International Journal of Energy Economics and Policy

ISSN: 2146-4553

available at http: www.econjournals.com

International Journal of Energy Economics and Policy, 2025, 15(3), 37-46.

Investigating the Impact of Energy Price Volatility on Borsa Istanbul Chemical Petroleum Plastic Index Returns[#]

Serkan Yilmaz Kandir[1]*, Gozde Elbir Mermer[2]

[1]Department of Business Administration, Faculty of Economics and Administrative Sciences, Cukurova University, Balcali, Adana, Türkiye, [2]Institute of Social Sciences, Cukurova University, Balcali, Adana, Türkiye. *Email: skandir@cu.edu.tr

Received: 11 December 2024 **Accepted:** 20 March 2025 **DOI:** https://doi.org/10.32479/ijeep.19201

ABSTRACT

The study aims to investigate the impact of coal and electricity price volatility on Borsa Istanbul (BIST) chemical petroleum plastic index (CPPI) return. Sample of the study spans from August 2009 to December 2020. In this study, volatility in electricity and coal prices are modeled with autoregressive conditional heteroscedasticity models. In the regression model including the BIST CPPI return, it is investigated whether the electricity and coal price volatility coefficients are statistically significant. When we examine the models showing the impact of electricity and coal volatility on BIST CPPI return, we conclude that the electricity and coal price volatility coefficients are statistically insignificant.

Keywords: Volatility, Autoregressive Conditional Heteroscedasticity Models, Coal Prices, Electricity Prices, Index Return
JEL Classifications: C58, G10, Q41

This study is generated from the PhD thesis entitled "Investigation of the Effect of Energy Price Volatility on Share Returns of Borsa Istanbul Companies" accepted by the Institute of Social Sciences of Çukurova University on June 7, 2023.

1. INTRODUCTION

With the advancement of science and technology, energy is used in all aspects of life such as agriculture, industry, public services, transportation and all industries (Koç and Şenel, 2013, p.41). In the International Energy Agency's report which is entitled Turkey 2021 Energy Policy Overview, it is stated that electricity energy constitutes the third place energy resource after oil and natural gas in total energy consumption in 2018 (IEA, 2021). The manufacturing industry is the most energy consuming industry. When the industry is considered, the chemical industry has a significant place both in production and in foreign commerce. Because it is a branch of industry that provides intermediate goods and raw materials to many industries (Republic of Turkey Ministry of Trade, 2021, p.1).

Energy prices are the most volatile among all commodity prices. The volatility in energy prices has economic and financial effects (Omisakin et al., 2009, p.207). The impact of energy price volatility is reflected in production costs and this also affects production (Aminu, 2019, p.487). It is assumed that the change in production affects the stock prices of companies (Acaravcı et al., 2012, p.1646). Furthermore, the impact of the change in energy prices on stock prices varies depending on whether companies are producers or consumers of that energy resource (Huang et al., 1996, p.5). Risk is modeled using various volatility models. This situation is very significant for investors to evaluate the risks that may occur in the future, as well as to compare their gains and losses. Volatility is investigated both in international research and in studies and in studies that focus on domestic Turkish market and various econometric models are widely used for modeling volatility. The measurement of volatility is a significant issue for market predictability. The majority of studies in this field employ Autoregressive conditional heteroscedasticity (ARCH)-GARCH models (Gürbüz and Şahbaz, 2022, p.322).

In this study, BIST chemical petroleum plastic industry which is one of the manufacturing subsectors of Borsa Istanbul, is selected as sample. In the literature, there are limited number of studies analyzing the impacts of volatility in electricity and coal prices on the BIST chemical petroleum plastic index (CPPI) returns. Therefore, the impact of volatility in electricity and coal prices on the BIST CPPI returns is investigated in the study.

The rest of the paper is organized as follows. The literature is summarized in Section 2. Data and methodology are explained in Section 3. Empirical findings are reported in Section 4. Section 5 concludes the paper.

2. LITERATURE REVIEW

In the literature, there are a limited number of studies analyzing the impacts of volatility in electricity and coal prices on the BIST CPPI returns. In these studies, the impact of energy price volatility on stock returns is analysed by using various methods. The significant findings from these studies are summarized below.

Hadsell et al. (2004) analyze electricity wholesale price volatility using the TARCH model. The study includes five United States markets (California-Oregon Border, Palo Verde, Cinergy, Entergy, and Pennsylvania-New Jersey-Maryland). Daily data is used, covering the period from May 1996 to September 2001. Negative and statistically significant results are obtained for these five markets. Serletis and Shahmoradi (2006) employ the multivariate GARCH-M model to measure the volatility of natural gas and electricity prices in their study. Sample period spans from January 1, 1996 to November 9, 2004. Findings reveal that there is a bidirectional causality relationship between natural gas and electricity prices. Regnier (2007) investigates oil and energy prices volatility for the period January 1945 to August 2005. The standard deviation of price differences is used to measure volatility. Results suggest that crude oil, refined oil, and natural gas prices are more volatile compared to other products produced in the United States. Aydın (2010) tests the Turkish electricity price volatility using ARCH, GARCH, EGARCH, TGARCH and PGARCH models in his study. Sample period spans from August 1, 2006, to December 31, 2008. Hourly prices are included in the analysis. Results indicate that the best model explaining electricity price volatility is EGARCH.

Efimova and Serletis (2014) measure the volatility in the United States energy markets (crude oil, natural gas and electricity) for the period January 2, 2001, to April 26, 2013. The univariate and multivariate GARCH model is applied in the study. Results show that there is a significant level of interaction between these three markets. Diaz et al. (2016) investigate the effect of the change in oil price volatility (WTI-West Texas Intermediate and Brent oil) on the G7 countries stock returns (France, Canada, Germany, Japan, Italy, USA and the United Kingdom). Monthly data is used for the period January 1970 to December 2014. The GARCH (1, 1) model is used to define the time series of oil price volatility of each country. In order to determine the impact of oil price volatility on stock returns, the unconstrained VAR model is applied, which includes the variables (interest rate, industrial production index, share prices and oil price volatility). Findings reveal that global oil price volatility has a more significant effect on local stock markets than local oil price volatility and this effect differs between oil exporting and importing countries.

Saltik et al. (2016) examine the volatility of crude oil (WTI-West Texas Intermediate) and natural gas (Henry Hub) prices. They considered two periods: January 2009 to April 2014 and January 2010 to April 2014. The analysis is performed using the GARCH model and its versions (IGARCH, GJGRACH, EGARCH, FIGARCH, FIAPARCH). The findings show that there is a high level of volatility in both crude oil and natural gas series. Ulusoy and Özdurak (2018) test the impact of oil price volatility on selected companies (Exxon Mobil Company, Chevron Company, ConocoPhillips and Hess Companies) and currencies (Turkish Lira [TRY], Mexican Peso [MXN] Russian Ruble [RUB] and Dollar Index [DXY], Canadian dollar [CAD], Euro [EUR], Swiss Franc [CHF], British Pound [GBP], Japanese Yen [JPY]). Sample period spans from September 15, 2008, to February 9, 2017. The GARCH model, Exponential GARCH (EGARCH-Exponential GARCH) model and Granger causality test are employed. Findings indicate that the impact of oil prices volatility is permanent in the stock prices of the companies. Ciarreta et al. (2020) examine the electricity price volatility in Spain by taking into account renewable energy regulations and the structural breaks. The period from January 7, 2002, to December 31, 2017, is selected and the GARCH model is applied. As a result of the study, two structural breaks are detected. The first is the abolishment of the tariff guarantee, and the other is the establishment of a market-focused regulation based on investment and operating costs. Additionally, findings reveal that stable regulatory policies reduce volatility.

Marwanti and Robiyanto (2021) investigate the impacts of oil and gold price volatility on stock returns in Indonesia during both the pre-Covid-19 outbreak and the outbreak period. The GARCH (1, 1) model is used. The analysis is continued by estimating the regression model to determine whether oil and gold price volatility has an impact on stock returns. Findings indicate that pre-Covid-19 outbreak and the outbreak period, oil and gold price volatility do not have an impact on stock returns. Joo and Park (2021) study the impact of oil price volatility on stock returns. Ten oil importing countries (China, Fansa, Germany, India, Italy, Japan, Korea, the Netherlands, Spain and the United States) are included in the sample and sample period spans from May 2007 to December 2019. Quantitative regression model and quantitative on quantitative regression model are employed. Results indicate that oil price volatility has a statistically significant impact on stock returns. Bouazizi et al. (2022), investigate the impact of oil price volatility on stock market returns and exchange rate of oil importing developed countries countries (Japan, Germany and United States of America). Daily data is used and the sample period is between May 20, 1987 and December 9, 2019. ARCH (GARCH, GJR, EGARCH, IGARCH and APARCH) family models and Granger causality model are employed. The appropriate models of oil returns are ARMA (2, 2)-GJR (1, 2) model for Germany and ARMA (2, 2)-GJR (2, 2) model for Japan and the USA. The findings indicate that the conditional variances of stock market returns, oil returns and foreign exchange market returns seem to have a long-term relationship across various countries. Furthermore, results from Granger causality tests reveal a significant effect of oil price volatility on the majority of foreign exchange markets and stock markets.

Ofori-Boateng et al. (2022), investigate the impact of fluctuations and volatility of five globally traded commodities prices (coffee cocoa, cotton, gold and oil) on stock returns on the Ghana Stock Exchange. Daily data is used and GARCH (1, 1) model is employed. The data spans from October 3, 2005, to December 31, 2019. Findings indicate that fluctuations and volatility of commodities' prices have a significant impact on the stock returns. Khan et al. (2023) investigate how oil price volatility affected stock returns during the three major oil wars (1998 Saudi Arabia-Venezuela oil war, 2014-2016 conflict, 2020 Saudi Arabia-Russia oil war) that occurred between October 1991 and June 2020. Oil price volatility is tested with the GARCH model. A vector autoregressive model is used for analysing the relationship between oil price shocks and the stock returns of oil and gas companies. Findings show that oil price volatility has an impact on the stock returns of both oil and natural gas companies.

3. DATA AND METHODOLOGY

The type and sources of the data are presented in Table 1. Electricity price data is derived from the official Energy Market Operating Company website, specifically from the Day Ahead Market section. The sample period spans from August 2009 to December 2020 and monthly observations are used. In addition, coal price data is obtained from the website www.verikaynagi.com. Monthly data on the BIST chemistry petroleum plastic index, one of the Borsa Istanbul industrial subsector indices, and the BIST100 price index are obtained from the FINNET 2000 Plus database.

The BIST100 and Borsa Istanbul industrial subsector index returns are obtained by taking the logarithmic difference using the following formula:

$$R_{i,t} = ln\,(p_{i,t}) - ln\,(p_{i,t-1})$$

$R_{i,t}$: The logarithmic return of index i at the time t

$p_{i,t}$: Closing price of index i at time t

$p_{i,t-1}$: Closing price of index i at time t-1.

After generating the returns for one of the industrial subsectors of Borsa Istanbul the BIST CPPI and BIST100, including electricity prices in the study, the Augmented Dickey-Fuller (1981) (ADF) unit root test and the Kwiatkowski, Phillips, Schmidt, and Shin (1992) (KPSS) test are conducted to test for stationarity for all

Table 1: Data

Data	Data Type	Source
BİST100 price idex	Index	FINNET 2000 Plus
Electricity price	Price	Energy Market Operating Company
Coal price	Price	www.verikaynagi.com
BİST chemical petroleum plastic	Index	FINNET 2000 Plus

variables. When performing unit root tests for the electricity series, the test procedure is implemented as suggested by Dolado et al. (1990). Dolado et al. (1990) unit root test procedure is not applied to the return series because of these series are trend-free. After the stationarity tests, ARCH models (ARCH, GARCH, EGARCH and TGARCH) are used to model the electricity price volatility.

Engle introduced the ARCH process in his article published in 1982. The ARCH (q) model is as follows (Engle, 1982, p.994):

$$Y_t = a + b'X_t + \varepsilon_t \quad Y_t|I_{t-1} \ \square\ N\,(b'X_t, h_t)$$

$$h_t = \alpha_0 + \alpha_1\varepsilon^2_{t-1} + \alpha_2\varepsilon^2_{t-2} + \ldots + \alpha_q\varepsilon^2_{t-q}$$

$$h_t = \alpha_0 + \sum_{i=1}^{q}\alpha_i\varepsilon^2_{t-i}$$

In the equation above, t represents the time index; Y_t, the conditional mean; h_t, the conditional variance; I_{t-1}, the information set including all the information at time t-1; X_t, the vector of independent variables;α and α_0 constant values; α_i, the ARCH effect on the conditional variance; b, the parameter vector; ε_t, the error term; q, symbolizes the lag length of the error term squares. In this study, the ARCH effect is tested with the Ljung and Box (1978) Q test statistic before applying the ARCH model.

The GARCH model was developed by Bollerslev (1986). In the GARCH (p,q) model, "p" represents the lag of conditional variance, and "q" indicates the number of lagged squared errors. In general, a GARCH (p,q) process is represented as follows (Bollerslev, 1986, p. 309):

$$Y_t = a + b'X_t + \varepsilon_t \quad \varepsilon_t|I_{t-1} \ \square\ N\,(0, h_t)$$

$$h_t = \alpha_0 + \sum_{i=1}^{q}\alpha_i\mu^2_{t-i} + \sum_{j=1}^{p}\beta_j h_{t-j}$$

The ARCH effect on the conditional variance is represented by α_i.β_j symbolizes the GARCH effect on the conditional variance. h_{t-j}, denotes the lagged conditional volatility.

The Exponential GARCH (EGARCH) model, which models the leverage effect, was developed by Nelson (1991) and is represented as follows (Asteriou and Hall, 2007, p. 268):

$$\varepsilon_t\,|I_{t-1} \ \square\ N\,(0, h_t)$$

$$ln\left(h_t\right) = \alpha_0 + \sum_{i=1}^{q}\alpha_i\frac{|\varepsilon_{t-i}|}{\sqrt{h_{t-i}}} + \sum_{i=1}^{q}\tilde{a}_i\frac{\varepsilon_{t-i}}{\sqrt{h_{t-i}}} + \sum_{J=1}^{p}\beta_j ln\left(h_{t-j}\right)$$

This equation is in log-linear form for the conditional variance. α_0, α_i.β_j and γ_i are the parameters to be estimated. The γ parameter measures the leverage effect (Enders, 2015, p.156). β symbolizes the persistence of shocks for the conditional variance.

The Threshold ARCH (TGARCH) model was developed by Glosten et al. (1993) and Zakoian (1994) examines how positive and negative shocks affect conditional variance, as in the EGARCH model. The Dt-i, in the model denotes the dummy variable. If $\varepsilon_{t-i} < 0$, then Dt-i = 1. If $\varepsilon_{t-i} \geq 0$, then Dt-i = 0 (Enders, 2015, p.156). The representation of the TGARCH model is as follows:

$$h_t = \alpha_0 + \sum_{i=1}^{q}\left(\alpha_i \varepsilon_{t-i}^2 + \gamma_i \varepsilon_{t-i}^2 D_{t-i}\right) + \sum_{j=1}^{p}\beta_j h_{t-j}$$

The regression model that estimates the impact of volatility in electricity and coal prices on BIST chemical petroleum plastic returns is as follows:

$$R_{i,t} = a + b_1\hat{h}_{t(\text{electricity})} + b_2\hat{h}_{t(\text{coal})} + b_3 R_{BIST100,t} + \varepsilon_{i,t}$$

$R_{i,t}$, represents i index return in period t; a, the constant term; b, the regression coefficients of the independent variables; $\hat{h}_t$, the volatility variable in the predicted GARCH model; $R_{BIST100,t}$, represents BIST100 index return in period t and $\varepsilon_{i,t}$, represents the error term. After creating regression models, a normality test is conducted. The dummy variables to be added to the model are determined by examining the standardized residuals. After the dummy variables are created by examining the standard errors of the model are also included in the model, the model are also retested with the normality test. After the model estimation, diagnostic tests such as the Normality test (Jarque and Bera, 1987), Heteroskedasticity test (Breusch-Pagan, 1979; Godfrey, 1978), Ramsey Reset test (Ramsey, 1969), and Autocorrelation test (Ljung and Box, 1978) are employed to test the validity of the model.

4. EMPIRICAL FINDINGS

Table 2 shows the unit root test results for the series used in the study. Since unit root tests are performed with return series, intercept and none models are tested. The ADF test results for the return variables (ΔLNCPPI and ΔLNBIST100) indicate that the returns come from a stationary process. The KPSS test results also show that the returns come from a stationary process. When conducting unit root tests for the electricity and coal series, the test procedure recommended by Dolado et al. (1990) is followed.). Dolado et al. (1990) unit root test procedure is not applied to the return series because these series are trend-free.

The trend and intercept model are estimated in the ADF unit root test for the logarithmic electricity price series (LNELECTRICITY).

Table 2: Unit root test results for the return series

Series	Model	ADF	KPSS
		τ	LM
ΔLNBIST100	Intercept	−12.05362***	0.114433
	None	−11.90478***	
ΔLNCPPI	Intercept	−11.86161***	0.071879
	None	−11.41201***	

The symbol Δ denotes the differencing operator. The SIC information criterion is used to determine the lag length, allowing for a maximum of 12 lags. ***, **, and * indicate that the null hypothesis is rejected at the 1%, 5%, and 10% significance levels, respectively

Since the probability value of the trend is 0.0000 < 0.05, the null hypothesis is rejected and concluding that this series contains a deterministic trend (Table 3).

The process of logarithm of the coal series (LNCOAL) is tested for including a stochastic trend and deterministic trend, following the procedure suggested by Dolado et al. (1990). The test result, using the θ_3 distribution table, indicates that there is no deterministic trend in the model. Then, while a stochastic trend exists, it is tested whether there is also a drift using the θ_1 distribution table (Table 4). When the obtained result is evaluated according to the 10% significance level, the hypothesis is rejected and tested with the standard normal distribution (z). As a result of the test, it is determined that the LNCOAL series came from a process involving a stochastic trend. When the obtained result is evaluated according to the 5% significance level, the hypothesis could not be rejected and the none model is tested. It is determined that the series comes from a process containing a stochastic trend. The difference of the logarithmically transformed coal series (ΔLNCOAL) is then calculated. As a result of the ADF test for LNCOAL, it is determined that the series come from a stationary process. The KPSS test for the intercept model also indicates that the series is stationary.

4.1. Modelling The Electricity Price Volatility

The electricity price series and the logarithmically transformed electricity series used in the study are shown in Figure 1. These series exhibit irregular increases and decreases between August 2009 and December 2020. As a result of the unit root tests, the logarithmically transformed electricity series is trend-stationary.

Table 5 shows the results obtained from the regression analysis on the trend and one-lagged LNELECTRICITY series. The results indicate that the model is significant and that there is an ARCH effect in the model. ARCH models are tested for the trend and one-lagged LNELECTRICITY series up to three lags.

When examining Table 6, the most suitable model for the LNELECTRICITY Series is determined based on significant parameters, lower AIC and SIC information criteria, and highest R^2 and Loglikelihood values. It can be observed that the ARCH (1) model is the most appropriate model among the ARCH models tested. The results indicate that there is no autocorrelation problem in the model. The volatility variable (elarch1) is generated from the ARCH (1) model, and the residual series (elresidsq) is obtained.

$$LNELECTRICITY_t = 1.917 + 0.0027t + 0.589LNELECTRICITY_{t-1} + \varepsilon_t$$

$$\widehat{h}_{t(electricity)} = 0.035 + 0.247\varepsilon_{t-1}^2$$

4.2. Modelling The Coal Price Volatility

The coal price series and the percentage (%) increase in coal prices (ΔLNCOAL) are presented in Figure 2. These series exhibit irregular increases and decreases between August 2009 and December 2020. It can be observed that the series showing the percentage (%) change in coal prices fluctuates around a certain mean.

Figure 1: Electricity price series and logarithmic electricity series (LNELECTRICITY)

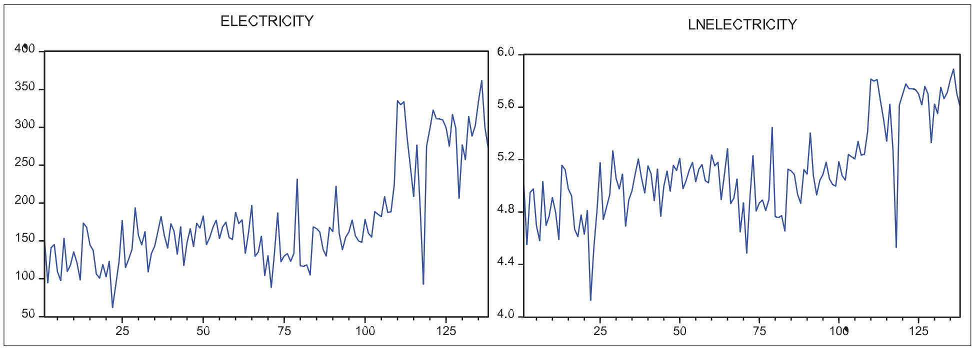


Table 3: LNELECTRICITY series uniıt root results

Series	Model	ADF		KPSS
		τ	Trend	LM
Lnelectricity	Trend and intercept	−7.028806***	TC: 0.003396 t ist.: 5.1409171 (0.0000)	0.236352***

TC represents the coefficient of the trend and t ist. represents the t statistic value of the trend. The value in parentheses shows the probability value of the trend. The SIC information criterion is used to determine the lag length, allowing for a maximum of 12 lags. ***, **, and * indicate that the null hypothesis is rejected at the 1%, 5%, and 10% significance levels, respectively

Table 4: Coal series uniıt root results

LNCOAL				
Model	ADF			KPSS
	τ	ϕ	z	LM
Trend and intercept	−1.886780	1.993681		0.228107***
Intercept	0.115977	4.250766*	0.115977	1.387129***
None	2.926200			
ΔLNCOAL				
Model	ADF			KPSS
	τ			LM
Intercept	−6.717780***			0.143421
None	−5.884386***			

The symbol Δ represents the differencing operator. The SIC information criterion is used to determine the lag length, allowing for a maximum of 12 lags. ***, **, and * indicate that the null hypothesis is rejected at the 1%, 5%, and 10% significance levels, respectively

Table 5: Regression analysis on the series with a trend and one lag of LNELECTRICITY

Variables	Coefficient	Std error	t-statistic	Prob.
Constant	2.491665	0.357059	6.978297	0.0000
Trend	0.003399	0.000661	5.140917	0.0000
$LNELECTRICITY_{t-1}$	0.467394	0.075775	6.168199	0.0000
	R^2=0.617900 F=108.3467 F (Prob.)=0.000000			
Diagnostic test results				
Q (1)	0.3194 (0.572)	Q^2 (1)	5.4757 (0.019)	
Q (4)	4.1296 (0.389)	Q^2 (4)	6.1207 (0.190)	
Q (12)	20.795 (0.053)	Q^2 (12)	10.886 (0.539)	
F_H	1.498610 (0.2272)			
F_R	11.61514 (0.0009)			
χ^2_{JB}	21.26002 (0.000024)			

F_H the heteroscedasticity test statistic, F_R Ramsey Reset test statistic, χ^2_{JB} Jarque-Bera Normality test statistic. Q (1), Q (4) and Q (12) as well as Q^2 (1), Q^2 (4) and Q^2 (12) are the calculated values for the 1st, 4th, and 12th lags of errors and squared errors, respectively. The values in parentheses indicate the probability (prob.) values

The results of the regression analysis on the one-lagged ΔLNCOAL series in Table 7 indicate that the model is significant and that there is an ARCH effect in the model. ARCH models are tested for the one-lagged ΔLNCOAL series up to three lags.

When Table 8 is examined, we find that the TGARCH (1, 1) model has the smallest information criteria (AIC and SIC) and the highest loglikehood value. In addition, the coefficient is obtained as negative in the TGARCH table. However, when we examine the coefficients once at a time, it is observed that these coefficients do not make the variance negative within the sample interval. Therefore, it is determined that the TGARCH model is the most appropriate model. Consequently, the volatility variable (carch1 series) is created and the series express as the square of the errors and tried to be estimated (cresidsq series) is obtained. These series are demonstrated in Figure 3.

$$\Delta LNCOAL_t = 0.68\ \Delta LNCOAL_{t-1} + \varepsilon_t$$

$$\hat{h}_{t(coal)} = 0.00003 + 0.68 + 0.50 - 1.16\varepsilon^2_{t-1} D_{t-1}$$

4.3. BIST100 (XU100) Analysis

BIST100 (XU100) price index and BIST100 index return demonstrated in Figure 4. Irregular increases and decreases are observed in BIST100 price index between August 2009 and December 2020. It is observed that the series showing fluctuates around a certain mean in BIST100 return.

4.4. The Impact Of Energy Price Volatility On Borsa Istanbul CPPI Return

BIST chemical petroleum plastic price index (CPPI) and the index return are demonstrated in Figure 5. Irregular increases and decreases are observed in CPPI between August 2009 and December 2020. It is observed that the series showing fluctuates around a certain mean in CPPI return.

Figure 2: Coal price series and the percentage increase in coal price (ΔLNCOAL)

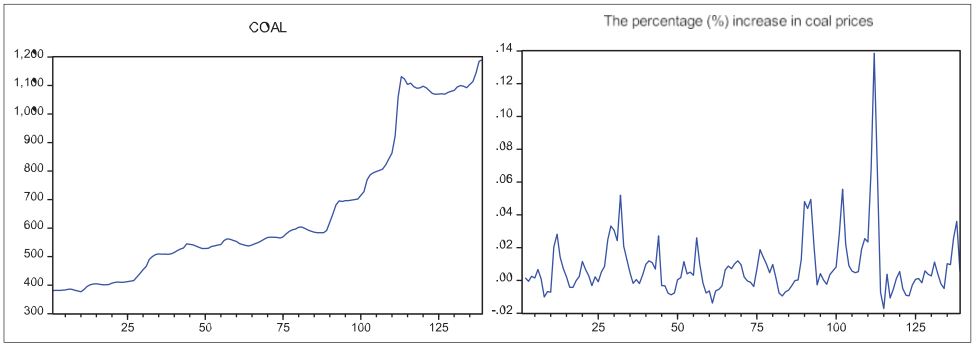


Table 6: ARCH models for LNELECTRICITY series

Variables	ARCH (1)	GARCH (1,1)	EGARCH (1,1)	TGARCH (1,1)
Mean equation				
Constant	1.916998 (0.0000)	1.899545 (0.0000)	2.384922 (0.0000)	2.192054 (0.0000)
Trend	0.002749 (0.0001)	0.002752 (0.0001)	0.003600 (0.0000)	0.003058 (0.0000)
LNELECTRICITY $_{t-1}$	0.588511 (0.0000)	0.591816 (0.0000)	0.486548 (0.0000)	0.530358 (0.0000)
Variance equation				
Constant	0.035439 (0.0000)	0.038356 (0.0114)	−0.922005 (0.0078)	0.017673 (0.1616)
ε_{t-1}^{2}	0.247407 (0.0444)	0.248535 (0.0420)		0.014064 (0.8756)
h_{t-1}		−0.062948 (0.8262)		0.476549 (0.1319)
$\frac{\lvert\varepsilon_{t-1}\rvert}{\sqrt{h_{t-1}}}$			−0.082997 (0.6188)	
$\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}$			−0.363163 (0.0010)	
ln (ht-1)			0.688827 (0.0000)	
$\varepsilon_{t-1}^{2} D_{t-1}$				0.236706 (0.1848)
R^2	0.610496	0.610025	0.610289	0.615888
AIC	−0.203874	−0.189573	−0.201460	−0.177870
SC	−0.097305	−0.061690	−0.057756	-0.028673
Loglikelihood	18.96535	18.98573	21.60586	19.18406
Q (1)	3.1308 (0.077)	3.1139 (0.078)	0.1929 (0.661)	1.3854 (0.239)
Q (4)	5.1434 (0.273)	5.0728 (0.280	3.0470 (0.550)	4.2355 (0.375)
Q (12)	18.702 (0.096)	18.827 (0.093)	18.509 (0.101)	17.061 (0.147)
Q^2 (1)	0.0018 (0.966)	0.0041 (0.949)	0.7342 (0.392)	0.1214 (0.728)
Q^2 (4)	0.7233 (0.948)	0.7483 (0.945)	1.8089 (0.771)	1.1744 (0.882)
Q^2 (12)	5.6961 (0.931)	5.8663 (0.923)	8.6802 (0.730)	7.0838 (0.852)

AIC symbolizes the Akaike Information Criterion, and SC symbolizes the Schwartz Information Criterion. *Q (1)*, *Q (4)* and *Q (12)* as well as Q^2 *(1)*, Q^2 *(4)* and Q^2 *(12)* are the calculated values for the 1st, 4th, and 12th lags of errors and squared errors, respectively. The values in parentheses indicate the probability (prob.) values

Table 7: Regression analysis on one lagged ΔLNCOAL series

Variables	Coefficient	Std error	t-statistic	Prob.
ΔLNCOALt-1	0.709792	0.060428	11.74604	0.0000
Diagnostic test results				
Q (1)	3.9969 (0.046)	Q^2 (1)	18.856 (0.000)	
Q (4)	12.831 (0.012)	Q^2 (4)	29.776 (0.000)	
Q (12)	25.967 (0.011)	Q^2 (12)	32.186 (0.001)	
F_H		36.40501 (0.0000)		
F_R		7.452466 (0.0072)		
χ^2_{JB}		885.8199 (0.000000)		

F_H the heteroscedasticity test statistic, F_R Ramsey Reset test statistic, χ^2_{JB} Jarque-Bera Normality test statistic. *Q* (1), *Q* (4) and *Q* (12) as well as Q^2 (1), Q^2 (4) and Q^2 (12) are the calculated values for the 1st, 4th, and 12th lags of errors and squared errors, respectively. The values in parentheses indicate the probability (prob.) values

Figure 6 shows the standardized errors obtained from the prediction results of the model.

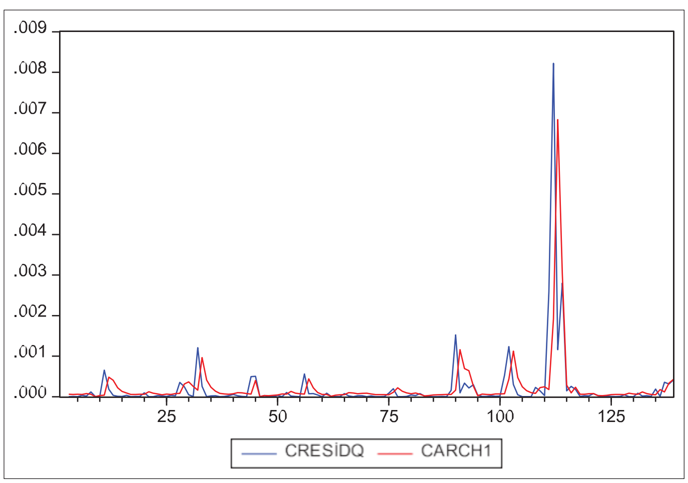
Table 9 demonstrates the results of the regression model. According to the results of the diagnostic tests, regression model is set up correctly. The dummy variables in the model denote the dates of August 2018 and June 2019. Monthly data for the CPPI indicate that there is an increase in August 2018 and a decrease in June 2019. An unexpected increase occurred due to change in electricity prices in August 2018, and the industry was also affected by this uncertainty in energy prices (Afa Energy Consultancy, 2019). In June 2019; there is a 7% increase in the BIST100 index, an 8% increase in the electricity price and a 0.5% decrease in the coal price.

Table 8: ARCH Models for ΔLNCOAL series

Variables	ARCH (1)	GARCH (1,1)	EGARCH (1,1)	TGARCH (1,1)
Mean equation				
$\Delta LNCOAL_{t-1}$	0.786507 (0.0000)	0.331640 (0.0000)	0.684841 (0.0000)	0.676430 (0.0000)
Variance equation				
Constant	8.84E-05 (0.0000)	4.32E-05 (0.0000)	−2.943194 (0.0003)	2.66E-05 (0.0000)
ε_{t-1}^{2}	0.483646 (0.0009)	1.448615 (0.0000)		0.677116 (0.0000)
h_{t-1}		−0.009051 (0.7671)		0.500328 (0.0000)
$\frac{\lvert\varepsilon_{t-1}\rvert}{\sqrt{h_{t-1}}}$			0.094966 (0.3708)	
$\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}$			0.548941 (0.0000)	
ln (ht-1)			0.699168 (0.0000)	
$\varepsilon_{t-1}^{2} D_{t-1}$				−1.163354 (0.0000)
R^2	0.398999	0.235007	0.405293	0.404707
AIC	−6.076051	−6.150302	−6.220622	−6.327904
SC	−6.012110	−6.065047	−6.114054	−6.221335
Loglikelihood	419.2095	425.2957	431.1126	438.4614
Q (1)	1.7270 (0.189)	8.8298 (0.003)	1.9742 (0.160)	1.6855 (0.194)
Q (4)	4.4469 (0.349)	11.033 (0.026)	5.8593 (0.210)	4.1618 (0.385)
Q (12)	17.682 (0.126)	35.905 (0.000)	17.904 (0.119)	17.348 (0.137)
Q^2 (1)	1.4625 (0.227)	0.1710 (0.679)	0.5608 (0.454)	0.0835 (0.773)
Q^2 (4)	2.3621 (0.669)	1.1476 (0.887)	1.2972 (0.862)	1.2896 (0.863)
Q^2 (12)	5.6871 (0.931)	21.155 (0.048)	5.0992 (0.955)	6.6892 (0.877)

AIC denotes the Akaike Information Criterion, and SC symbolizes the Schwartz Information Criterion. *Q (1), Q (4)* and *Q (12)* as well as Q^2 *(1)*, Q^2 *(4)* and Q^2 *(12)* are the calculated values for the 1st, 4th, and 12th lags of errors and squared errors, respectively. The values in parentheses indicate the probability (prob.) values

Figure 3: Pedicted series (Carch1) and predicted the square resid of coal series (Cresidsq)



When we examine the model that demonstrates the impact of the volatility in monthly electricity and coal prices on the BIST chemical, petroleum, and plastic index (CPPI) returns, we find that the coefficients for electricity and coal price volatility are statistically insignificant. In the literature; Park and Ratti (2008), Ulusoy and Özdurak (2018), Joo and Park (2021), Bouazizi et al. (2022), Ofori-Boateng et al. (2022) and Khan et al. (2023) conclude that the volatility in energy prices has an impact on stock returns. Marwanti and Robiyanto (2021) analyzed the impact of oil price volatility on stock returns and found that oil price volatility does not have a significant effect on stock returns.

The finding of insignificant impact of electricity and coal price volatility on stock returns in our study supports the conclusion of Marwanti and Robiyanto (2021) that energy price volatility does not affect stock returns. It does not support the studies conducted by Park and Ratti (2008), Ulusoy and Özdurak (2018), Joo and Park (2021), Bouazizi et al. (2022), Ofori-Boateng et al. (2022), Khan et al. (2023).

The chemical industry provides intermediate goods and raw materials to many industries (Ministry of Trade, 2021, p. 1). The chemical industry is a branch of manufacturing industry that enhances the quality of life, prevents diseases, and contributes to the prevention and treatment of illnesses. Additionally, it plays a vital role in meeting the needs of humanity in clothing and nutrition, as well as addressing the requirements of cleanliness and hygiene (The Republic of Turkey Ministry of Industry and Technology, Chemical Industry, 2021, p. 25). The industrial studies and assessments indicate that the chemical industry was affected by the global economic downturn during the COVID-19 pandemic. However, it is noted that the increased demand for cleaning, hygiene, medical, and packaging products both in Turkey and the world partially express the losses experienced by the chemical industry during the pandemic period (Republic of Turkey Ministry of Industry and Techcnology, Chemical Industry, 2021, p. 59).

According to the balance table for the year 2020 published in the statistics section of the Republic of Turkey Ministry of Energy and Natural Resources, it is observed that approximately 5% of electricity consumption and 5% of coal consumption are carried

Figure 4: BIST100 price index and BIST100 index return

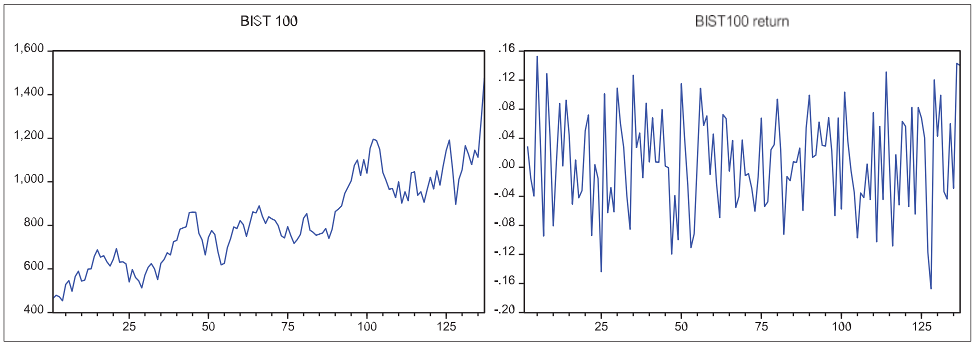


Figure 5*:* CPPI and CPPI return

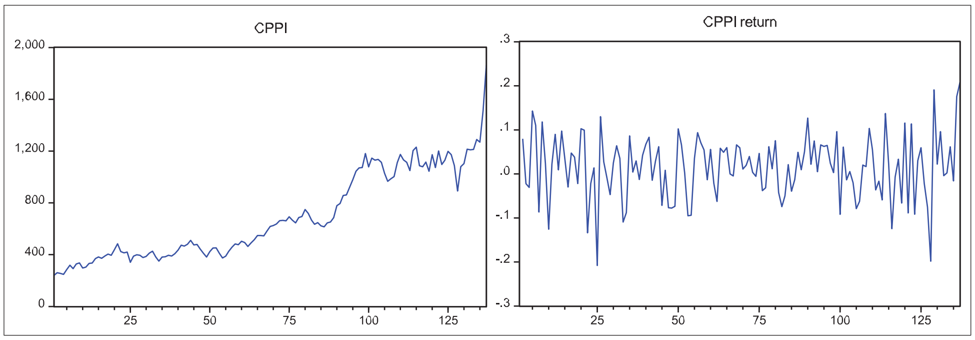
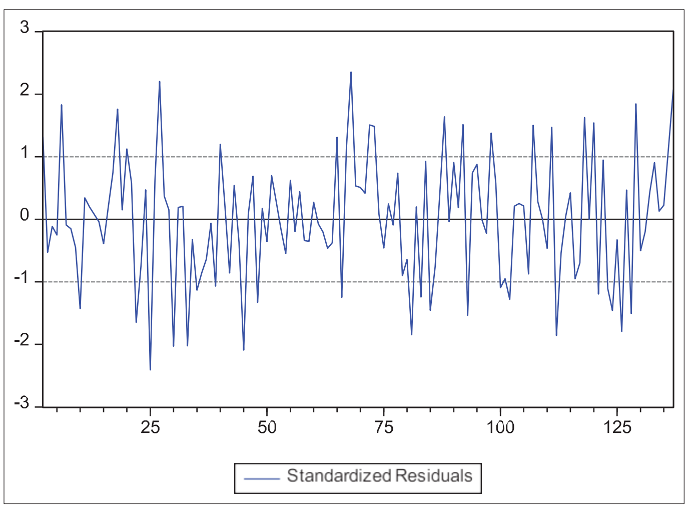


Figure 6: Standardized errors for the BIST chemical petroleum plastic model (Standardized Residual)



out by enterprises engaged in the manufacturing of chemicals, petroleum, and plastics (KPMG, 2020, p.5). The data required for calculating the weights of companies operating in the BIST chemicals, petroleum, and plastics industry in the CPPI is obtained from Borsa İstanbul via email. Using the obtained data, the weights of companies in the BIST chemicals, petroleum, and plastics industry in this index are calculated by the authors. As a result of the calculation, the companies are ranked in terms of their weights in the index. Furthermore, sustainability and activity reports of companies in the index are derived from their websites and the Public Disclosure Platform to review their announcements about topics such as energy consumption, production, and energy conservation.

Table 9: The regression model

ΔLNCPPI				
Variables	**Coefficient**	**Std error**	**t-statistic**	**Prob.**
EPV	0.048641	0.086114	0.564849	0.5731
CPV	1.40E-13	9.53E-14	1.466057	0.1450
ΔLNBIST100	0.913236	0.048371	18.87998	0.0000
$D_{08/2018}$	0.142011	0.037901	3.746910	0.0003
$D_{06/2019}$	−0.142260	0.039167	−3.632148	0.0004
Diagnostic test results				
Q (1)	0.2368 (0.627)	Q^2 (1)		2.2670 (0.132)
Q (4)	2.7933 (0.593)	Q^2 (4)		3.8890 (0.421)
Q (12)	6.2244 (0.904)	Q^2 (12)		11.376 (0.497)
F_H		0.974542 (0.4359		
F_R		0.748460 (0.3886)		
χ^2_{JB}		0.374608 (0.829192)		

EPV: Electricity price volatility, CPV: Coal price volatility, F_H: The heteroscedasticity test statistic, F_R: Ramsey reset test statistic, χ^2_{JB} : Jarque-Bera Normality test statistic. The values in parentheses indicate the probability (prob.) values. August June 2018 and June 2019 dummy variables are symbolized as $D_{08/2018}$ and $D_{06/2019}$, respectively. Q (1), Q (4) and Q (12) as well as Q^2 (1), Q^2 (4) and Q^2 (12) are the calculated Ljung-Box Q test statistic values for the 1st, 4th, and 12th lags of errors and squared errors, respectively

The data for calculating the weights of companies in the BIST chemical, petroleum, and plastic sector within the XKMYA index is acquired from the Borsa Istanbul Data Store. The establishment of a production facility to generate electrical energy, the production of electrical and thermal energy, and the sale of the produced electrical and thermal energy to consumers take place in the scope of the activities of a company ranking third among twenty-nine companies in the BIST chemicals, petroleum, and plastics index with a weight of 11.74%. A company ranking seventh with a weight of 4% in the index specifies that the generated electrical energy meets its own energy needs, and the surplus energy is sold in the market. A company ranking eighth with a weight of 3.89% in the index reveals that it is engaged in electricity production by installing a solar energy system. We assume that index return is not affected by energy price volatility due to the fact that there are electricity generating companies ranking at the top of the index list due their weight in the BIST chemicals, petroleum, and plastics index. Additionally, the chemical industry plays a crucial role in meeting the intermediate and raw material needs of many industries. Therefore, it is important for companies operating in these other industries to ensure smooth operations.

5. CONCLUSION

The price of energy tends to impact all agents of the economy, including households, businesses, and government (Yu et al., 2022, p.1225). Energy is one of the inputs that contributes production and, therefore, is an influential factor on economic growth (Aminu, 2019, p. 487). Energy prices are a significant cost item. Thus, increases in energy prices can affect operating costs. Increases in the costs of companies can affect economic activities and in turn economic activities can affect share prices. (Acaravcı et al., 2012, p.1648).

The aim of this study is to investigate the impacts of volatility in electricity and coal prices on the BIST CPPI returns. After the ADF and KPSS unit root tests, ARCH models (ARCH, GARCH, EGARCH, and TGARCH) are used to model the volatility in electricity and coal prices. Subsequently, a regression model is established to analyze the impact of volatility in electricity and coal prices on the BIST CPPI returns.

When we evaluate the findings from the analysis, we find that the volatility coefficients of electricity and coal prices are statistically insignificant for the BIST CPPI. We assume that companies within this index, that generate their own electricity seem to be less affected by the volatility of energy prices.

As a result of the literature review, we observe a a limited number of studies analyzing the impacts of volatility in electricity and coal prices on the BIST CPPI returns in Turkey. In this manner, this study would contribute to the finance literature. Furthermore, investors would also benefit from the results of the study. This study would serve as a guide for investors to evaluate the impact of energy price volatility on index returns before making any investment decisions. In addition, according to the results of the study, companies producing their own energy needs would be less affected by energy price volatility. Accordingly, we suggest that companies would increase their own energy production to reduce sensitivity to electricity prices. Additionally, while this study focuses on industrial index returns, future research would extend the analysis to individual firms or regional base.

REFERENCES

Acaravcı, A., Ozturk, I., Kandır, S.Y. (2012), Natural gas prices and stock prices: Evidence from EU-15 countries. Economic Modelling, 29(5), 1646-1654.

Afa Energy Consultancy. (2019), Electricity and Natural Gas Price Increases Reflected to Consumers in August 2018. Available from: https://www.afaenerji.com/blog/2019/10/14/agustos-2018-tarihinde-tuketicilere-yansitilan-elektrik-ve-dogal-gaz-zamlari [Last accessed on 2021 Nov 22].

Aminu, N. (2019), Energy prices volatility and the United Kingdom: Evidence from a dynamic stochastic general equilibrium model. Energy, 172, 487-497.

Asteriou, D., Hall, S. (2007), Applied Econometrics. New York: Palgrave Macnillan.

Aydın, K. (2010), Türkiye Elektrik Piyasasında Fiyat Değişimlerinin Analizi. [The Analysis of Price Changes in the Turkish Electricity Market] PhD Thesis, Sakarya: Sakarya University.

Bollerslev, T. (1986), Generalized autoregressive conditional heteroskedasticity. Journal of Econometrics, 31(3), 307-327.

Bouazizi, T., Mrad, F., Hamida, A., Nafti, S. (2022), Effects of conditional oil volatility on exchange rate and stock markets returns. International Journal of Energy Economics and Policy, 12(2), 53-71.

Breusch, T.S., Pagan, A.R. (1979), A simple test for heteroscedasticity and random coefficient variation. Econometrica: Journal of the Econometric Society, 47(5), 1287-1294.

Ciarreta, A., Pizarro-Irizar, C., Zarraga, A. (2020), Renewable energy regulation and structural breaks: An empirical analysis of Spanish electricity price volatility. Energy Economics, 88, 1-11.

Diaz, E.M., Molero, J.C., De Gracia, F.P. (2016), Oil price volatility and stock returns in the G7 economies. Energy Economics, 54, 417-430.

Dickey, D.A., Fuller, W.A. (1981), Likelihood ratio statistics for autoregressive time series with a unit root. Econometrica: Journal of the Econometric Society, 49(4), 1057-1072.

Dolado, J., Jenkinson, T., Sosvilla-Rivero, S. (1990), Co-integration and unit roots. Journal of Economic Surveys, 4(3), 249-273.

Efimova, O., Serletis, A. (2014), Energy markets volatility modelling using GARCH. Energy Economics, 43, 264-273.

Enders, W. (2015), Applied Econometric Time Series. 4th ed. United States of America: Wiley Pres.

Engle, R.F. (1982), Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. The Econometric Society, 50(4), 986-1007.

Glosten, L.R., Jagannathan, R., Runkle, D.E. (1993), On the relation between the expected value and the volatility of the nominal excess return on stocks. The Journal of Finance, 48(5), 1779-1801.

Godfrey, L. G. (1978), Testing for multiplicative heteroskedasticity. Journal of econometrics, 8(2), 227-236.

Gürbüz, S., Şahbaz, A. (2022), Investigating the volatility spillover effect between derivative markets and spot markets via the wavelets: The case of Borsa İstanbul. Borsa Istanbul Review, 22(2), 321-331.

Hadsell, L., Marathe, A., Shawky, H.A. (2004), Estimating the volatility of Wholesale electricity spot prices in the US. The Energy Journal, 25(4), 23-40.

Huang, R. D., Masulis, R. W., & Stoll, H. R. (1996), Energy shocks and financial markets. Journal of Futures markets, 16(1), 1-27.

IEA-International Energy Agency. (2021), Turkey 2021 Energy Policy Review. Available from: https://iea.blob.core.windows.net/assets/cc499a7b-b72a-466c-88de-d792a9daff44/Turkey_2021_energy_policy_review.pdf [Last accessed on 2021 Oct 11].

Jarque, C.M., Bera, A.K. (1987), A test for normality of observations and regression residuals. International Statistical Review/Revue Internationale de Statistique, 55(2), 163-172.

Joo, Y.C., Park, S.Y. (2021), The impact of oil price volatility on stock markets: Evidences from oil-importing countries. Energy Economics, 101, 105413.

Khan, M.H., Ahmed, J., Mughal, M., Khan, I.H. (2023), Oil price volatility and stock returns: Evidence from three oil-price wars. International Journal of Finance and Economics, 28(3), 3162-3182.

Koç, E., Şenel, M. C. (2013), Dünyada ve Türkiye'de enerji durumu genel değerlendirme. [The energy situation general assessment in the world and in Turkey] Mühendis ve Makina, 54(639), 32-44.

KPMG. (2020), Chemistry Industrial Overview. Available from: https://l24.im/02YCFu [Last accessed on 2021 Nov 10].

Kwiatkowski, D., Phillips, P.C.B., Schmidt, P., Shin, Y. (1992), Testing the null hypothesis of stationarity against the alternative of a unit root. Journal of Econometrics, 54(1-3), 159-178.

Ljung, G.M., Box, G.E.P. (1978), On a measure of lack of fit in time series models. Biometrika, 65(2), 297-303.

Marwanti, M.M., Robiyanto, R. (2021), Oil and gold price volatility on indonesian stock market in the period of Covid-19 pandemic. Jurnal Manajemen dan Kewirausahaan, 23(2), 129-137.

Nelson, D.B. (1991), Conditional heteroskedasticity in asset returns: A new approach. Econometrica: Journal of the Econometric Society, 59(2), 347-370.

Ofori-Boateng, K., Agyapong, E.K., Ohemeng, W., Annor, L.D.J. (2022), Commodity price volatility and stock market returns in an emerging economy. International Social Science Journal, 72(244), 321-337.

Omisakin, O., Adeniyi, O., Omojolaibi, A. (2009), A vector error correction modelling of energy price volatility of an oil dependent economy: The case of Nigeria. Pakistan Journal of Social Sciences, 6(4), 207-213.

Park, J., Ratti, R.A. (2008), Oil price shocks and stock markets in the US and 13 European countries. Energy Economics, 30(5), 2587-2608.

Public Disclosure Platform (KAP-Kamuyu Aydınlatma Platformu). Available from: https://www.kap.org.tr/tr [Last accessed on 2021 Jun 10].

Ramsey, J.B. (1969), Tests for specification errors in classical linear least-squares regression analysis. Journal of the Royal Statistical Society: Series B (Methodological), 31(2), 350-371.

Regnier, E. (2007), Oil and energy price volatility. Energy Economics, 29(3), 405-427.

Republic of Turkey Ministry of Energy and Natural Resources - Republic of Turkey Energy Affairs General Directorate. National Energy Balance Tables. Available from: https://enerji.gov.tr/eigm-raporlari [Last accessed on 2022 Nov 21].

Republic of Turkey Ministry of Industry and Technology. (2021), Chemical Industry Report 2022. Available from: https://www.sanayi.gov.tr/plan-program-raporlar-ve-yayinlar/sektor-raporlari/mu0111011413 [Last accessed on 2021 Oct 10].

Republic of Turkey Ministry of Tarde. Chemical Industry. (2021), Available from: https://www.sanayi.gov.tr/plan-program-raporlar-ve-yayinlar/sektor-raporlari/mu0110011408 [Last accessed on 2021 Nov 10].

Saltik, O., Değirmen S., Ural, M. (2016), Volatility modelling in crude oil and natural gas prices. Procedia Economics and Finance, 38, 476-491.

Serletis, A. & Shahmoradi, A. (2006), Measuring and testing natural gas and electricity markets volatility: Evidence from Alberta's deregulated markets. Studies in Nonlinear Dynamics & Econometrics, 1-18

Ulusoy, V., Özdurak, C. (2018), The impact of oil price volatility to oil and gas company stock returns and emerging economies. International Journal of Energy Economics and Policy, 8(1), 144-158.

Yu, X., Li, Y., Shen, X., Rao, Y., Liu, Y. (2022), State-dependent hedge strategy for crude oil spot and futures markets. Borsa Istanbul Review, 22(6), 1221-1237.

Zakoian, J.M. (1994), Threshold heteroskedastic models. Journal of Economic Dynamics and control, 18(5), 931-955.