of the study of Gencyurek and Demireli (2019, 66) is to realize the effect of the uncertainty of the oil market on the uncertainty of the stock market indices of developing countries by variance causality analysis. In the study where the daily data of 2012-2018 period was analyzed, variance causality approach was used. As a result of the analysis, no volatility propagation was identified from the oil market to the MSCI Developing Countries Index. Oyelami and Yinusa (2019,256) investigated the relationship between commodity prices and stock exchanges from sub-Saharan Africa perspective and in the context of the Johannesburg stock exchange and the Nigeria stock exchange, two major stock markets in Africa, as a result, they determined that there is a significant and long-term two-way relationship between commodity prices and security returns.

3. DATA SET AND METHODOLOGY

Variation of approaches modeling conditional variance and developments in this area assist to obtain a lot of useful information, from revealing the change of risk of a financial variable over time to analyzing its asymmetric properties. Development of ARCH and GARCH models, which are used in analyzing the risk structure of a single financial product or financial market, by Bollerslev, Engle and Wooldridge (1988) for VEC parameterization solution technique for more than one-time series created the multivariate GARCH modeling called the VEC-GARCH model. Using of BEKK (Baba, Engle, Kraft and Kroner) parameterization to develop the multivariate model by Engle and Kroner (1995) led to the emergence of another model called BEKK-GARCH in this field. But however, Bollerslev (1990) developed the CCC-GARCH model by proposing Constant Conditional Correlations (CCC) parameterization, which takes conditional variances as well as conditional correlations in the solution of the multivariate GARCH model. Tse and Tsui (2002) and Engle (2002), on the other hand, used Dynamic Conditional Correlations (DCC) parameterization in the CCC-GARCH model instead of constant conditional correlations parameterization and developed the DCC-GARCH model, which can be applied for multivariable and high-dimensional datasets (Bauwens et al., 2006: 89).

The reason for preferring to use DCC-GARCH model in this study is that it can determine the interaction and transfer of volatility between the financial variables under consideration and provides information about the change in correlations between the rate of return of these variables over time. The DCC-GARCH model can be shown as follows:

$$r_t = \alpha + \sum_{i=1}^{k} \beta r_{t-i} + y_t \qquad (1)$$

$$y_{A,t} = \sqrt{h_{A,t} \varepsilon_{A,t}} \qquad (2)$$

$$y_{B,t} = \sqrt{h_{B,t}\varepsilon_{B,t}} \tag{3}$$

$$\rho_t = cov\left(\varepsilon_{A,t}, \varepsilon_{B,t}\right) = (1-\theta_1-\theta_2)\rho + \theta_1\rho_{t-1} + \theta_2\psi_{t-1} \tag{4}$$

$$\begin{bmatrix} h_{A,t} \\ h_{B,t} \end{bmatrix} = \begin{bmatrix} y_1 \\ y_2 \end{bmatrix} + \begin{bmatrix} \phi_{11} & \phi_{12} \\ \phi_{21} & \phi_{22} \end{bmatrix} \begin{bmatrix} y_{A,t-1}^2 \\ y_{B,t-1}^2 \end{bmatrix} + \begin{bmatrix} \delta_{11} & \delta_{12} \\ \delta_{21} & \delta_{22} \end{bmatrix} \begin{bmatrix} h_{A,t-1} \\ h_{B,t-1} \end{bmatrix} \tag{5}$$

The $r_t = \alpha + \sum_{i=1}^{k} \beta r_{t-i} + y_t$ equation above is the average model following the k-order vector autoregressive (VAR) process. ρ_t is the correlation coefficient that changes over time. ρ is a $N\ x\ N$ sized positive-defined matrix with diagonal elements "1", , ψ_{t-1} on the other hand, is a $N\ x\ N$ sized matrix whose elements are the function of the historical values of the variable y_t (Tse and Tsui, 2002: 352). In order for the ρ correlation matrix to be positively defined, there are two conditions that must be met. These are: $0 \le \theta_1, \theta_2 < 1$ ve $\theta_1 + \theta_2 \le 1$. $h_{A,t}$ and $h_{B,t}$ in the equation system (5) indicate the volatility of variables A and B, respectively, while $r_t = \left(r_{A,t};\ r_{B,t}\right)'$ and $y_t = \left(y_{A,t};\ y_{B,t}\right)'$, on the other hand, shows the bivariate structure of GARCH modeling (Hepsağ and Akçalı, 2016).

The parameters of ϕ_{11} and δ_{11} in the equation system (5) above indicate the continuity of the volatility of the variable A, while the parameters of ϕ_{22} and δ_{22} show variable B. The fact that these parameters are statistically significant and close to 1 indicates that volatility convergence occurs in these variables and it is permanent. The parameters of ϕ_{12} and δ_{12} are used to assess the presence of volatility interaction. Accordingly, statistically significant parameters of ϕ_{12} and δ_{12} indicates the presence of volatility transfer from variable B to variable A. The significance of ϕ_{21} and δ_{21} parameters indicates the presence of volatility transfer from variable A to variable B. It is stated that, generally, as a result of maintaining the effect of the information causing price changes due to the volatility convergence observed in daily data (Mandelbrot, 1963), in time, high returns are realized after high-yielding periods, and low returns after low-yielding periods and that returns of absolute value tend to accumulate in a certain period of time (Brooks, 2008: 380). Volatility heritability relates to the extent and duration of the effects of shocks on the volatility of the variable examined, while volatility transfer, on the other hand, is about increasing the effectiveness of spreading a shock in the market in other markets. For example, in the event of the presence of an asymmetrical effect on volatility transfer, a negative situation in one market affects another market more than good news (Koutmos et al., 1995). Data and empirical findings are shown in Table 1.

Table 1. Data and Empirical Findings

BIST 100 INDEX
GOLD ($)
SILVER ($)
COPPER ($)
OIL ($)
NATURAL GAS ($)

In the study investigating the volatility interaction between the prices of BIST 100 INDEX, GOLD ($), SILVER ($), COPPER ($), OIL ($), NATURAL GAS ($), the observational period here consists of daily frequencies. The data used in the study belong to the period of 2015 January-2019 December and stock indexes and commodity prices were obtained from Matriksdata. In this study the period between January 2015 and December 2019 was selected due to better representing the recent past years.

The first logarithmic differences of the closing prices of all variables were taken, and thus, the rates of return were calculated. Figure 1 and Table 2 show the graphs and descriptive statistics of the return series of BIST-100, GOLD, SILVER, COPPER, OIL, NATURAL GAS, respectively.

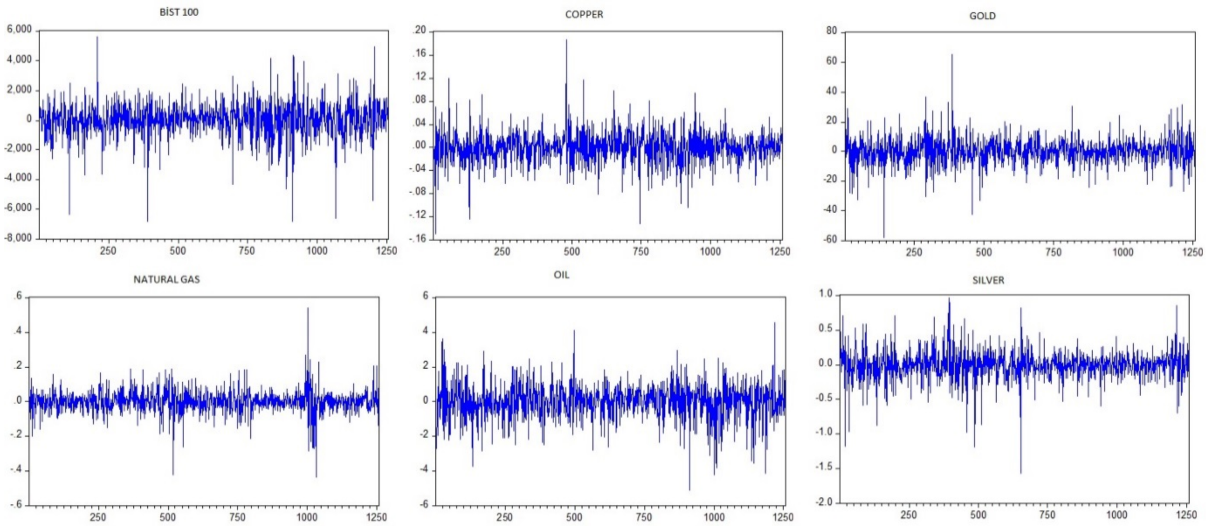

Figure 1. Development of Returns of Variables in Time (First-degree differences taken)

Table 2. Descriptive Statistics for the Return of Variables Series

	COPPER__$_	GOLD__$_	NATURAL_GAS__$_	OIL__$_	SILVER__$_	BIST_100_INDEX
Mean	2.613072	1251.034	2.725917	56.84003	16.17176	90934.58
Median	2.637300	1251.600	2.747000	56.12500	16.24200	90501.48
Maximum	3.248500	1533.980	4.473000	84.27700	20.37500	119398.0
Minimum	1.957400	1046.430	1.611000	27.08000	13.64900	68230.47
Std. Dev.	0.323440	92.00436	0.424765	11.20638	1.350640	12745.55
Skewness	-0.142527	0.471396	0.384458	0.006986	0.428776	0.247022
Kurtosis	2.193627	3.877891	5.047927	2.613800	3.032165	2.020707
Jarque-Bera	38.31199*	86.91884*	250.6267*	7.821978*	38.57046*	63.01211*
Sum	3284.632	1572549.	3426.478	71447.92	20327.90	1.14E+08
Sum Sq. Dev.	131.3942	10631791	226.6137	157732.1	2291.232	2.04E+11
Observations	1257	1257	1257	1257	1257	1257

* This implies statistical significance at the 1% significance level.

When descriptive statistics of BIST 100 INDEX, GOLD ($), SILVER ($), COPPER ($), OIL ($), NATURAL GAS ($) returns are analyzed, it is found that the average values of the return series are smaller than the standard deviation values. This is consistent with the information that the financial time series often follow a random walk process (Ding and Vo, 2012: 16). Considering the kurtosis values of return series, on the other hand, it is seen that the distributions of the series are more orthogonal than the normal distribution. When Jarque-Bera test statistics are examined, it is also understood that the distribution of the return series is not normal. Considering these features, it can be stated that price indices of BIST 100 INDEX, GOLD ($), SILVER ($), COPPER ($), OIL ($), NATURAL GAS ($) have typical financial time series features.

In order not to encounter a high-frequency problem, the estimated DCC-GARCH models are approached as binary structures. In the study investigating the volatility interaction and transfer relationship between BIST 100 INDEX, GOLD ($), SILVER ($), COPPER ($), OIL ($), NATURAL GAS ($) through DCC-GARCH models, firstly, vector autoregressive (VAR) models with appropriate rank among the variables were estimated and the residual variance of these models was obtained. Then, DCC-GARCH models were estimated using residues from VAR models. Table 3, Table 4, Table 5, Table 6 and Table 7 show DCC-GARCH model results predicting volatility interaction between BIST 100 INDEX, GOLD ($), SILVER ($), COPPER ($), OIL ($), NATURAL GAS ($), respectively.

Table 3. DCC-GARCH Model Results for BIST-100 and COPPER ($) Variables

	Coefficients	Standard Errors	t-Stats	Probability Values
γ_1	0.830989	0.684344	1.214285	0.2246
γ_2	0.123652	0.300353	3.741105	0.0002*
ϕ_{11}	0.904958	0.744743	-1.215128	0.02243**
ϕ_{12}	0.016318	0.324455	-3.132380	0.0017*
ϕ_{21}	0.805790	0.669656	1.203290	0.2289
ϕ_{22}	0.736494	0.290117	0.125789	0.0089*
δ_{11}	0.070891	0.685858	-1.065660	0.02866**
δ_{12}	0.216044	0.282254	-4.308339	0.0000*
δ_{21}	0.804716	0.753152	1.068464	0.2853
δ_{22}	0.122388	0.309258	3.629293	0.0003*
θ_1	0.727618	0.681834	-1.067148	0.2859
θ_2	0.116409	0.280590	-0.414873	0.6782

* implies statistical significance at the 1% significance level, ** at 5% and *** at 10% significance level.

Based on the results of DCC-GARCH model of BIST-100 and COPPER ($) index returns given in Table 3, ϕ_{11} and δ_{11} parameters specifying the permanence of BIST-100 volatility are statistically significant at 5% significance level. As the 0.97 value, which is the sum of these two parameters, is close to value 1, it is understood that BIST-100 volatility clustering occurs and volatility has a lasting effect in this market. ϕ_{22} and δ_{22} parameters expressing continuity of COPPER ($) volatility and they are statistically significant at 1% significance level, besides, as the 0.85 value, which is the sum of these coefficients, is close to value 1, it is seen that COPPER ($) volatility clustering occurs and volatility has a lasting effect in this market. On the other hand, ϕ_{12} parameter expressing the presence of interaction from COPPER ($) volatility to BIST-100 volatility is statistically significant at 1% level and δ_{12} parameter at 1% level. Accordingly, 1% shock, which increases volatility in COPPER ($), increases BIST-100 volatility at the level of 0.01%. In the presence of volatility interaction from BIST-100 volatility to COPPER ($) volatility, since both ϕ_{21} and δ_{21} parameters are statistically insignificant parameters at 5% significance level, there is no volatility relationship from BIST-100 index to COPPER ($). Considering the volatility relationship of BIST-100 and COPPER ($), it can be said that there is a one-way volatility relationship and transfer from COPPER ($) volatility to BIST-100 volatility. In addition, θ_1 and θ_2 parameters expressing the dynamic correlation relationship between BIST-100 and COPPER are not statistically significant at 5% significance level, and accordingly, there is a positively and not very strong correlation relationship between these returns, besides, it is statistically insignificant depending on time.

Table 4. DCC-GARCH Model Results for BIST-100 and GOLD ($) Variables

	Coefficients	Standard Errors	t-Stats	Probability Values
γ_1	0.707076	0.225225	-3.139419	0.0017*
γ_2	0.286400	0.178828	7.193516	0.0000*
ϕ_{11}	0.775606	0.248535	3.120712	0.0018*
ϕ_{12}	0.187693	0.194690	-6.100445	0.0000*
ϕ_{21}	0.700126	0.222575	-3.145568	0.0017*
ϕ_{22}	0.882266	0.174992	1.041570	0.2976
δ_{11}	0.105501	0.228664	3.522641	0.0004*
δ_{12}	0.214972	0.190363	-6.382410	0.0000*
δ_{21}	0.880858	0.250406	-3.517717	0.0004*
δ_{22}	0.826385	0.206484	5.455070	0.0000*
θ_1	0.799338	0.228764	3.494158	0.0005*
θ_2	0.117780	0.188019	-0.626427	0.00310*

* implies statistical significance at the 1% significance level, ** at 5% and *** at 10% significance level.

Based on the results of DCC-GARCH model of BIST-100 and GOLD ($) index returns given in Table 4, ϕ_{11} and δ_{11} parameters specifying the permanence of BIST-100 volatility are statistically significant at 5% significance level. As the 0.87 value, which is the sum of these two parameters, is close to value 1, it is understood that BIST-100 volatility clustering occurs and volatility has a lasting effect in this market. Only the δ_{22} parameter, one of the parameters expressing the continuity of GOLD ($) volatility, is statistically significant at 1% significance level and as the 0.88 value, which is the value of the coefficient, is close to value 1, it is understood that GOLD ($) volatility clustering occurs and volatility has a lasting effect in this market. On the other hand, ϕ_{12} parameter expressing the presence of interaction from GOLD ($) volatility to BIST-100 volatility is statistically significant at 1% level, while δ_{12} parameter at 1% level. Accordingly, 1% shock, which increases volatility in GOLD ($), increases BIST-100 volatility at the level of 0.01%. In the presence of volatility interaction from BIST-100 volatility to COPPER ($) volatility, since both ϕ_{21} and δ_{21} parameters are statistically insignificant parameters at 5% significance level, there is no volatility relationship from BIST-100 index to GOLD ($). Considering the volatility relationship of BIST-100 and GOLD ($), it can be said that there is a one-way volatility relationship and transfer from GOLD ($) volatility to BIST-100 volatility. However, θ_1 and θ_2 parameters expressing the dynamic correlation relationship between BIST-100 and GOLD are statistically significant at 1% significance level, and accordingly, among these returns, there is a statistically significant correlation relationship with time varying positive and not very strong.

Table 5. DCC-GARCH Model Results for BIST-100 and SILVER ($) Variables

	Coefficients	Standard Errors	t-Stats	Probability Values
γ_1	0.691260	0.212867	-3.247382	0.0012*
γ_2	0.301937	0.165502	7.866578	0.0000*
ϕ_{11}	0.658358	0.235068	3.226120	0.0013*
ϕ_{12}	0.204802	0.180062	-6.691045	0.0000*
ϕ_{21}	0.684646	0.210484	-3.252720	0.0011*
ϕ_{22}	0.197505	0.161775	1.220864	0.2221
δ_{11}	0.090756	0.216730	3.648570	0.0003*
δ_{12}	0.229167	0.177091	-6.940861	0.0000*
δ_{21}	0.864885	0.237469	-3.642091	0.0003*
δ_{22}	0.841997	0.191981	5.948493	0.0000*
θ_1	0.784839	0.216964	3.617370	0.0003*
θ_2	0.131790	0.174846	-0.753751	0.4510

* implies statistical significance at the 1% significance level, ** at 5% and *** at 10% significance level.

Based on the results of DCC-GARCH model of BIST-100 and SILVER ($) index returns given in Table 5, ϕ_{11} and δ_{11} parameters specifying the permanence of BIST-100 volatility are statistically significant at 5% significance level. As the 0.75 value, which is the sum of these two parameters, is close to value 1, it is understood that BIST-100 volatility clustering occurs and volatility has a lasting effect in this market. Among the parameters expressing the continuity of SILVER ($) volatility, only δ_{22} parameter is statistically significant at 1% significance level, besides, as the 0.84 value, which is the value of the coefficient, is close to value 1, it is seen that SILVER ($) volatility clustering occurs and volatility has a lasting effect in this market. On the other hand, ϕ_{12} parameter expressing the presence of interaction from SILVER ($) volatility to BIST-100 volatility is statistically significant at 1% level and δ_{12} parameter at 1% level. Accordingly, 1% shock, which increases volatility in SILVER ($), increases BIST-100 volatility at the level of 0.01%. In the presence of volatility interaction from BIST-100 volatility to SILVER ($) volatility, since both ϕ_{21} and δ_{21} parameters are statistically insignificant parameters at 5% significance level, there is no volatility relationship from BIST-100 index to SILVER ($). Considering the volatility relationship of BIST-100 and SILVER ($), it can be said that there is a one-way volatility relationship and transfer from SILVER ($) volatility to BIST-100 volatility. In addition, θ_1 parameter, expressing the dynamic correlation relationship between BIST-100 and SILVER, is statistically significant at 5% significance level, and accordingly, there is a positively and not very strong correlation relationship between these returns, besides, it is statistically insignificant depending on time.

Table 6. DCC-GARCH Model Results for BIST-100 and OIL ($) Variables

	Coefficients	Standard Errors	t-Stats	Probability Values
γ_1	0.282771	0.374002	-2.756069	0.004496*
γ_2	0.079677	0.383379	-5.207829	0.008354*
ϕ_{11}	0.259459	0.366567	-4.707808	0.004791*
ϕ_{12}	0.193631	0.373292	6.518711	0.006040*
ϕ_{21}	0.710787	0.297831	2.386545	0.000170*
ϕ_{22}	0.270192	0.276928	-2.975673	0.003292*
δ_{11}	0.401760	0.381346	1.053532	0.002921*
δ_{12}	0.132067	0.416437	5.317136	0.007511*
δ_{21}	0.274495	0.410234	4.669118	0.005034*
δ_{22}	0.469332	0.417785	-3.405310	0.006852*
θ_1	0.756326	0.340280	-2.222659	0.000262*
θ_2	0.169864	0.292094	2.581540	0.005609*

* implies statistical significance at the 1% significance level, ** at 5% and *** at 10% significance level.

Based on the results of DCC-GARCH model of BIST-100 and OIL ($) index returns given in Table 6, ϕ_{11} and δ_{11} parameters specifying the permanence of BIST-100 volatility are statistically significant at 1% significance level. As the 0.65 value, which is the sum of these two parameters, is close to value 1, it is seen that BIST-100 volatility clustering occurs and volatility has a lasting effect in this market. ϕ_{22} and δ_{22} parameters expressing continuity of OIL ($) volatility are statistically significant at 1% significance level, besides, as the 0.68 value, which is the sum of these coefficients, is close to value 1, it is seen that OIL ($) volatility clustering occurs and volatility has a lasting effect in this market. On the other hand, ϕ_{12} parameter expressing the presence of interaction from OIL ($) volatility to BIST-100 volatility is statistically significant at 1% level and δ_{12} parameter at 1% level. Accordingly, 1% shock, which increases volatility in OIL ($), increases BIST-100 volatility at the level of 0.01%. In the presence of volatility interaction from BIST-100 volatility to OIL ($) volatility, since both ϕ_{21} and δ_{21} parameters are statistically insignificant parameters at 5% significance level, there is no volatility relationship from BIST-100 index to OIL ($). Considering the volatility relationship of BIST-100 and OIL ($), it can be said that there is a one-way volatility relationship and transfer from OIL ($) volatility to BIST-100 volatility. In addition, θ_1 and θ_2 parameters expressing the dynamic correlation relationship between BIST-100 and OIL are statistically significant at 1% significance level, and accordingly, there is a positively and not very strong correlation relationship between these returns, besides, it is statistically insignificant depending on time.

Table 7. DCC-GARCH Model Results for BIST-100 and NATURAL GAS ($) Variables

	Coefficients	Standard Errors	t-Stats	Probability Values
γ_1	0.102176	1.896082	-3.053888	0.009570*
γ_2	0.238887	0.469449	2.508867	0.006108*
ϕ_{11}	0.542102	0.369705	5.113879	0.009093*
ϕ_{12}	0.954349	0.131952	-7.232567	0.000000*
ϕ_{21}	0.072523	1.794068	-4.040424	0.009678*
ϕ_{22}	0.008160	0.405539	3.094096	0.009250*
δ_{11}	0.209874	1.891252	2.110971	0.009116*
δ_{12}	0.232264	0.653598	-1.355362	0.007223*
δ_{21}	0.042660	0.329416	-5.129503	0.008970*
δ_{22}	0.982283	0.126901	7.740548	0.000000*
θ_1	0.181262	1.842164	4.098396	0.009216*
θ_2	0.055459	0.593401	-3.093460	0.009255*

* implies statistical significance at the 1% significance level, ** at 5% and *** at 10% significance level.

Based on the results of DCC-GARCH model of BIST-100 and NATURAL GAS ($) index returns given in Table 7, ϕ_{11} and δ_{11} parameters specifying the permanence of BIST-100 volatility are statistically significant at 1% significance level. As the 0.75 value, which is the sum of these two parameters, is close to value 1, it is understood that BIST-100 volatility clustering occurs and volatility has a lasting effect in this market. ϕ_{22} and δ_{22} parameters expressing continuity of NATURAL GAS ($) volatility are statistically significant at 1% significance level, besides, as the 0.98 value, which is the sum of these coefficients, is close to value 1, it is seen that NATURAL GAS ($) volatility clustering occurs and volatility has a lasting effect in this market. On the other hand, ϕ_{12} parameter expressing the presence of interaction from NATURAL GAS ($) volatility to BIST-100 volatility is statistically significant at 1% level and δ_{12} parameter at 1% level. Accordingly, 1% shock, which increases volatility in NATURAL GAS ($), increases BIST-100 volatility at the level of 0.01%. In the presence of volatility interaction from BIST-100 volatility to NATURAL GAS ($) volatility, since both ϕ_{21} and δ_{21} parameters are statistically insignificant parameters at 5% significance level, there is no volatility relationship from BIST-100 index to NATURAL GAS ($). Considering the volatility relationship of BIST-100 and NATURAL GAS ($), it can be said that there is a one-way volatility relationship and transfer from NATURAL GAS ($) volatility to BIST-100 volatility. In addition, θ_1 and θ_2 parameters expressing the dynamic correlation relationship between BIST-100 and NATURAL GAS are statistically significant at 1% significance level, and accordingly, there is a positively and not very strong correlation relationship between these returns, besides, it is statistically insignificant depending on time.

4. CONCLUSION

This study aims to examine the volatility structures of Turkish Stock Market in the context of Borsa Istanbul 100 index (BIST-100) and commodity prices in the context of gold, silver, copper, crude oil and natural gas prices as of the period of 2015 January-2019 December, which is the last five-year period over daily closing prices using GARCH model, in other words, volatility interaction and dynamic correlation relationship. There is a positively and not very strong correlation relationship between BIST-100 and all other commodities returns, besides, it is statistically insignificant depending on time.

It was found both positive and negative relations between the variables of commodity prices and stock markets in the literature. Besides, it was not found any significant relationship between variables in some studies. In this study a positive weak relationship was detected between commodity prices and stock markets and thereby revealed that obtained results are compatible with studies in the literature such as Al-Mudhaf and Goodwin (1993), Sadorsky (1999), Reitz and Westerhoff (2007), Boyer and Filion (2007), Nangolo and Musingwini (2012), Arouri and Rault (2012), Mensi et al. (2013), Hamma et al. (2014), Gyasi (2016), De Nicola et al. (2016), Ibrahim et al. (2018), Oyelami and Yinusa (2019). It is suggested that commodity investments are preferable in portfolio and risk management owing to low relationship between stock markets and commodity prices

Besides all these evaluations, it is possible to conclude that the volatility between the BIST-100 index and commodity prices has constant effects and a comprehensive volatility clustering arises.

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